Road congestion and public transit

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Abstract – We propose a novel approach to estimate the marginal external congestion cost of motor vehicle travel and associated welfare losses, while allowing for hypercongestion, i.e. when the road supply curve is backward bending. We apply this approach to the city of Rome, using quasi-experimental variation in public transit supply to address endogeneity issues. We find that the marginal external cost of travel is substantial. Although hypercongestion is rare in our data, it accounts for about 30 percent of congestion-related welfare losses. We demonstrate that the marginal congestion-relief benefit of public transit supply is sizeable and approximately constant over the full range of public transit supply levels. These results suggest that substantial welfare gains can be obtained not only by introducing road pricing, but also by adopting quantity-based measures (e.g. adaptive traffic lights) to avoid hypercongestion. Our study also supports the introduction of separate lanes for buses, as we show that road congestion has a strong effect on travel time delays of bus travelers.

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1. Introduction

Road congestion is a major issue in cities throughout the world. To deal with this problem, policymakers have several options, including road tolls, quantity-based restrictions (e.g. road-plate rationing), subsidized public transit supply and transport infrastructure expansion. None of these options comes at a low cost. Tolls, fuel taxes, and quantity restrictions are politically controversial (Parry and Small, 2005; Small and Verhoef, 2007), while transit supply and infrastructure expansions are expensive (Parry and Small, 2009; Duranton and Turner, 2011). It is therefore important to know how large the welfare losses that we can avoid by adopting these policies are. Yet, quite surprisingly, we still know very little about the costs of congestion in cities.

The main objective of this paper is to measure the welfare losses of road congestion in large cities. We estimate these losses based on traffic observations from a wide set of roads in Rome, the Italian capital. We quantify the marginal external costs and the deadweight losses of congestion on motor vehicle travelers. We also estimate the costs of congestion on bus travelers, who constitute a substantial share of the travel market in Rome. Finally, we evaluate the effectiveness of public transit supply as a tool to alleviate road congestion.

Evaluating the welfare losses of congestion is conceptually simple, but estimating them is far from trivial. Estimation requires knowledge of the relation between travel (time) costs and traffic flow (the 'road supply curve'). However, the supply relation on heavily congested roads is backward bending, a phenomenon which is labelled as *hypercongestion* (Arnott and Inci, 2010; Arnott, 2013). Hence, this relation cannot be estimated using standard econometric techniques. Keeler and Small (1977) address this issue by estimating travel time as a function of flow and then inverting the estimated function. We improve upon their methodology by following a transportation science literature which estimates the effect of vehicle density on travel time and then derive the travel time-flow relation by applying fundamental identities (for an overview, see Hall, 1996).[1] The latter literature estimates the causal effect of density on travel time without accounting for endogeneity issues. Common unobservable shocks, e.g. road accidents, may affect density and travel time simultaneously, producing an omitted variable bias. More fundamentally, density is the product of flow and travel time. Hence, any measurement error in travel time induces a positive correlation with density. The first contribution of this paper is to deal with the issue of hypercongestion, while proposing an instrumental variable approach to account for the endogeneity in the relation

[1] In a dynamic model of congestion, Henderson (1974) also models travel time as a function of density, measured as the quantity of commuters on a road at a given time. See also Henderson (1981).

between travel time and density. We exploit changes in public transit supply in Rome, due to labor strikes, as an instrument for density.

A second important contribution of our paper is that we employ our road supply estimates to quantify the marginal external cost of congestion and the resulting deadweight losses, while explicitly accounting for hypercongestion. We find that these losses are substantial. Furthermore, although hypercongestion is present in only about 2 percent of the observations, we find that about 30 percent of the welfare losses of congestion are due to hypercongestion alone. We show that the welfare losses due to travel delays in the presence of hypercongestion, are an order of magnitude – about 50 times – higher than the welfare losses realized when on the equilibrium lies on the upward-sloping part of the road supply curve. These results suggest that policy interventions to curb congestion, such as road pricing, can bring to significant welfare gains. However, even if pricing is unavailable (for instance due to political constraints), it may be possible to achieve large gains just by removing hypercongestion, for example by adopting traffic management measures such as adaptive traffic lights (Kouvelas et al., 2017).

We argue that a complete analysis of the costs associated with road congestion ultimately requires considering how *all* road users are affected. Congestion will not only impose travel time losses on motor vehicle travelers but also on bus travelers. Accordingly, we estimate the costs of congestion on bus users. In cities such as Rome, where buses are the mainstay of the transit system and rarely travel on dedicated corridors, these costs are potentially large. We show that the marginal external cost on bus travelers is substantial and that about one third of the welfare losses due to motor vehicle congestion are borne by bus travelers. These results are important not only because existing literature typically ignores the effect of motor vehicle congestion on bus travelers, but also because it delivers clear policy implications. Specifically, our results provide an economic foundation for traffic management interventions such as the design of separate bus lanes (see, e.g., Basso and Silva, 2014).

Having established that congestion produces non-negligible welfare losses, we turn our attention to one of the most commonly advocated remedies: the provision of (subsidized) public transport. In Rome, as in many other cities, public transport subsidies are large, especially given the relatively limited modal share of transit.[2] Yet, little is known about the

[2] In most OECD countries, subsidies to public transit range from 30% to 90% of operating costs (USDOT, 2011, Kenworthy and Laube, 2001). In Rome, similarly to other European cities, around 28% of total passenger-kms are taken by transit. In the US, public transit carries less than 1% of passenger kilometers, but receives about 25% of all transit funding (USDOT, 2011). Despite this, political support for subsidies is substantial (Cummings and Manville, 2015).

congestion-relief benefit of public transit – i.e., the reduction in motor vehicle and bus travel times due to the provision of public transit services. We follow a recent literature that uses a quasi-experimental approach exploiting shocks in transit supply due to labor strikes, but we propose two fundamental data novelties. First, we observe strikes that vary at the *intensive* margin. Specifically, we have information about hourly reductions in public transit supply during strikes (in vehicle kilometers), which allows us to estimate the *marginal* congestion relief benefit of public transit. This is relevant because policy decisions typically focus on marginal transit supply changes, whereas complete shutdowns are an uncommon policy option. Second, we estimate the congestion relief benefit to motor vehicle – car and motorcycle – travelers, as well as to bus travelers.

We show that the *marginal* congestion benefit of public transit supply is sizeable and approximately constant over the full range of public transit supply levels. Nevertheless, it appears that the *total* congestion relief benefit is moderate. This suggests that there is room for a range of policies that reduce congestion (e.g., bus lanes, increase in parking prices) to increase the efficiency of transport. We show that bus travelers benefit several times more than motor vehicle travelers from a marginal reduction in road congestion.[3]

Our work relates to different strands of literature. Regarding the welfare losses of congestion, numerous papers measure the relationship between travel time (or speed) and traffic flow at the level of single roads (see Small and Verhoef, 2007, for an overview), but none addresses the fundamental endogeneity issue discussed earlier. Furthermore, most papers rely on limited samples of roads to quantify the marginal external congestion costs and the welfare losses in a city.[4] In recent work, Couture et al. (2016) estimate aggregate travel supply relations for a large sample of North American cities. Akbar and Duranton (2016) estimate travel supply and demand relationships at a citywide level for Bogotà, exploiting travel surveys and Google Maps data. Our work is complementary to theirs. We adopt a disaggregate framework that measures costs at the level of single roads. Our approach may be less representative of travel costs at a wide area level, for example because it does not account for the possibility that drivers avoid heavily congested roads by taking detours. On the other hand, our approach provides a more fine-grained view of congestion costs at the street level. We show that, even though heavy congestion may be locally concentrated (e.g., because only

[3] Strong reductions in travel time for public transit travelers result through reductions in road congestion is in line with the study by Small (2004).

[4] Geroliminis and Daganzo (2008) use similar road level data to estimate a speed-density curve for the city of Yokohama. They do not focus on estimating external costs and welfare losses.

a few roads are jammed at a certain moment), the implied welfare losses it produces are relevant in the aggregate.[5]

The standard way of measuring of the marginal external cost uses directly postulates a relationship between travel time and flow in order to derive the optimal road tax, as suggested by Pigou (1920). We demonstrate that this way of measuring the marginal external costs provides a severe underestimate and is, thus, not informative about the optimal road tax given hypercongestion. This observation is noteworthy because the latter (Pigouvian) measure is still frequently used in the academic literature (e.g., Mayeres et al., 1996), in authoritative reports by the US Federal Highway Administration (e.g., FHWA, 1997) and in much-cited handbooks (e.g., Maibach et al., 2008). We believe we are the first empirical study which estimates the marginal external cost of flow while acknowledging that travel time is a function of density. Our paper also contributes to the literature on the costs of congestion by providing evidence on the spillover effects of congestion on bus travelers. To our knowledge, we are the the first to provide this sort of evidence for a whole city.

Our paper also belongs to a growing literature that aims to evaluate the congestion relief benefit of public transit. Focusing on different cities, Anderson (2014), Adler and van Ommeren (2016), and Bauernschuester et al. (2016), have used quasi-experimental approaches exploiting transit strikes, showing that the congestion-relief benefit is significant.[6] We contribute to this literature by analyzing the marginal effects of partial service shutdowns. Furthermore, by measuring the travel time losses of congestion for bus users, we evaluate the congestion-relief benefit also on transit users themselves.

Finally, in a broader perspective, our paper contributes to a diverse literature estimating the importance of transport externalities and the effects of transport policy. Davis (2008) analyzes the effects of driving restrictions on air quality. Chay and Greenstone (2005) examine the social costs of air pollution, including transport-related emissions. Duranton and Turner (2011; 2012; 2016) and Duranton et al. (2014) examine the consequences of highway expansion for congestion, city growth and trade and the effects of urban structure on driving and congestion externalities. Baum-Snow (2010) demonstrates the effect of highway expansion on commuting flows. Anderson and Auffhammer (2013) examine car weight

[5] Akbar and Duranton also devise a strategy to deal with endogeneity issues, based on reconstructing trip counterfactuals. We tackle this problem differently (see above).

[6] Using aggregate numerical models, Nelson et al. (2007) and Parry and Small (2009) find that during peak hours subsidies in excess of 90% of operating cost are justified for Washington D.C., Los Angeles and London. Börjesson et al. (2015) show that, despite the adoption of road tolls, substantial subsidies are still welfare enhancing in Stockholm.

externalities. Other papers have looked at housing externalities (e.g., Rossi-Hansberg et al., 2010) and economies of density (Ahlfeldt et al., 2015). Combes and Gobillon (2015) survey the literature on agglomeration externalities.

The paper proceeds as follows. In section 2, we introduce the theory that underlies our empirical identification strategy. Section 3 presents the empirical models to estimate the marginal external costs of motor vehicle travel as well as the congestion relief benefit of transit. We then characterize Rome's transportation market in section 4 and describe the data. Section 5 provides our main results: the marginal external cost of motor vehicle travel on motor vehicle and bus travelers as well as the effect of public transit supply on motor vehicle travel time.[7] In section 6, we examine the welfare effects of public transport subsidies while adjusting public transit supply. Section 7 concludes.

2. Theoretical background

We develop a simple theoretical framework to guide the estimation of the road supply curve, the marginal external cost of congestion and the ensuing welfare losses, as well as the congestion relief benefit of public transit supply. We consider an isotropic road in a stationary steady-state. Private motor vehicles (cars and motorbikes) share the road with buses. Individuals choose whether to travel and which mode to use depending on generalized travel costs. Road congestion affects the travel time of motor-vehicle travelers T – as well as of bus travelers T^{PT}.

2.1 The road supply curve

We first focus on the road supply curve. In line with the transport engineering literature (e.g. Helbing, 2001), we assume that travel time T is an increasing and convex function of the *density* of motor vehicles on the road, D:

(1) $$T = h(\mathrm{D}),$$

where $\partial T/\partial D > 0$.[8] Using (1) and the fact that density is defined as $D = FT$, where F denotes the flow of motor-vehicle travelers, we find:

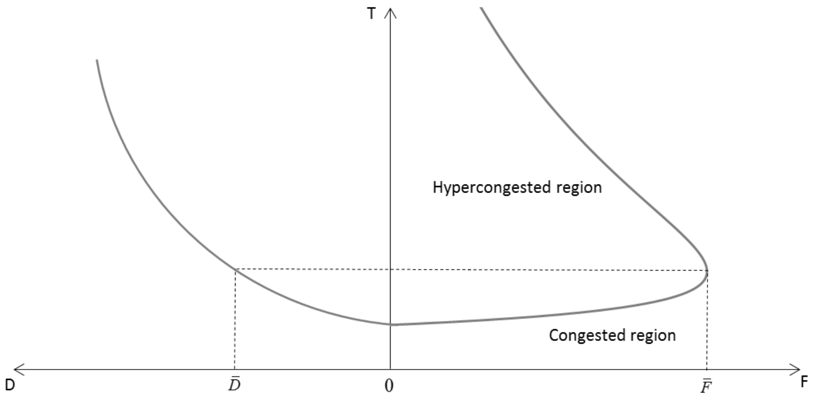
[7] We also discuss some other results (reported in appendix) including: the effect public transit fares on motor vehicle travel time as well as flow, the effect of public transit supply on motor vehicle flow as well as the relationship between motor vehicle travel times and bus travel times.

[8] For the moment, we ignore that motor vehicle travel time depends directly on the number of buses. We account for this effect in the empirical analysis.

(2) $$\frac{dT}{dF} = \frac{\frac{\partial h(D)}{\partial F}}{1 - \frac{\partial h(D)}{\partial T}} = \frac{\frac{\partial T}{\partial D}T}{1 - \frac{\partial T}{\partial D}F},$$

which describes the relationship between T and F.[9] To understand this relationship, note that when density is zero, flow is zero as well. Higher density raises travel time and, given (2), flow if $\partial T/\partial D < 1/F$. However, as density increases, the point where $\partial T/\partial D > 1/F$ is reached, so $dT/dF < 0$ and $dF/dD < 0$.[10] Greater density of vehicles has a positive direct effect on flow, but a negative indirect effect because vehicles travel at lower speed. When the latter dominates, the travel time-flow relationship bends backwards, and there is *hypercongestion*. Figure 1 provides an illustration.[11]

Figure 1 - Fundamental diagram of traffic congestion.



The above discussion implies that there is a maximum flow, defined as $\bar{F} = \frac{1}{\frac{\partial T}{\partial D}}$, and a corresponding level of density $\bar{D}$. To illustrate, let us assume that $T = \beta e^{\alpha D}$, where $\alpha, \beta > 0$. Note that we adopt this functional form in the empirical analysis. We show there that this form provides a very accurate description of the travel time-density relation for the roads in our sample (we test it against more general statistical relationships). In this case, we have

(3) $$\frac{dT}{dF} = \frac{2\alpha T}{1 - \alpha D} \Longrightarrow \bar{D} = \frac{1}{\alpha}, \bar{F} = 1/(\alpha\beta e)$$

[9] Similarly it can be shown that: dF/dD=(1-F ∂T/∂D)/T, which describes the relationship between F and D. Note that dT/dF and dF/dD have the same sign.
[10] Convexity of *h(.)* is crucial for this argument: if the function is linear, hypercongestion does not occur.
[11] There is a debate in the literature about whether hypercongestion is a stable equilibrium for the theoretical models analysing this issue. See Small and Verhoef (2007) and, for more recent contributions, Arnott and Inci (2010) and Fosgerau and Small (2013).

Given these assumptions, the maximum flow is such that $T = \beta e$. Hypercongestion thus occurs when $D > \overline{D}$.

2.2 The demand for transport

There is a given number of individuals in the transport market, denoted by N, who have perfect information. We assume that each individual takes at most one trip, and all trips are of equal length, normalized to one. Individuals can travel by private motor vehicles or public transit and are heterogeneous in their reservation utility of travel by each mode. Aggregate travel demand for motor vehicles and transit are negatively sloped and with positive cross-price elasticities. The generalized price of public transit, p_{PT}, increases with travel time, T^{PT}, and the fare, f, whereas it decreases with transit supply S (e.g. through lower waiting times). Hence, p_{PT}=$p_{PT}(T^{PT}, f, S)$. In total, there are N_{PT} public transit travelers, F motor-vehicle travelers and N_P non-travelers. The generalized price of motor-vehicle travel is equal to T. We have

(4) $$N = N_{PT}(p_{PT}, T) + F(T, p_{PT}) + N_P(p_{PT}, T),$$

where $N_{PT}(.,.)$ and $F(.,.)$ are decreasing in their first argument and increasing in their second argument, whereas $N_P(.,.)$ is increasing in both arguments.

2.3. The effect of public transit strikes

We normalize the supply of public transit (veh-kms) during regular service to one, and denote by $S \in [0,1]$ the share of service available per unit of time. This quantity is defined as the ratio between the quantity of service actually provided and the scheduled supply with regular service. If a public transit strike takes place, S will be less than one. Because motor vehicles and public transit are substitutes, demand for motor-vehicle transport goes up, so in the new equilibrium, T and D increase. If the road is not hypercongested, the number of motor vehicle travelers (i.e., traffic flow) goes up during a strike. However, in presence of hypercongestion, the number of motor vehicle travelers may decrease. The economic loss produced by the ensuing travel time increase is the (negative of) *the congestion relief benefit of public transit to motor-vehicle travelers*. Furthermore, because T goes up, if transit and private vehicles share the road, T^{PT} increases as well. Hence, demand for motor-vehicle travel increases even more. In addition, there is a travel time loss to public transport travelers, the (negative of) *the congestion relief benefit of public transit to public transport travelers*. Finally, because T and p_{PT} both go up, N_P goes up as well.

2.4 Equilibrium

To facilitate the interpretation of the empirical results later on, we make three major assumptions about the equilibrium. First, we take one hour as our unit of time. Hence, *hourly* demand and supply are equal to each other. We ignore any variation in demand within the hour. The main consequence is that we have underestimates of the welfare losses of congestion, because travel time is a convex function of density. Second, we assume that the demand function is linear with a given slope: any temporal variation in demand occurs because of shifts in the intercept.[12] Furthermore, we assume that any temporal variation in the demand function is *exogenous* to traffic conditions (e.g., workers have to be at work at a certain time). Hence, we disregard that demand functions are interrelated during the day, for example because of rescheduling of trips to avoid excessive congestion.

2.5 Welfare analysis

The total cost for society of motor-vehicle travel equals $F\,T$ (we normalize the value of travel time to one). The standard quantity capturing the distortions on the transport market is the marginal external cost of motor-vehicle travel. This cost is defined as the difference between the time cost to society of a marginal motor-vehicle user and the time cost to this user. One of our objectives in the empirical analysis is to measure this cost. We consider the travel cost of bus users below.

We introduce now two measures of the marginal external cost, which we will label as the *immediate measure*, denoted by *mec*, and the *overall measure*, denoted by MEC. The *mec* captures the *immediate* external costs of one additional motor vehicle traveler that increases density when entering the traffic flow.[13] To obtain it, we *partially* differentiate the total societal cost with respect to flow and subtract the average cost *T*:

$$(5) \qquad mec = \frac{\partial[FT(D)]}{\partial F} - T = \frac{\partial T}{\partial D}\frac{\partial D}{\partial F}F + T - T = \frac{\partial T}{\partial D}\frac{\partial D}{\partial F}F = \frac{\partial T}{\partial D}TF = \frac{\partial T}{\partial D}D.$$

This expression shows that the marginal external cost *of flow* is equal to the marginal effect of *density* on travel time multiplied with the density of motor-vehicle travelers. This measure of the external cost is worthy of consideration for several reasons. It is used to calculate the optimal road tax, as suggested by Pigou (1920). Furthermore, it is frequently used in the academic literature (e.g., Mayeres et al., 1996), in authoritative reports by the US

[12] This is a standard assumption in empirical welfare analysis.

[13] The equivalent thought experiment is that *current* density is increased, because current inflow is *exogenously* increased by one

Federal Highway Administration (e.g., FHWA, 1997) and in much-cited handbooks (e.g., Maibach et al., 2008).

Let us now focus on the overall measure, MEC. Total differentiation of the social costs and subtracting the average cost T shows that:

$$(6) \qquad MEC = \frac{d[FT(D)]}{dF} - T = \frac{dT}{dF}F + T - T = \frac{dT}{dF}F = \frac{\frac{\partial T}{\partial D}D}{1 - \frac{\partial T}{\partial D}F},$$

Note that the numerator of this expression is equal to mec.[14]

Let us now focus on equilibria where the road is *not* hypercongested, so $1 - \frac{\partial T}{\partial D}F$ ispositive and less than one. An increase in density, e.g. due to an upward shift in the demand for motor vehicle travel, causes an increase in the steady-state flow. It follows that MEC is positive and always exceeds *mec*.[15] The difference between these two measures is substantial when flow approaches its maximum. To illustrate, assume again that $T = \beta e^{\alpha D}$. Then $MEC = \alpha D\, T/(1 - \alpha D) = mec/(1 - \alpha D)$. For densities close to, but not equal to, 1/α, the overall measure is an order of magnitude higher than the partial measure. Hence, the immediate measure usually provides a substantial underestimate of the marginal external cost.

We will use the MEC as a key input for our welfare analysis. Let us suppose that there are no other distortions and that the government aims to maximize welfare. The standard prescription is to introduce a road tax equal to *MEC*. The tax will then induce an optimal flow below the equilibrium flow (when the road is initially not hypercongested). The welfare gain is straightforward to calculate. It depends, among other things, on the shape of the demand function. For example, when demand is horizontal, the welfare gain (the eliminated deadweight loss) is exactly equal to optimal flow times the ensuing reduction in travel time. By contrast, if demand is vertical one gets the well-known result that the welfare gain is zero (because there is no reduction in travel time). See Figure 2, where we show the average cost function – hence, travel time as a function of flow –as well as the marginal social cost, MSC, for the part where the average cost function is upward sloping. MEC is the difference between the MSC and the average cost function T.

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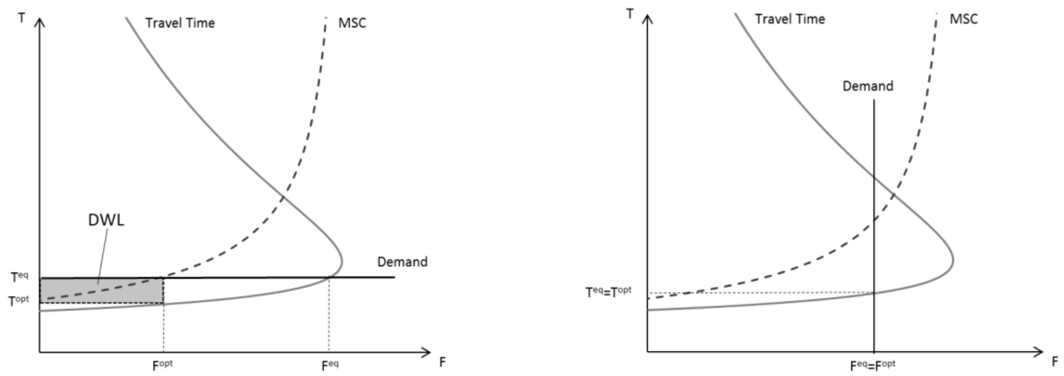
[14] Equation (6) suggests that when F is close to $\bar{F}$, which equals $1/(\partial T/\partial D)$, the external cost of adding one vehicle is infinite, which is not intuitive (given that travel time is finite when $F = \bar{F}$). However, noting that the number of vehicles is discrete, it appears that for $F = \bar{F} - 1$, MEC is equal to $\bar{F}T$, which is finite.

[15] This result is intuitive, because the immediate measure ignores the reversed effect of travel time on density and therefore flow. Another way of viewing this is by noting that the overall measure takes into account that outflow is endogenously reduced by the increase in inflow. The formal demonstration is as follows: the marginal change in density, dD, induced by a marginal increase in (in)flow is equal to T. The *overall* induced change in (out)flow is then equal to $T\partial F/\partial D = T\partial(D/T)/\partial D = 1 - F\partial T/\partial D$, which is smaller than one.

We focus now on equilibria where the road is hypercongested, i.e. such that $1 - \frac{\partial T}{\partial D} F$ is negative. Given hypercongestion, an increase in density (e.g., due to a shift in the demand function) causes an increase in travel time and a *reduction* in the flow. Therefore, (6) implies that MEC is *negative*. Furthermore, it is straightforward to show that the marginal social cost, MSC, which equals $T/(1 - \frac{\partial T}{\partial D} F)$, is also *negative.* This is intuitive: any steady-state equilibrium with a higher flow level and lower travel time is welfare improving. This implies that an equilibrium with hypercongestion can never be optimal. Any policy measure which prevents hypercongestion is thus welfare improving. Note, furthermore, that in an equilibrium with hypercongestion, the immediate measure of marginal external cost, mec, is positive. However, this measure is uninformative about the optimal road tax.

Figure 2 - Deadweight loss (DWL) from congestion with horizontal and vertical demand.



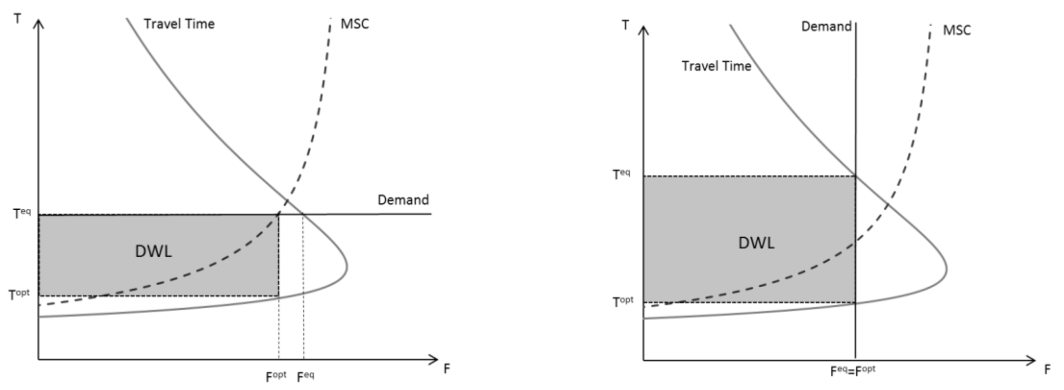
In principle, governments may prevent hypercongestion by imposing a large toll on vehicles entering the parts of the road network where density exceeds the level associated maximum flow. However, because (as we show below) hypercongestion is a quite sporadic and local phenomenon, implementing this kind of pricing could be difficult, as it would require varying the toll by roads and time on a short notice. Furthermore, as Figures 2 and 3 suggest, on a given road the equilibrium with hypercongestion may not be unique (this depends on the shape of the demand function, for instance).[16] Therefore, pricing instruments alone may not be well-suited to control it. Indeed, the first-best toll is equal to the MEC evaluated at the optimal allocation, which, as pointed out before, lies on the upward sloping part of the supply curve. This tax may not be sufficient to avoid hypercongestion. More

[16] Our data analysed later on actually suggest that demand is not inelastic enough to generate multiple equilibria.

realistically, governments can intervene by adopting *quantity* restrictions (possibly in combination with pricing instruments). These include (second-best) policies such as adaptive traffic lights. This conclusion is backed by traffic-engineering studies which show that reducing inflow of traffic into cities by letting vehicles waiting longer for traffic lights when entering the city reduces hypercongestion, resulting in an equilibrium with lower travel times (Kouvelas et al., 2017).

But what can we gain by avoiding hypercongestion? An objective of our empirical investigation is to evaluate the magnitude of the loss to society when roads are hypercongested. Specifically, we determine the loss compared to the optimal equilibrium. Again, this welfare gain depends, among other things, on the demand function.[17] When the latter is horizontal, the welfare gain is equal to the product of the optimal flow and the reduction in travel time. If the demand is perfectly inelastic, the welfare gain is equal to product of the optimal flow times the travel-time reduction. Therefore, contrary to the non-hypercongested case, there is a (substantial) welfare gain even if demand is vertical. Indeed, hypercongestion is a very inefficient way of "producing" travel. See Figure 3.

Figure 3 – Equilibria and deadweight loss of hypercongestion with horizontal demand (left panel) and vertical demand (right panel)



Let us now focus on the effect of congestion on bus travelers. We have noted that the *generalized* price of public transit, p_{PT}, increases with travel time, T^{PT}. Not surprisingly, if

[17] Another interesting exercise is to determine the loss to society in the hypercongested equilibrium in comparison to the congested one, *at given flow*. The deadweight loss is then equal to the reduction in travel time multiplied with the flow, regardless of the shape of the demand function

buses share the road with other vehicles, the travel time of buses is strongly correlated with the travel time motor-vehicle travelers, T. We note two empirical observations about bus travel time. First, it is substantially higher than motor vehicles' travel time (for instance, because of the time spent stopping at bus stops). Second, bus speed depends on motor vehicles' speed in a linear way with a marginal effect less than one. These observations imply the following relationship between the travel times of public transit and of motor vehicles:

$$(T^{PT})^{-1} = \theta T^{-1} - \mu, \;\; \mu > 0; \; 0 < \theta < 1; \; T^{-1} - \mu > 0 \tag{7}$$

Hence:

$$\frac{\partial T^{PT}}{\partial T} = \frac{\theta T^{-2}}{(\theta T^{-1} - \mu)^2} > 1. \tag{8}$$

The marginal effect of motor-vehicle time on travel time of public transit is larger than one, and the relation between bus and motor-vehicle time is concave. For sufficiently small μ, so that public transit speed is proportional to motor-vehicle speed, the marginal effect is a constant:

$$\frac{\partial T^{PT}}{\partial T} \approx \frac{1}{\theta}. \tag{9}$$

Hence, one approach to calculate the marginal external cost of motor-vehicle travel on bus users is as follows:

$$MEC\ on\ bus \; = \frac{dT}{dF}\frac{N_{PT}}{\theta F}. \tag{10}$$

This approach is indirect, as it uses information on the relationship between bus and motor-vehicle travel times. We also employ an alternative, direct approach to estimate the marginal external cost borne by bus travelers. Specifically, we assume that $T^{PT} = \gamma e^{\sigma D}$and then overall differentiate T^{PT} $w$ith respect to flow. It can be shown that:

$$MEC\ \ on\ bus \; = \frac{dT}{dF} N_{PT}\left[\frac{\sigma}{\alpha}(1 - \alpha D)\frac{T^{PT}}{T} + \alpha D \frac{T^{PT}}{T}\frac{dT^{PT}}{dT}\right] > \frac{dT}{dF} N_{PT}\frac{\sigma}{\alpha}\frac{T^{PT}}{T}. \tag{11}$$

We find that σ is only slightly higher than α, and that $\frac{T^{PT}}{T}$ is approximately equal to $\frac{1}{\theta}$, so the direct and indirect approach provide very similar results.

3. Empirical Approach

We are interested in estimating the marginal external cost of congestion on motor-vehicle drivers. To do so, we need information about the relationship between motor-vehicle travel time and flow. Clearly, given hypercongestion, i.e. if the relationship between T and F is backward bending, the relationship is not an injective function. Therefore, one cannot apply standard econometric techniques to estimate it. We proceed as follows: we first estimate the effect of density on travel time using (1) and then combine this estimate with (2) to derive dT/dF.[18] Given estimates of h, denoted by $\hat{h}$, for each observation of D, we will calculate the predicted travel time $\hat{T} = \hat{h}(\mathrm{D})$, as well as the predicted flow $\hat{F} = \mathrm{D}/\hat{T}$. We will show that the travel-time flow relationship obtained using $\hat{T}$ and $\hat{F}$ accurately predicts the observed travel-time flow relationship.

Let us now assume that h is an exponential function, so $T = \beta e^{\alpha D}$. This specification implies that the logarithm of travel time is a linear function of density. We have observations which vary by road and hour. We will therefore assume that $logT_{i,t,D}$, at road i, hour *t* and day D is a linear function of density $D_{t,D}$, given several controls $X_{t,D}$, road fixed-effects τ_i and an error term $u_{i,t,D}$, so that:

(12) $$logT_{i,t,D} = \tau_i + \alpha D_{t,D} + \kappa' X_{t,D} + u_{i,t,D}.$$

Road fixed effects capture time-invariant differences in road supply such lane width, the speed limit as well as the distance to the next intersection. The controls $X_{t,D}$ include weather (i.e. temperature using a third-order polynomial, precipitation) and many time controls: hour-of-weekday fixed effects (e.g., Monday morning between 9 and 10 a.m.) and week fixed effects. These time controls aim to capture for unobserved changes in supply (e.g. due to road improvements which only occur during certain periods). We emphasise however that the estimates without these controls are almost identical. We cluster standard errors by hour, so we allow $u_{i,t,D}$ and $u_{j,t,D}$ to be correlated.[19]

Observe that, in the transport engineering literature, equations relating travel time to density such as (12) are estimated with OLS, therefore ignoring potential endogeneity issues. One econometric difficulty is that density is most likely endogenous, because it is defined as the flow multiplied with travel time – which is the dependent variable of interest. This may be problematic as in many studies – including the current one – density is not explicitly observed but derived from observations of flow and travel time. Therefore, any measurement error in travel time causes a positive correlation between travel time and density resulting in an

[18] Keeler and Small (1977) address this issue by estimating flow *directly* as a quadratic (and therefore possible non-monotonic) function of travel time and then invert the estimated function. There are two difficulties with this approach. First, such an approach usually does not provide the causal effect of flow on travel time. Second, even if the goal would be to obtain the best fit between flow and travel time, it appears, at least for the data of Rome, that one has to estimate more parameters, while obtaining a worse fit. This result is intuitive, because the relationship between (log) travel time and density is monotonic, and almost perfectly linear, whereas the relationship between flow and travel time is nonmonotonic.

[19] Hence, each cluster contains a number of observations equal to the number of road segments observed.

overestimate of the effect of density.[20] Measurement error is not the only source of endogeneity. For example, many unobserved supply shocks (e.g. road closures, accidents…) may simultaneously affect density and travel time.[21] In the estimation procedure, to deal with endogeneity issues, we will use an instrumental variable approach using variation in the share of public transit, S, due to strikes, which causes an exogenous demand shock to motor-vehicle' road travel. Note that the use of time controls in (12) has an additional rationale when employing an instrumental variable approach. Time controls also capture any variation in the supply of *scheduled* public transit (i.e., the schedule in the absence of strikes), which makes it more plausible that public transit share is exogenous.

One issue when using public transit strikes as an instrument is that changes in public transit supply directly change the number of vehicles on the road, which may invalidate the assumption that bus strikes are valid instruments of motor-vehicle density. This is a minor issue however, because, in Rome, on average 1 percent of all vehicles refers to buses (per hour, only six buses pass a road). Nevertheless, we have addressed this issue by estimating models where we explicitly acknowledge that an increase in public transit increases the number of vehicles on the road. For example, when we assume that one single bus causes the same travel delays as 10 motor vehicles, we still get identical results when instrumental variables approaches.

A second issue is that (12) may be a restrictive specification. To deal with that we specify log travel time as a quadratic function of density and apply control functions approaches to instrument density. A third issue is that it is unlikely that the marginal effect of density is equal for all roads. We therefore allow the marginal effect on density to be road-segment specific.[22]

Given estimates based on (12), we can estimate MEC using (2). Intuition suggests however that this approach does not generate precise estimates when F approaches $\overline{F}$, because the supply curve is vertical. More formally, this can be demonstrated when assuming that $\partial T/\partial D$ is a random variable with a given standard deviation, $var(\partial T/\partial D)$. Recall from

[20] One expects a downward bias in case of measurement error in flow, using a standard attenuation bias argument of classical measurement error in the independent variable (Wooldridge, 2002, p.75). Simulations – available upon request – indicate that measurement error in travel time is a fundamental issue, e.g., when the standard deviation of measurement error in travel time is only 10 percent of the standard deviation of travel time, then the upward bias in the estimate of α is about 30 percent, whereas measurement error in flow has an almost negligible downward bias.

[21] The weather can also be a factor. We control for weather conditions in our empirical analysis. See below.

[22] A third, but minor, issue is that an increase in demand may have an ambiguous effect on density due to the presence of multiple equilibria during hypercongestion. As we will demonstrate that hypercongestion happens seldom in our data, and that multiple equilibria are even more unlikely, we ignore this issue.

standard statistical theory that the ratio of two random variables does not have a well-defined variance. It is then standard to approximate the variance using a Taylor expansion. Using such an approach it can be shown that the variance of MEC can be written as follows:

$$var(\text{MEC}) \approx \frac{var(\partial T/\partial D)\,D^2}{\left(1-\frac{\partial T}{\partial D}F\right)^4}. \tag{13}$$

The denominator of this expression contains a power of *four*. Combined with (2), this implies that the estimate of MEC divided by its standard error goes to zero when F approaches $\overline{F}$. Thus, the estimates for marginal external cost for levels of flow close to its maximum may be unreliable. Although there are only few observations of flow close to the maximum in our data, we will exclude these observations (our estimate of the total welfare loss of congestion remains unaffected by this issue).

We also aim to estimate the marginal external cost of congestion on bus travelers. In the empirical analysis, because we have data per year and cannot distinguish between roads, we use aggregate data on bus travelers time. However, we are able to estimate the effect of motor-vehicle travel time on bus travel time, see (9), which allows us to calculate (10). Furthermore, we can estimate the effect of log motor-vehicle density on bus travel time, σ, which allows us to calculate (11).

We also estimate the effect of public transit strikes on travel time. In the literature discussing these estimates, it is common to use linear models (e.g, Anderson, 2014). We will follow this literature, hence the dependent variable, $T_{i,t,D}$, is estimated as a linear function of public transit share $S_{t,D}$ using the same type of data and controls as in (12), so that:

$$T_{i,t,D} = \tau_i + \varphi S_{t,D} + \rho' X_{t,D} + \epsilon_{i,t,D} \tag{14}$$

where the coefficient φ captures the marginal effect of public transit share, $\partial T/\partial S$.[23] We estimate (14) using weighted regression where the weights are proportional to the (hourly) flow per road to make the estimated t φ representative for the average motor-vehicle traveler in our sample and cluster standard errors by hour.[24] In a similar way, we estimate the marginal effect of public transit share on motor-vehicle travel flow $F_{i,t,D}$, hence, $\partial F/\partial S$. [25]

[23] The week fixed effects in this specification also control for the effect of a substantial public transit fare increase in May 2012. To control for unobserved factors that vary between days, we will also estimate models with day fixed effects.

[24] In the sensitivity analyses, we demonstrate that our results are robust with the way we cluster standard errors.

[25] One substantial public transit fare increase took place during our period of observation. This allows us to estimate the effect of a public fare change on motor-vehicle travel time using a discontinuity regression approach. We use this estimated effect as a robustness analysis and as input for welfare analysis.

4. Data

4.1 Rome

Rome is Italy's capital and largest city, with a population of 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 the metropolitan area of Rome there are 1.65 billion motor vehicle trips per year, equivalent to 21.5 billion passenger kilometers or 14.5 billion vehicle-kms, 42 percent of which takes place during peak hours (using information from Citta' di Roma, 2014).[26] The rest of the trips take place either by walking or by bicycle. The city is one of the worst performing European cities in terms of air pollution and road congestion. The average speed on inner-city roads can be as low as 15km/h on weekdays.

Table 1 – Descriptives for the Rome metropolitan area

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

Source: own calculations based on information for the year 2013, from Rome's General Traffic Plan (PGTU, 2014).

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 1.6 cars per household. The high car ownership rate combined with substantial public transit

[26] According to the Rome municipality, 376,024 motor-vehicle trips take place 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. Further, 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 use then an occupancy of 1.4 (1.51) passengers per vehicle in peak (resp. off peak) hours). To obtain the quantity of passenger-kms, we multiply annual trips by the average trip length of 13km as reported by the Rome municipality (PGTU, 2014).

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.

Rome has a restricted access zone for motorized traffic, ZTL (Zona a Traffico Limitato).[27] This restricted access zone is a small part of Rome's historic center where car inflow is restricted to permit holders who can enter during certain hours of the day. Permits are mainly for businesses and government officials. We observe hourly the inflow and outflow of vehicles for this zone, but have no information about traffic within the zone.[28]

4.2 Public transit in Rome

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

The provision of public transit services in Rome is assigned to a large provider, ATAC SpA (almost entirely owned by the Rome municipality), and several much smaller bus companies, operating under the banner of Roma TPL. ATAC covers approximately 90% of the transit market, operating about 360 bus and tramlines, with a fleet of 2,700 buses and 165 trams. It also operates three metro lines with 83 metro carriages, and three train lines connecting Rome with the region of Lazio. [29] See Table 2.

Table 2 – Public transit stock in Rome

Public transit company	Buses	Metro (cars)	Train (cars)	Employees
Atac SpA	2,700 (+165 trams)	83	55	11,696
Roma Tpl Scarl	450			839
Total	3,315	83	55	12,525

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

[27] Restricted access is not new to Rome's historic center. In the 1st century BC, Julius Caesar banned wheeled traffic from entering Rome during the first ten hours of daylight (Cary, 1929).
[28] The city lifts restrictions on strike days, but the zone´s vehicle in- and outflow is less than 1% of all trips in the city. This suggests that the effect of the latter policy on average travel time within the city is small.
[29] The number of metro lines is exceptionally low for a European city of comparable size. Archeological excavations and financial issues have historically hindered construction. The third metro line (Metro C) is partly operational since June 2015, which is outside our observation period.

4.3 Transit strikes in Rome

Information on strikes is provided by the Italian strike regulator (Commissione di Garanzia per gli Scioperi). Due to the availability of traffic data (see below), our period of observation spans from January 2nd 2012 to May 22nd 2015, i.e. 769 working days. There are 43 public transit strike days during this period.[30] 27 of these strikes took place only in Rome (and possibly the Lazio region), whereas the other 16 are part of national strikes that possibly affected other transportation modes, e.g. aviation.[31] We do not distinguish between which providers are affected by the strike.[32] There is a strike on 6% of the days on our observation period – strikes are a frequent occurrence in Rome. This observation is relevant, because strike frequency may increase the likelihood of car ownership, and thus the elasticity of demand responses during strikes.

All strikes in our data were announced to the public several days in advance. Seven were partially cancelled (by one of the participating unions). We refer to the latter as *semi-cancelled* strikes in the sensitivity analysis (in Appendix A). An additional three announced strikes were fully *cancelled* shortly before taking place. We will refer control for the cancelled strike days.[33]

Italian law does not allow full transit service shutdowns during strikes. 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 holiday months, i.e. in February, August and most of September. 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 A). Most strikes take place on Mondays and, in particular, Fridays (see Figure A2 in Appendix A). We do not observe strikes on weekends, so we exclude all weekends from our analysis (regulation restricts striking on weekends). We also

[30] Strike activity is distributed about equally over the years with at least 7 strikes a year. We ignore 7 additional strikes which occurred during on days where traffic data is insufficient. Strikes are usually due to workers' grievances due to unpaid wages.

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

[32] Strikes of different public transit providers usually coincide see Figure A3 in the Appendix (maybe because unions are not firm specific and overlap multiple providers). Hence, we may ignore which provider is affected although these firms operate in different geographical areas.

[33] We do not find any effect of these cancelled strikes on motor-vehicle travel time. Given an estimation strategy based on public strike *days*, it is useful to interpret the effect of the cancelled strikes as a placebo test. Because we identify based on public strike hours, and are able to include day fixed effects, the placebo test is redundant.

exclude nighttime hours because there is no public transit service between midnight and 5am.[34]

In contrast to earlier studies on transit strikes (Anderson 2014, Bauernschuester et al. 2015, Adler and van Ommeren 2016), we have information about hourly strike *intensity*. Specifically, Rome's Mobility Agency (Agenzia per la Mobilita') provided us with the share of scheduled service (based on the regular schedule during non-strike days) that actually took place during strike hours. This implies that we can 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 on each particular segment of the network.[35]

Figure 4 – Public transit share for strikes

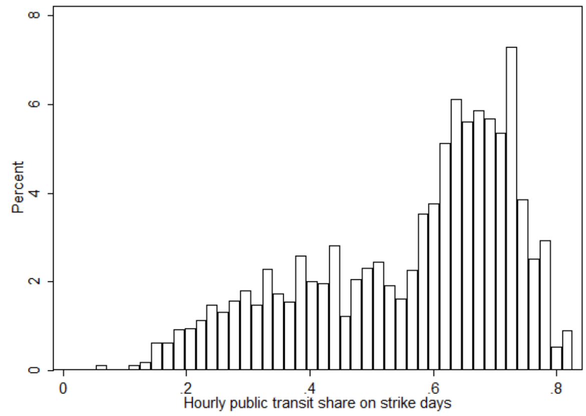
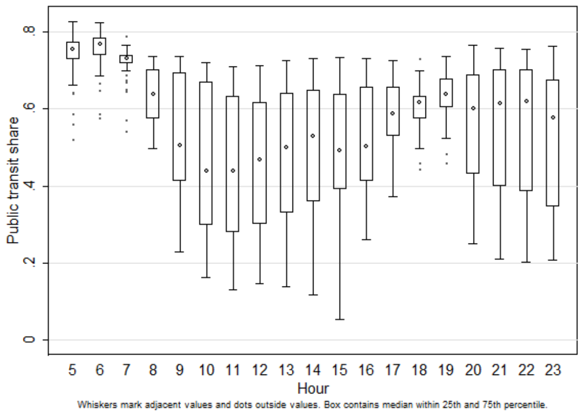


Figure 5 –Public transit share per strike hour



During strike hours there are, on average, 839 buses/trams operating, in comparison to 1,496 buses/trams during non-strike hours. There is substantial variation in the hourly share of public transit available during strikes, as can be seen in Figure 4. This share varies between 0.05 and 0.83, the average being 0.56. Note that we observe relatively few strike (peak) hours with a very low intensity due to the regulatory scheme, which mandates a high minimum service level during peak hours. In Figure 5, we provide the range and three quantiles for the distribution of transit available share distribution over the the day. The median share is highest during the 8 a.m. morning peak (about 0.75) and the 7 p.m. evening peak hour (about

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

[35] This feature of the data is of little importance to our study. During strikes, the public transit agency allocates available buses to the most important lines (those serving the largest volume of passengers). In all likelihood, the agency would behave similarly if it had to reduce service permanently, e.g. due to budget cuts. Furthermore, we expect transit users to change to other bus lines during strikes. Because we are interested in the effect on traffic at the city level, observing which lines are affected is not crucial.

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 in the share is also much higher.

We also have information on the *scheduled* service level (i.e., the number of buses operating per hour) for five main bus lines on non-strike days.[36] Assuming that the other bus lines follow the same schedule, it appears that the total number of operational buses in Rome does not vary between 8am and 5pm except when there are strikes (Figures A4 and A6 in Appendix A), supporting the use of strikes as a way of identifying the effects of public transit supply.

4.4 Motor-vehicle traffic data

Our data on motor vehicle traffic is provided by Rome's Mobility Agency. It contains information on hourly flow and travel time for 33 measurement points in Rome, for a period from the 2nd of January 2012 to the 22nd of May 2015.[37] Motor vehicles are cars, commercial trucks and motorbikes, as the measurement stations do not distinguish between these types of vehicles.

The measurement locations, chosen by the Agency, include twelve one-lane roads – all located in the city center and with a speed limit of 50km/h (1.2 min/km). The other 21 roads contain 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 the speed limit of 50 km/h. Information from the measurement locations is sometimes missing (meters are sometimes malfunctioning). During some hours, we have information from only a couple of measurement locations. To avoid identification based on a few measurement locations, we only include hourly information from a measurement location when at least 19 other measurement locations are observed in our data (we exclude 2.2 percent of total observations).

We measure *flow* in *number of motor vehicles per minute per lane* and *travel time* in *minutes per kilometer*. We calculate density based on the observed flow and travel time. This means that *density* is measured in number of motor vehicles per kilometer. We exclude extreme outliers.[38] In total, we have 422,691 hourly observations for motor vehicle flow,

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[36] See http://www.atac.roma.it/page.asp?p=18.

[37] See Figure A5 in the Appendix for a map of the measurement locations. We also have information on eleven additional measurement locations that we ignore because they are too close to traffic lights, hence information particularly on flow becomes unreliable or present *extreme* variation in flow over the period observed. This variation is likely due to malfunctioning of loop detectors or road supply changes (e.g., closure of lanes).

[38] We drop few observations when travel time either exceeds 5 min/km or is below 0.4 min/km, when flow is zero or exceeds 2,100 vehicles per hour. The results are robust to the inclusion of these outliers.

density and travel time.[39] We give descriptive information in Table 3. Approximately five percent (23,018) of these observations is during strikes.

On average, travel time is roughly 1.3 min/km, which implies that the average speed is approximately 50 km/h. Note that this average speed is far above the average speed of a trip, mainly because we exclude waiting time near traffic lights and extremely congested roads in the inner-city. Hence, if anything, we underestimate the presence of congestion. Furthermore, in our data, flow per lane is above 11 vehicles per minute and density is about 13 motor vehicles per kilometer. The distributions of travel time, flow and density can be found in Figures A7 to A9 of Appendix A.[40]

Table 3 – Average values, travel time, density and flow

	Travel time	Density	Flow	Obs.
Strike	1.365	14.6	11.1	23,018
No strike	1.327	13.4	10.5	399,673
Total	1.330	13.5	10.6	422,691

Note: Travel time in minutes per kilometer; density in vehicles per kilometer; flow in vehicles per minute per lane.

In Figures 6 and 7, we provide information about average travel time and density by hour of the day (information about average travel flow by hour of the day can be found in Appendix A, see Figure A10). These figures indicate that on average travel time, density and flow are higher during strikes.[41] In these figures, we single out intensive strikes – whereby the public transit available share is below 0.5. Travel time, density and flow appear systematically larger during intensive strikes. Figure 3 also shows clearly that during peak hours the increase in travel time is substantially larger, implying that the marginal effect of public transit strikes is higher during these hours. Not surprisingly, the figures also indicate that traffic flow, density and travel times are larger in peak than in off peak hours. Travel time, flow and density are respectively 13, 38 and 50 percent larger during the peak.

The above figures provide information for average traffic conditions, and thus mask substantial differences between roads. In Figures 9 and 10, we depict the backward bending travel time-flow curve – for a road that clearly shows signs of hypercongestion – and for a

[39] Information on the month of August 2012 and a few other days are missing. August 2012 is missing, because the data collection agency moved office in this month. The few other days are missing for unknown reason.

[40] We weigh all descriptive statistics for travel time by flow, as we are interested in the travel time *per traveler*.

[41] It is possible that the composition of motor vehicles changes during strikes, which causes additional welfare losses. It should be noted that in Rome public transit travelers tend not to have motorcycles/scooters (which are mainly used by young travelers independent of traffic conditions), but tend to have access to cars, so the increase in flow is likely predominantly by cars.

road where hypercongestion is absent: indeed, travel time is monotonically increasing with flow.

Figure 6 – Travel time by hour of the day

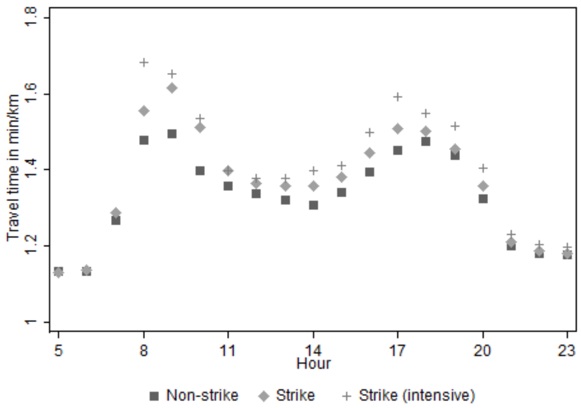
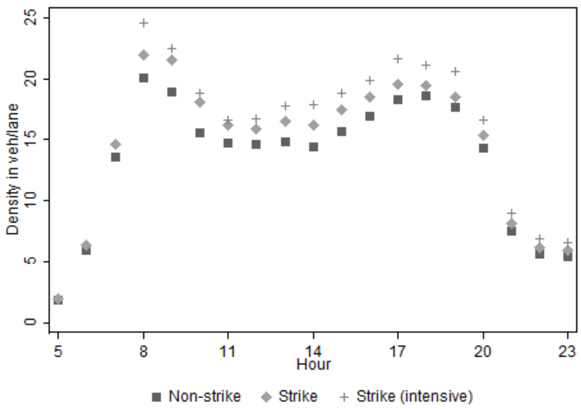


Figure 7 – Density by hour of the day

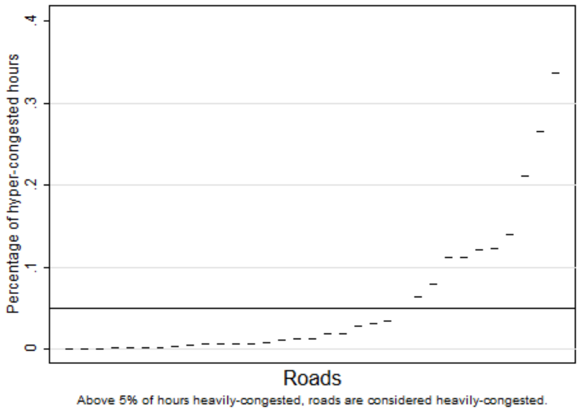


The congestion relief effect of public transit may differ between roads because of differences in their congestion level. We define a road as heavily congested during a certain hour when the speed on that road is less than 60 percent of free-flow speed, defined by the 95 percent percentile of the speed distribution observed on that road. Using this definition, roads in our sample are heavily congested about one hour per day, or 5 percent of the time. However, there is extreme variation between roads. Figure 8 shows for all roads the average number of hours per day that a road is heavily congested. In the figure (and in the empirical analysis below), we single out 10 “heavily-congested” roads, defined as such because they are heavily congested (according to our definition above) at least one hour per day.[42] On average, these 10 roads are heavily congested three hours per day.

In theory, a road is hypercongested when, for given flow, the travel time lies on the backward bending portion of the supply curve. However, in practice it is not always clear whether this condition applies. To illustrate, consider the road in Figure 9 – which clearly exhibits hypercongestion – and focus on observations of flow around 25 motor vehicles per minute, but where travel times are in between the (to be estimated) backward-bending supply curve. It is a priori unclear whether these observations refer to hours where the road is congested or hypercongested.

[42] The same 10 roads show a backward bending relation between travel time and flow, indicating the presence of hypercongestion for some hours.

Figure 8 – Daily number of heavily congested hours per road (33 roads)



To deal with this issue, we define a road as hypercongested in a given hour if and only if traffic density exceeds the level associated with maximum flow (formally defined as $\overline{D}$, see expression (3) in Section 2.1). For each road, we calculate this level using our estimates of the travel time-density relationship on an hourly basis (see Section 5.1 below). Note that this definition implies that if a road is hypercongested for only a couple of minutes during a certain hour, we do not consider it as hypercongested. Hence, we most likely underestimate the pervasiveness of hypercongestion. Note also that the above definition of 'heavily congested road' does not imply that a road is hypercongested. Traffic on a road may be very slow on a given hour for reasons not directly related to density (e.g., because a high share of cars cruises for parking). However, all roads that we identify as hypercongested in a given hour also turn out to be heavily congested.

Figure 9 – Hypercongested road

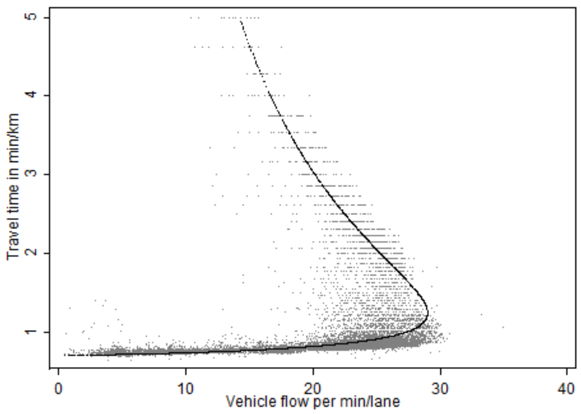
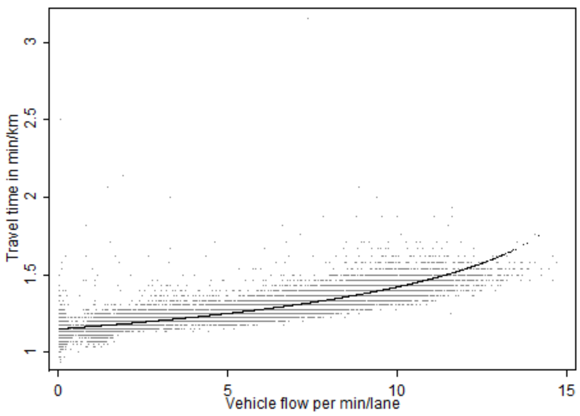


Figure 10 – Congested road

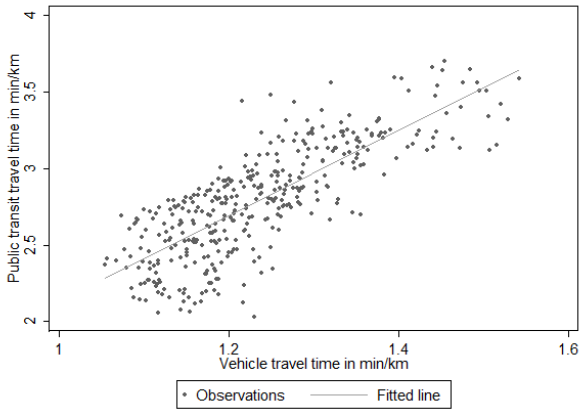


Finally, note that we will estimate functions which assume that the logarithm of travel time is a linear function of density. In the Appendix, in Figure A12, we show this relationship for the same road depicted in Figure 9. We note that this assumption is very accurate. For other roads, a similar conclusion applies.

4.5 The effect of road congestion on bus travel times

The Rome Mobility Agency provided us with information on the in-bus travel time. Specifically, we observe the hourly average travel time of buses for the 19 hours in a day --from 5am to midnight— where transit service is active, from 2012 to 2015. This average is computed on a yearly basis, distinguishing hours per the service schedule. There are six different service schedules in a year: one for weekdays, one for weekends and one for festive days during the schoolyear period (from September to May) and three corresponding schedules for the summer period (from June to August).[43] We have a total of 380 hourly observations.

Figure 11 – Travel times of public and private motor vehicles



The average bus travel time is 2.79 minutes per km, twice the average travel time of motor vehicles. Because buses rarely travel on dedicated lanes in Rome, we expect travel times of public transit and motor vehicles to be strongly correlated. Figure 11, where we plot the hourly observations of bus travel time and motor vehicle travel time, confirms this expectation. The data indicate a correlation of 0.79 between these travel times. Furthermore, a one-minute increase in motor vehicle travel time is associated with an increase in bus travel

[43] For example, one observation is the average bus travel time from 11am to 12am for weekdays from January 2012 to May 2012 and from September 2012 to May 2013. Another observation is the average travel time from 11am to 12am on weekends over the same period, and so on. Information for August 2012 and the second half of 2015 is missing.

time of 2.8 minutes.[44] Consequently, higher congestion levels imply *much* larger time losses for bus travelers than for motor-vehicle travelers. This suggests that the external congestion costs on bus travelers may be substantial. We examine this issue below.

5. Empirical Results

5.1 Welfare losses of road congestion

5.1.1 Travel time losses of motor-vehicle travelers

To estimate the marginal external cost of congestion through travel time losses of motor-vehicle travelers, we first estimate the effect of motor-vehicle density on travel time of motor-vehicle travelers. In column 1 of Table 4, we provide the results assuming a linear effect of density on log travel time (see (12)). We find that a marginal increase in density (one vehicle per kilometer) increases log travel time by 0.024. Hence, increasing density (per lane) by one vehicle increases travel time by approximately 2 percent. When we estimate the same model with 2SLS using the share of available public transit as an instrument, we find a smaller effect of 0.020 see column 2 (the instrument is strong, with an F value above 100). This implies that the OLS estimates provide a non-negligible upward bias of almost 20 percent, as anticipated in Section 3.

To examine whether the above specification is restrictive, we also include a quadratic term of density in the estimation for column 3. As is suggested by the negligible increase in the R^2, a quadratic approach does not fundamentally change the results. When we account for endogeneity of density given the quadratic specification, by applying a control-function approach (column 4), we again find a smaller effect of density implying that OLS provides an upward bias.

Table 4 –Log travel time

	(1) OLS	(2) IV	(3) OLS	(4) IV
Density	0.0238***	0.0202***	0.0268***	0.0177***
	(0.000101)	(0.000959)	(0.000388)	(0.000719)
Density^2			-0.0000425***	-0.0000653***
			(0.00000631)	(0.00000241)
Number of Obs.	422,691	422,691	422,691	422,691
R^2	0.925		0.925	

Note: The dependent variable is logarithm of travel time. Controls are included but not tabulated. The hourly strike intensity is the instrument for IV. Robust standard errors clustered by hour-of-day in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[44] This effect is so pronounced, because i) bus *speed* appears almost one-to-one related to motor-vehicle speed, ii) average bus speed is much less than average motor vehicle speed; iii) the marginal effect of speed on travel time is equal to minus the inverse of speed *squared*.

We then re-estimate the linear specifications for each road separately, allowing the effect of density to be road specific. This approach is preferable, because the travel-time density relationship may depend on road characteristics such as maximum speed limit, distance to upstream bottlenecks etc. These road-specific estimates are available upon request. Table 5 reports the average results. In the OLS specification, for each road, the effect is positive, with an average effect of 0.024 (see Table 5). Note that the standard deviation of this effect is about 0.01, supporting the idea that the estimated effects differ between roads.

Table 5 –Log travel time, road-specific estimates of density

	(1) OLS	(2) IV
Average effect of density	0.0224	0.0181
Standard deviation of effect of density	(0.00934)	(0.0110)
Number of Obs.	422,691	321,687

Note: We estimate the marginal effect for each road separately given controls and then report the average as well as the standard deviation of the effect of density.

Concerning the IV specification, we have examined the instrument's strength for each road separately. For all but five roads (i.e. about ninety percent of the roads in our sample), the F-test far exceeds the recommended value of 10.[45] The estimated effect of density is positive for 25 among the 28 remaining roads, whereas it is negative for three. This finding is, in our view, not particularly worrying for a number of reasons. First, because we have a large number of estimates, random variation is likely to result in a few estimates with the wrong sign. Second, the F test for weak instruments of these three roads is substantially lower than for the other roads that generate positive effects, which is unlikely to be accidental. Third, the OLS estimates of these three roads indicate small positive effects. Finally, the logic of our instrument, i.e. strikes do not directly influence travel time of motor vehicles, may not hold for a few roads because the ratio of buses to cars is much higher than for the average road (about 1 percent).

The second column of Table 5 reports the IV results for the 25 roads with the positive coefficient and a strong instrument. We find that the average effect of density is about 0.018 (including those with a negative coefficient reduces the average estimate somewhat to 0.015).

[45] For the roads where the instrument is weak, the test is equal to 1, 2, 4, 6, and 8 respectively. For these five roads, the Hausman t-test (Wooldridge, 2002, page 120) is less than two (in absolute value) suggesting that the OLS and IV estimates are statistically equivalent.

Again, the OLS estimates are severely upward biased, by about 30 percent.[46] This upward bias is also statistically significant for most roads: for 20 of the 25 roads, the Hausman t-test exceeds two (in absolute value). As discussed in Section 3, measurement error in travel time is most likely one of the main reasons for this bias.[47]

We use the IV estimates to predict each road's supply curve – i.e. the travel-time flow relationship – as explained in Section 2.1. Figure 6 provides an example of such prediction for one road (black line). The predicted travel-time flow relationship is backward-bending, in line with empirical traffic studies (Helbing, 2001; Geroliminis and Daganzo, 2008).[48]

Based on these estimates, we calculate when hypercongestion occurs on the roads we observe. Given our specification that $T = \beta e^{\alpha D}$, hypercongestion occurs when $D > 1/\alpha$, where α is the estimated effect of density on log travel time (see expression (3) above). Our estimates imply that hypercongestion occurs in about 2 percent of the time, on average. Given our observation in Section 4.4 that roads are about 5 percent of the time heavily congested, it turns out that about 40 percent of roads that are heavily congested are also hypercongested. During the morning peak hours, however, the proportion of hypercongested roads is higher: about 60 percent of heavily congested roads are hypercongested (see Figure A11).

Table 6 summarizes the main results of this section.[49] The first column reports the main measures describing the observed traffic conditions, including the MEC (computed only for the hours where roads are not hypercongested). This measure is useful as it is indicative of the level of the optimal road tax. It shows that the marginal external time cost of a motor-vehicle travelling one km is about 0.53 minutes on average.[50] This value is substantial, given that the average travel time per km is 1.33 minutes.

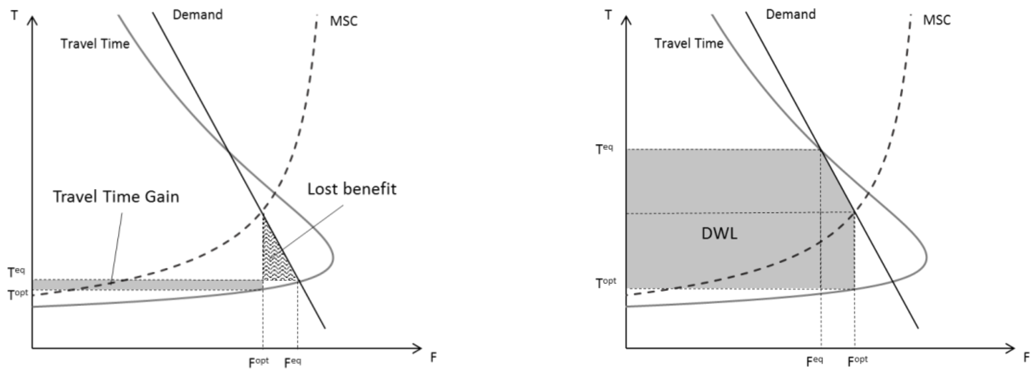
As argued above, our measure of marginal external cost of travel flow, MEC, always exceeds the immediate measure, *mec,* which is famous because of Pigou (1920), and subsequent literature (e.g., Mayeres et al., 1996; FHWA, 1997; Maibach et al., 2008). According to our estimates, *mec* is 0.36, so the estimated marginal external costs are about 40 percent higher when the proper definition is used.

---

[46] This conclusion holds even more if we include all 33 roads. The IV effect is then about 33% lower.
[47] Our finding of an upward bias of about 30 percent is consistent with a lognormal distributed measurement error in travel time with a standard deviation equal to 10 percent of the standard deviation of log travel time.
[48] These results are also in line with simulation studies (e.g., May et al., 2000; Mayeres and Proost 2001; Newbery and Santos, 2002).
[49] For computational reasons, we provide results using a 10% random sample.
[50] We report here the weighted average of the marginal external time cost for a road, using the flow per road as weight.

To express these estimates in monetary terms, we assume a value of time for private vehicle users equal to 15.59€/h.[51] Hence, the marginal external time cost of a motor-vehicle km is €0.137 (0.53*15.59€/60). Combining this estimate with information about the yearly total number of motor-vehicle kilometers in Rome (see Table 1) suggests an aggregate annual external cost of congestion on motor-vehicle travelers in the order of €1.4 billion per year. Recall that we compute this cost excluding the hours where roads are hypercongested.

Figure 12 – Deadweight loss avoided when moving from congested (left panel) and hypercongested (right panel) equilibrium to the optimal allocation.



We now describe how we compute the welfare losses of (hyper)congestion. The first step is to characterize the demand function for travel. Rather than attempting to estimate this function, we assume that travel demand on a given road r is linear, with the following specification: $T = \tau_{r,h} + \varphi F$. Observe that demand for all roads has the same, time-invariant, slope φ. We let the intercepts $\tau_{r,h}$ vary by hour and road. The value of these intercepts can be calculated given the assumption that, on a given road-hour pair, the market is in equilibrium. Given φ, T and F, one calculates $\tau_{r,h}$ .In the following, we consider the case where $\varphi = 0$, i.e. a horizontal inverse demand function, and negatively-slope demands with $\varphi =$ -0.1, -0.3 or -2. The implied corresponding average demand elasticity are then either minus infinity, -1.5, - 0.5 or -0.07. Hence, we consider a rather broad spectrum of demands spanning from perfectly elastic to almost perfectly inelastic.

The next step is to characterize the *optimal equilibrium* – in terms of density, flow and

[51] This is the median value proposed by Rotaris et al. (2010) for Milan, the second largest city in Italy.

travel-time – corresponding to each observed equilibrium (per hour and road).[52] To do so, we combine the information on demand with an estimate of the road-specific road supply curve using the IV estimates in Table 5. Optimality requires that marginal benefit equals marginal social cost. Hence, in the optimal equilibrium, $\tau_r + \varphi$ F = $T + MEC$ must hold. Given $T = \beta e^{\alpha \mathrm{D}}$, and *MEC*=αD T /(1 - αD), density can be found by numerically solving the following equation:

$$\tau_r + \varphi\ (\mathrm{D}/\ \beta e^{\alpha \mathrm{D}})\ = \beta e^{\alpha \mathrm{D}}\ +\ \alpha \mathrm{D}\ \beta e^{\alpha \mathrm{D}}\ /(1\ -\ \alpha \mathrm{D}) \quad (15)$$

Given the value of the optimal density, we calculate the corresponding optimal travel time and flow.

Finally, we calculate the welfare improvement of a policy that induces a shift from the observed equilibrium to the optimum. This improvement consists of the change in total consumer benefits (the area under the inverse demand function) minus the change in total cost (the difference between flow times average time in the optimum and in the observed equilibrium). Recall that the optimal equilibrium cannot lie on the hypercongested part of the supply curve (see Section 2.1). Observe that when starting from the hypercongested equilibrium, it is possible that both changes are welfare improving, specifically if flow increases. Figure 12 provides an illustration.

In Table 6 we report the results for different values of φ. We report the marginal external costs of one additional motor vehicle and the (per minute) welfare gain of optimal policy – averaged over all roads and hours of the day, expressed in minutes times motor vehicles. We decompose this welfare gain into a change in consumer benefits and a change in travel time costs. Moreover, we calculate the overall welfare gain from removing hypercongested equilibria only and the welfare gain per hypercongested equilibrium.

For brevity, we discuss the results in detail only for the case where $\varphi = -0.1$. As shown in Table 6, density decreases when moving from the observed to the optimal equilibria. The average reduction in density is substantial from 13.49 to 10.38 vehicles (about 25 percent). Average travel time falls from 1.33 to 1.26, so by 0.07 min/km, i.e. 5 percent. This reduction may seem small, but on some roads the drop in travel time is very substantial. For example, for the road depicted in Figure 9, average travel time falls from 0.96 to 0.81

[52] When the road supply curve is backward bending, multiple equilibria can occur, as the equilibrium may lay either on the congested or the hypercongested part of the road supply curve (see Figure 12). However, multiplicity arises only if the inverse demand function is steeper than the downward sloping part of the (inverse) road supply function. In our data, for the supply function, the implied travel time elasticity with respect to flow given the presence of hypercongestion is about -5, so the inverse supply function is very steep in the hypercongested part. Hence, multiplicity appears to be rather unlikely.

minutes, i.e. by about 15 percent. In addition, we see from Table 6 that the average flow decreases by about 15 percent. The induced welfare gain is equal to 1.05 motor vehicle minutes (per minute/kilometer/road lane), roughly twice the marginal external cost as measured in the observed equilibrium, so therefore about €0.26 per minute (per kilometer/road lane). This welfare gain comes into existence because travel time cost fall by 3.68 motor-vehicle minutes. This is a substantial drop, but the consumer benefits also fall substantially, by about 2.63 motor vehicle minutes.

To provide a sense of the relevance of hypercongestion, we also calculate the welfare gain when we only remove hypercongestion equilibria (into optimal equilibria). See the penultimate row in Table 6. Focusing again on the case where $\varphi = -0.1$, we obtain that, despite that the roads in our sample are hypercongested only 2 percent of the time, about 35 percent of the overall welfare gain (0.37/1.05) can be obtained from optimal policies on roads that are hypercongested. Observe that this result depends on the assumed slope of the demand function. When the demand for travel is very inelastic, $\varphi = -2$, about two thirds of the welfare gain (0.37/0.56) is due to the removal of hypercongestion. Nevertheless, even when the demand for travel is perfectly elastic, the welfare gain due to removal of hypercongestion is still substantial and equal to 17 percent of the overall welfare gain.

Table 6 – Welfare changes: observed and optimal equilibria

	Observed	Optimal φ=0	Optimal φ= - 0.1	Optimal φ= - 0.3	Optimal φ= - 2
Density (motor vehicles/km/lane)	13.49	6.71	10.38	11.71	13.06
Flow (motor vehicles/min/lane)	10.49	6.02	8.91	9.73	10.58
Travel time (min/km)	1.33	1.20	1.26	1.29	1.31
Hypercongestion	0.02	0	0	0	0
Marginal external cost , MEC (min)	0.53	0.18	0.29	0.36	0.49
Welfare gain (min/lane)		*1.38*	*1.05*	*0.81*	*0.56*
change in travel time cost		-7.35	-3.68	-2.37	-1.04
change in consumer benefits		- 5.83	- 2.63	- 1.55	- 0.48
removing hypercongested eq.		0.24	0.37	0.34	0.37
Welfare gain per hypercongested equilibrium		26.78	24.79	24.14	22.75

Note: These are averages for all roads and all hours. Hypercongestion measures the share of time that a road is hypercongested. We compute the marginal external cost for times when a road is *not* hypercongested.

Confirming the above results, the last row in Table 6 indicates that the welfare improvements are much larger on roads that are hypercongested. The average welfare gain on these roads is equivalent to 25 car minutes, so in monetary terms roughly €6 per minute (per kilometer/road lane). To put this in perspective, the *hourly* welfare gain of removing hypercongestion is about €700 for a standard two-lane road. The latter result depends very little on the slope of the demand function. For example, when φ is equal to -2, so demand is essentially inelastic, the welfare gain is still equivalent to 23 car minutes. Clearly, given hypercongestion it is possible to get substantial welfare gains even without reducing flow.[53]

We emphasize that the above results focus on the average welfare gain. When we focus on the heavily-congested road depicted in Figure 9, the welfare gains of policy are much more substantial. For this road, welfare gains are about twice the average and travel time reductions up to 25 percent are welfare improving.

To complete the picture, we show the marginal external cost for the observed equilibria (and when there is no hypercongestion) in Figure 13, as well as the welfare gain of optimal policy per hour of the day, when $\varphi = -0.1$ in Figure 14. Not surprisingly, the MEC and the overall welfare gain fluctuate over the day and the welfare gains of reducing congestion are *much* larger during peak hours.

Figure 13 – Marginal external cost

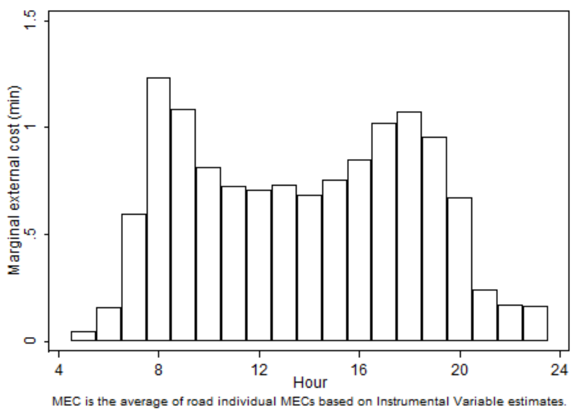
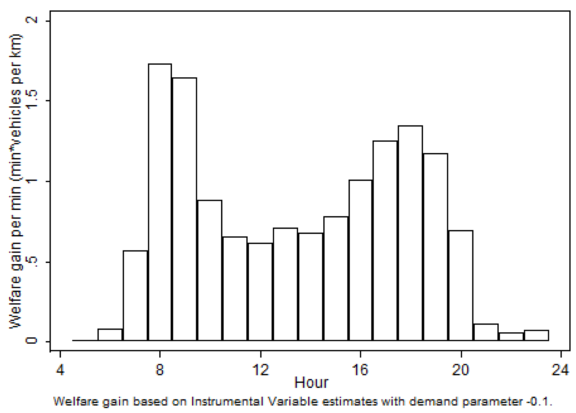


Figure 14 – Welfare gains



Taken together, the results of this section indicate that the welfare losses due to road congestion in Rome are substantial. However, some discussion of our results is in order. First, although we observe traffic data from many measurement locations that are quite evenly spread across the city, our sample may not be entirely representative of the road network in Rome. Second, we have to make assumptions on the underlying travel demand function,

[53] In Table 6, we have provided the marginal external costs, averaged over all observations. This masks uncertainty about the estimates of the marginal external cost for individual observations. To examine this, we focus on one observation for which density is 20 motor-vehicles per kilometer, flow is 20 motor-vehicle per minute and travel time is 1 minute per kilometer. Given the estimate and standard error of α, as provided in Table 4, (6) and (13) imply then that MEC is equal to 0.66 motor-vehicle minutes per lane with a standard error of 0.05. When density is 40, flow is almost 15 and travel time equals 2.7. MEC is then equal to about 20 with a standard error of 1. Consequently, the standard errors of the individual estimates are usually quite small.

because our data does not allow us to provide a fully-fledged estimation. Third, we estimate road supply curves at the individual road level, and not at an area- or network-wide level. Hence, our estimates of the external costs do not account for the possibility of avoiding heavily-congested roads by using different links within the road network.[54] A priori, this possibility has several implications. On the one hand, if individuals can reduce their travel time by, say, using secondary roads, we are likely to overestimate the average external costs of congestion. On the other hand, in a city like Rome, it is unclear to what extent drivers are able to avoid congested primary arteries without having to take substantial detours. In this case, the extra-vehicle kilometers may increase the aggregate travel time losses, implying that we are somewhat underestimating these costs.

5.1.2 Travel time losses of bus travelers

We now estimate the external cost of congestion of motor vehicles on bus travelers. We start with the approach based on (10). This expression states that the ratio of the marginal external time cost to bus travelers and to motor-vehicle travelers equals $\theta^{-1}N_{PT}/F$, where N_{PT}/F is the number of bus travelers relative to the motor-vehicle flow travelers, which is roughly 0.4 in Rome[55], and where θ^{-1}denotes the marginal effect of motor vehicle travel time on bus travel time. We estimate θ^{-1} by regressing bus travel time on motor vehicle travel time. The first column of Table 7 reports the estimate of a bivariate model. In the second column, we control for hour of the day, bus-schedule day and year. Given controls, we find that θ^{-1} equals roughly two, so substantially higher than one, with a standard error of 0.1. Hence, $N_{PT}/(\theta F)$ is equal to about 0.80. To give an idea of the implied order of magnitudes, let us assume that the value of time of bus vehicle travelers is 60 percent of that of motor-vehicle travelers.[56] Then the marginal external cost to bus travelers is in the order of 40 to 50 percent of the marginal external cost to motor-vehicle travelers. Consequently, the marginal external cost to bus travelers is quite large.

We also estimate the time losses to bus users via an alternative approach, based on (11). This approach uses estimates of the marginal effect of motor-vehicle density on log bus travel time, σ, using the aggregated bus schedule times. Recall that we have 380 observations.

[54] Akbar and Duranton (2016) provide citywide estimates of supply and demand functions for Bogota', using information from travel surveys and Google Maps.

[55] Given information about the average occupancy of buses, which is 42, provided to us by the city of Rome, this implies about 6 bus per hour per road.

[56] For Milan, Rotaris et al. (2010) report a median VOT of €9.54/h for bus travelers. We did not find corresponding studies for Rome.

We find that this marginal effect, given controls, is about 0.0188, see column 3 of Table 7. To examine whether this effect depends on the selection of the data, we have also estimated the effect of density on the log of motor-vehicle travel time, α. Given controls, we find that the effect of density on log bus travel time is slightly higher than the effect on log motor-vehicle travel time when using the same aggregated data, see column 4, so if we assume that σ =α, we obtain a conservative estimate.[57] Given that, on average, bus travel time, T^{PT}, is about twice the motor-vehicle travel time, *T*, it appears that the marginal external effect of a motor-vehicle traveler through longer travel times of bus travelers is at least half of its effect through longer motor-vehicle travel times, according to (11).[58] Hence, both approaches provide similar results.

Table 7 – Bus travel time and motor-vehicle travel time

	(1) Bus travel time	(2) Bus travel time	(3) Bus travel time (log)	(4) Bus travel time (log)	(5) Motor-vehicle travel time (log)	(6) Motor-vehicle travel time (log)
Motor-veh. travel time	2.792^{***}	1.996^{***}				
	(0.106)	(0.108)				
Density			0.0242^{***}	0.0188^{***}	0.0153^{***}	0.0169^{***}
			(0.000621)	(0.000896)	(0.000360)	(0.000486)
Controls	No	Yes	No	Yes	No	Yes
N	380	380	380	380	380	380
R^2	0.646	0.941	0.818	0.965	0.859	0.955

The dependent variable is bus travel time in min/km. Standard errors are robust. We control for hour, bus-schedule day and year. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Using the above results, we compute the marginal external cost of motor vehicle travel on bus users to be about 0.05€/veh-km, i.e. roughly 30% of the overall marginal external cost (0.137+0.05=0.172€/veh-km). As the aggregate external cost of congestion to motor-vehicle travelers is about €1.4 billion per year, the previous results suggest that the external cost of congestion to bus travelers is about €0.6 billion per year. Thus, the total external cost of congestion to motor vehicle and bus travelers combined is about €2 billion per year, that is

[57] This effect is somewhat smaller than the effect presented in column (1) of Table 4, which uses less aggregated data. The downward bias of the estimates shown in Table 7 is to be expected, since aggregation is rather substantial which usually results in a downward bias.

[58] This result supports the simulation study of Basso and Silva (2014) which concludes that the marginal contribution of transit subsidies to welfare improvements is much lower than that of reductions in road congestion through road tolls or the building of separate bus.

about 2% of the Rome metro area's GDP.[59] In sum, the results of this section suggest that a relevant share of the external congestion cost of congestion is borne by bus users.

5.2 The congestion relief benefit of public transit

We now turn to the congestion-relief benefit of transit. We first estimate the effect of public transit share on hourly vehicle flow and travel time.[60] We include controls for location, weather conditions and hour of the weekday, week of the year and month of the year.[61] These controls capture unobserved factors that affect traffic conditions and may be correlated with strikes. For example, unions may prefer to strike on certain days of the week to maximize the impact of their action. We also control for days with cancelled strikes.

Table 8 –Flow

	All roads (33)		Heavily congested (10)		One-lane (12)		Arterial roads (7)	
Morning peak: Public transit share	-1.07	***	-0.32		-1.39	***	-0.49	
	(0.20)		(0.27)		(0.20)		(0.36)	
Afternoon peak: Public transit share	-0.83	***	-0.85	***	-1.10	***	-0.79	***
	(0.12)		(0.17)		(0.15)		(0.25)	
Off-peak: Public transit share	-0.76	***	0.86	***	-0.84	***	-0.80	***
	(0.07)		(0.09)		(0.07)		(0.13)	
Controls								
Location	Yes		Yes		Yes		Yes	
Hour-of-weekday	Yes		Yes		Yes		Yes	
Month	Yes		Yes		Yes		Yes	
Week-of-year	Yes		Yes		Yes		Yes	
Weather	Yes		Yes		Yes		Yes	
Observations	422,691		117,790		158,427		81,981	
R^2	0.8354		0.8578		0.7141		0.8681	

Note: The dependent variable is flow expressed in veh/min/lane. Standard errors (in parenthesis) robust and clustered by hour. Significance levels indicated at 1%, ***, 5%, ** and 10%. *. The number in parenthesis in column titles indicates the number of roads.

Our main interest is in the effect of public transit supply on travel time. However, starting from the analysis of the effect on traffic flow (Table 8) facilitates the interpretation, because the presence of hypercongestion suggests that the effect of strikes on flow may be small. We distinguish between the effects of public transit share during the morning peak, the afternoon peak and off-peak. We report the estimation for the entire sample (column 1), as

[59] The GDP of Rome metro area in 2005 was roughly €94 billion. See https://en.wikipedia.org/wiki/Rome.

[60] 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.

[61] Hence, we include a dummy for each month in our dataset, interactions between week and year (169 dummies) and between hour and weekday (120 dummies).

well as for heavily-congested roads (column 2), for one-lane roads (column 3) and for large arterial roads (column 4). In the morning peak, provision of transit services decreases traffic flow on average by 1 vehicle per minute (first row of Table 8). That is, about 9.6% of the average flow.[62] The point estimates of the effects of public transit share are somewhat smaller during the afternoon peak and outside peak hours. In line with the idea that hypercongestion is relevant in Rome, the effect of public transit on flow in heavily-congested roads is statistically insignificant (Anderson, 2014, Small and Verhoef, 2007).[63]

Table 9 reports the results of the estimation of the effect of transit supply on travel time.[64] We find that public transit provision reduces travel time in peak morning hours by 0.245 minutes per km. The effect is substantially smaller during the evening peak (0.095) and off peak (0.065 min/km) in line with Figure 3. These are our main estimates that we will later use in the welfare analysis of Section 5.3. These estimates are significantly larger than the implied estimate used by Parry and Small (2009). However, although the effect is substantial, the estimate is smaller than that reported by Bauernschuster et al. (2016) and Adler and Van Ommeren (2016) for inner cities. There are at least two explanations for this finding. First, contrary to both studies, the effect we estimate relates to motor vehicles, i.e. cars as well as motorbikes. It is reasonable to assume that the effect of congestion on motorbikes is less pronounced. Because the latter have a peculiarly large modal share in Rome, the effect on motor vehicle travel time is most likely larger than the estimates reported in the table. A second explanation is the relatively low speed and high occupancy of buses, which provide most of the transit services in Rome. It is then reasonable to expect that supply shocks due to strikes have a smaller effect on modal choice in Rome than in other cities.

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, where the point estimate is equal to -0.524 min/km (see column 2). Hence, increased demand for car travel when public transit supply is reduced produces strong increases in travel time and traffic jams associated with hypercongestion (as there is little evidence of higher flows, see Table 3). By comparison, the travel time reductions on arterial roads, and in particular one-

[62] We find similar effects when estimating the same model using log of flow as dependent variable (see appendix). It is also in line with estimates for Rotterdam (Adler and Van Ommeren, 2016).

[63] In our analysis, we have excluded night times observations. During night times, 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 similarly, Anderson, 2014).

[64] We have estimated the same model using the logarithm of speed as the dependent variable. The results are very similar. In the literature, it is common to use travel time because welfare effects of congestion are defined by travel time losses.

lane roads (column 4), are systematically lower than on the most heavily congested roads. Nevertheless, the effect of public transit in one-lane roads during morning peaks is still substantial in magnitude (- 0.136 min/km, column 3).

Table 9 –Travel Time

	All roads (33)		Heavily congested (10)		One-lane (12)		Arterial roads (7)	
Morning peak: Public transit share	-0.245	***	-0.525	***	-0.136	***	-0.370	***
	(0.036)		(0.079)		(0.027)		(0.074)	
Afternoon peak: Public transit share	-0.095	***	-0.178	***	-0.041	**	-0.076	**
	(0.021)		(0.041)		(0.017)		(0.035)	
Off-peak: Public transit share	-0.065	***	-0.115	***	-0.042	***	-0.054	***
	(0.010)		(0.021)		(0.008)		(0.018)	
Controls as in Table 8	Yes		Yes		Yes		Yes	
Observations	422,691		117,790		158,427		81,981	
R^2	0.5865		0.5291		0.8276		0.1656	

*Note: The dependent variable is travel time, measured in min/km. Standard errors (in parenthesis) robust and clustered by hour. Significance levels indicated at 1%, ***, 5%, ** and 10%. *. The number in parenthesis in column titles indicates number of roads.*

Another way to demonstrate the importance of public transit during (morning) 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 Figure 11, the negative effect of public transit share on travel time is particularly strong during peak hours, but the effect on traffic flow is (almost) absent during these hours.

Figure 11 – Travel time

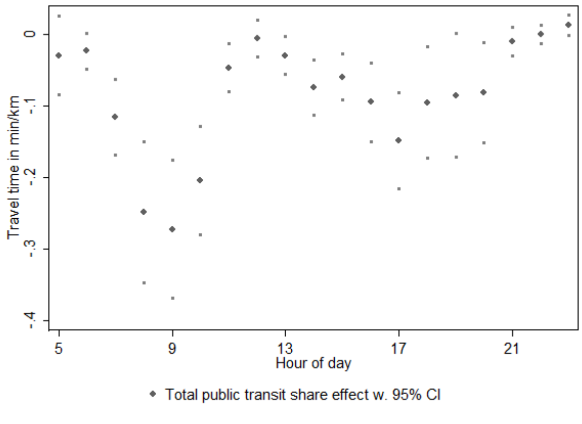
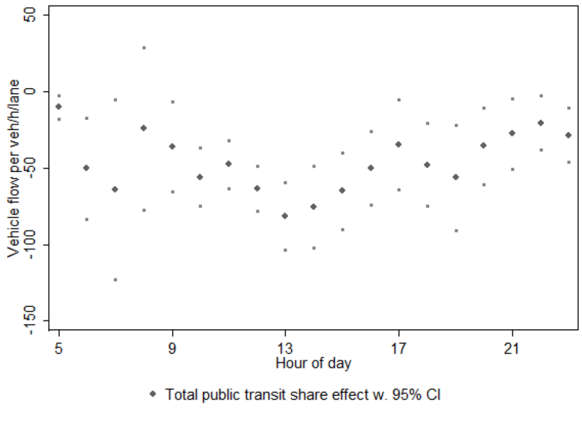


Figure 12 – Flow



We have also estimated models where we regress the presence of hypercongestion – as defined by our estimates in section 5.1.1 – on the public transit share using the same controls as in Table 8. We find that the effect is negative and equal to - 0.038. Given that the average level of hypercongestion is only 0.02, this suggests that reducing the current supply of public transit would approximately double the level of hypercongestion.

Taken together, these results imply that the effect of transit supply on road congestion in Rome is far from negligible. Disruptions in public transit service during strikes produce positive demand shocks for motor-vehicle travel, particularly during the morning peak when hypercongestion is more likely to be present. As a result, travel time substantially increases suggesting a relevant congestion relief benefit of public transit.

Note that previous estimates provide a measure of the *average* congestion-relief benefit of public transport. However, to interpret our results of the *marginal* congestion relief benefit of public transit, it is relevant to know whether the derived marginal effect of public transit share is constant, i.e. to what extent the effect of public transit on travel time is linear. To investigate this, we have estimated several nonlinear models, which all suggest nonlinear effects, where the marginal effect is more pronounced for shares between 0.4 and 0.8 than between 0.8 and 1. However, statistical tests indicate that we cannot reject the linear specification hypothesis, i.e. that the marginal effect of public transit share on travel time is constant.[65] We come to the same conclusion when we focus on the effect of public transport on flow. Here we present the results using a fifth-order polynomial of the public transit share in Figures 13 and 14.

Figure 13 – Travel time

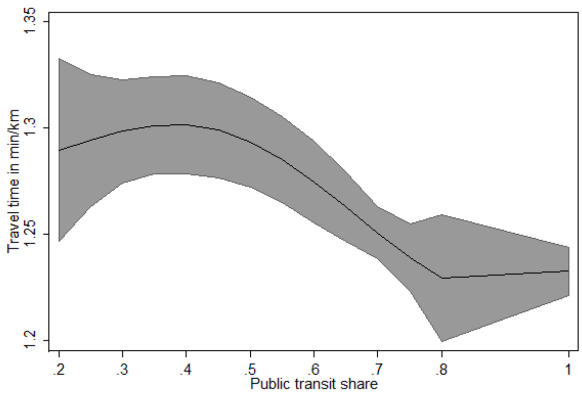
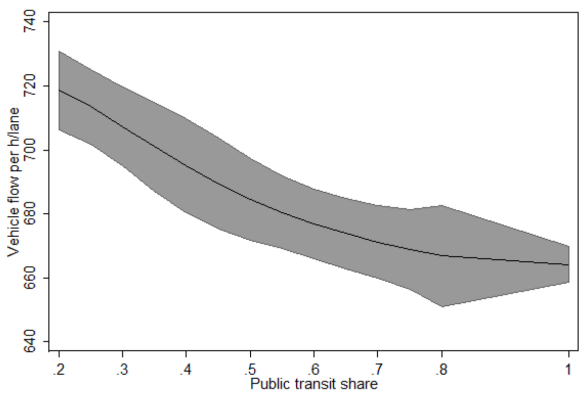


Figure 14 – Flow



One criticism of the above analysis is that we use exogenous variation in the public transit *share* rather than exogenous variation in the public transit *level*. Note that we control for the scheduled service level by including hour of the day dummies. Furthermore, note that the scheduled service level is constant, with a supply about 1800 buses, between 9 a.m. and 5 p.m. Hence, we have re-estimated the model for observations during these hours (177450

[65] 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 low.

observations). We find that then the standard errors are somewhat higher, but the results hardly change. For example, the estimated effect during peak hours is now -0.270 (with a standard error of 0.054), very close to the original estimate. Given this estimate, it appears that the *marginal effect of a single bus* during *one* peak morning hour on motor vehicles' travel time is about -0.00015 minutes per kilometer (-0.27/1800).

Finally, reductions in public transit supply can be regarded as an implicit overall public transit price increases to the transit traveler. In our data, we observe one substantial public transit increase in the price. We have investigated the effect of this price increase on motor vehicle travel time as a robustness check. Our results indicate that an increase in public transit prices by 50 percent increases motor-vehicle travel times by about 0.05 minutes per kilometer. The size of this effect is similar to a 20 percent reduction in public transit supply, which seems a reasonable result (see Appendix B for details).

5.3 The long-run congestion relief benefit of public transit for Rome

We now use the above estimates to quantify the overall congestion-relief benefit of public transit in Rome. According to our results, the marginal effect of public transit supply on road traffic is approximately constant. Hence, the short-run effect of a full shutdown of public transit services (consisting of 201 million vehicle-kms per year) results, on average, in 57 additional motor vehicles per hour per road lane during the peak and 45 additional vehicles off peak (see Table 8).

Furthermore, using the results of Table 9, it results in a 0.17 min/km increase in travel time in peak hours (averaging for morning and afternoon), and 0.065 min/km off peak. The (forgone) annual congestion relief benefit to motor-vehicle travelers is then about 38 million hours of travel time. Assuming that the value of time is 15.59 €/h, this benefit is valued at roughly €595 million.[66] This is equivalent to about 38% of the total public transport operating cost (1.56 billion euros in 2013), and about 30% of the total external costs of congestion. Note that these values do not include the welfare losses of transit users. We summarize these findings in the first column of Table 10. Based on the same estimates, we also consider the effect a 1% shutdown in public transit provision. This decrease costs €5.95 million in lost

[66] We multiply annual passenger-kms by private vehicles (see Table 1) by the estimated travel time increases in peak and off peak hours, and by the value of time. We assume that people who switch from private motor vehicles to public transit only benefit by half as much as people that already use public transit. Note that this measure does not include the loss of surplus to former transit users.

congestion relief benefits to motor-vehicle travelers but also €2.3 million to bus travelers.[67] The total loss due to extra congestion is thus 8.25 million euros annually, i.e. roughly 54 percent of the operating cost savings for the transit agency. We report these results in the second column of the table.

Another interesting exercise is to compute the marginal congestion relief benefit of an additional bus. On the 33 roads analyzed here, there are about 500,000 motor-vehicle travelers in the morning peak who, let's assume, travel on average 4 km on these roads, which is likely a conservative estimate. Hence, the marginal reduction in time delay is about 300 minutes. Assuming that the value of time is 9.54 Euros per hour, the marginal external benefit of a bus during peak hours is about 48 Euros. Given that there are about four morning peak hours, the external benefit of a bus during peak hours is at least 200 Euro per day.

Table 10 – Congestion relief benefit of public transport, aggregate calculations

	Full shutdown	Marg. shutdown (1% of total veh-km)
Assumptions		
Annual veh-km, private motor vehicles	14. 5 billion	
Annual veh-km, public transport	201 million	
Travel time increase cars (peak), min/veh-km	0.17 min/km	0.0017 min/km
Travel time increase cars (off-peak), min/veh-km	0.065 min/km	0.00065 min/km
Travel time increase buses (peak), min/veh-km		0.0034min/veh-km
Travel time increase buses (off-peak), min/veh-km		0.0013min/veh-km
Value of time of car travelers	€15.59/h	
Average op. cost public transport, veh-km	€7.76/veh-km	
Results		
Public transit congestion relief benefit, year	€595 million	€8.25 million
Operating cost saving, year	€1.56 billion	€15.2 million
Subsidy reduction	€1.03 billion	€15.2 million
Net congestion relief benefit (% of cost saving)	38%	54%

An important caveat regarding the interpretation of these results is that they are based on short-run estimates, exploiting temporary service disruptions. Hence, one should apply some caution when using them to predict long-run effects of (permanent) changes in transit supply. In Rome, car ownership is very high and strikes are frequent, suggesting that travelers may respond to them in a way that is more similar to a permanent service reduction than in other cities. Thus, our estimates are more likely to approximate long-run effects than previous literature using a similar methodology (e.g., Anderson, 2014). It is plausible that the main

[67] Combining the results of Table 9 mentioned above with the results of Table 7, the effect of a 1% decrease in transit services results in excess travel time for buses is 0.0034min/veh-km in peak hours and 0.0013min/veh-km off peak. Table 1 indicates that there are 66.7 million veh-kms of bus service in Rome per year in peak hours (average occupancy 51 pax/veh) and 67.7 million veh-km off peak (34pax/veh). Therefore, we calculate an extra total travel time of 0.192 million extra hours of travel time for bus users in peak hours and 0.049 off peak. Assuming the value of time for bus travelers is 9.54 euros/h, we get a total extra loss of 2.3 million euros.

difference between our estimates and long-term estimates is the possibility during strikes to cancel trips. Note that individuals who respond to strikes by canceling their trip likely have less leeway to do so in the long run and will switch to car use. Hence, long-run effects of reductions in supply on road congestion are most likely larger than indicated by our current estimates. Nevertheless, we emphasize that we do not capture the very long-run effects of transit supply changes, such as job, house and firm relocation, and maybe even the spatial structure of cities; hence, we interpret our estimates as only indicative of the long-run effects of changes in transit service.

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

The results of the previous section 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 close to optimal. Subsidies may also have other justifications (e.g., economies of scale, environmental externalities) but also produce a price distortion. We have ignored these issues up to now. Furthermore, for a proper evaluation of public transit subsidies one has to consider possible adjustments in service by the transit agency, in response to (subsidy-induced) changes in demand. To provide more insight on whether the current subsidy level is justified, we use the model of Parry and Small (2009). In this model, travelers choose between three travel modes (private motor-vehicle, bus, rail) and two time periods (peak vs. off-peak), while the (welfare-maximizing) public transit agency chooses transit supply and fares subject to a budget constraint. This model has been calibrated for several cities (Los Angeles, London, Washington DC), but not for Rome. We calibrate its parameters using our empirical estimates and data provided by the city of Rome (see Table C1 in Appendix C for details).

For consistency with our empirical analysis, we slightly adapt Parry and Small's model as follows. First, we assume that motor-vehicle travel time is a function of density.[68] Specifically, we assume that $T = \beta e^{\alpha \mathrm{D}}$, with $\alpha = 0.02$ (this is the estimate from Table 4, column 2). Consistent with this assumption, we compute the marginal external cost based on MEC as provided in (6). Secondly, we include the marginal external cost of motor-vehicle traffic on bus users, assuming (10), with $\frac{1}{\theta} = 2$ (as estimated in Table 7, column 2).[69] Finally, we calibrate the fare elasticity of transit passenger-kms using our own estimates and data

[68] Parry and Small postulate a time-flow relation, whereby travel time is a power function of flow.
[69] We assume a that there are on average six buses running on a road per hour and use the average peak and off peak occupancies of 51pax/veh and 34pax/veh respectively, as provided by the Rome municipality.

provided by the city of Rome (see Appendix B). We use an elasticity of 0.22, as suggested by our data. This elasticity is rather low in comparison to the elasticities assumed by Parry and Small. However, given that transit fares in Rome are much smaller than in comparable European cities, low fare elasticity seems quite reasonable. Our results hardly change when we use elasticities as assumed by Parry and Small.

Table 11 – Parry and Small model for Rome: optimal public transit subsidies

		Peak		Off peak	
Marginal external cost, motor vehicle travel. €cent/veh-km		32.95		12.89	
of which: on other motor vehicles travelers		20.84		9.31	
on bus travelers		12.11		3.58	
		Rail		Bus	
		Peak	Off-Peak	Peak	Off-Peak
Current subsidy, share of op. cost		0.76	0.76	0.74	0.69
Marginal welfare effects	Weighted Avg.				
Marginal benefit per €cent/pax-km[a]	0.10	0.31	-0.07	0.11	0.21
marginal cost/price gap	-0.24	-0.38	-0.41	-0.34	-0.21
net scale economy	0.12	-0.02	0.21	0.04	0.31
externality	0.15	0.53	0.14	0.31	0.02
other transit	0.08	0.19	0.11	0.10	0.09
Optimum subsidy, share of op. cost		>0.9	0.72	>0.8	>0.9

Notes

[a] This is the marginal welfare gain from a one cent-per-km reduction in the fare, in euro cents per initial passenger-km.
[b] The subsidy for each time period and mode is optimized holding the others at their current values.

Table 11 reports the results. The top panel reports the marginal external congestion cost per motor vehicle kilometer, which equals €0.29/veh-km in peak hours, and €0.11/veh-km during off peak (see the first row of Table 11). These costs are the sum of the external costs imposed on motor vehicle drivers (€0.21/veh-km in peak hours, €0.09/veh-km off-peak), as well as the external costs imposed on bus travelers (€0.086/veh-km in peak hours, €0.023/veh-km off-peak).

The bottom panel of Table 11 reports the marginal change in social welfare resulting from a marginal increase in the public transit subsidy (assuming this increase results in a fare reduction), starting from the current level. The reported “marginal benefit” is the marginal welfare gain from a one-cent-per-km reduction in passenger fare, expressed in cents per initial passenger-km. We decompose this effect into four components: (i) a welfare loss due to the increased gap between marginal production costs of producing public transit and public transit prices, (ii) a welfare gain due to additional economies of scale, (iii) a welfare gain due to a reduction in externalities (congestion and motor-vehicle pollution reduction) and (iv) the welfare benefit of diverting passengers from other transit modes for which the marginal social cost per passenger-km exceeds the fare. The marginal social benefit of a fare reduction is positive for rail and bus services, except for off-peak rail. The average marginal social benefit is equal to 0.1. This finding suggests that, despite their 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.[70] In addition, we find that in the optimum – in the absence of road pricing – subsidies should cover at least 72% of operating costs (bottom row in Table 11).

7. *Conclusion*

We estimate the marginal external cost of road congestion allowing for hypercongestion, i.e. when the road supply curve is backward bending. We use variation in public transit strikes to account for endogeneity issues. We use the same quasi-experimental approach to estimate the effect of public transit supply on road congestion. We demonstrate that, for the city of Rome, the marginal external cost is substantial: it is, on average, at least as large as half of private time travel cost, while reaching considerably higher levels during peak hours.

Our findings suggest that congestion relief policies bring substantial welfare gains. For the city of Rome, when roads are not hypercongested, the marginal external cost of motor vehicle travel is €0.17 per kilometer on average, but almost double during peak hours. We also find that the welfare losses produced by congestion can be up to 50 times larger for hypercongested than for normally congested roads. We found that an increase in road congestion which induces a one minute delay for each motor travel induces a two minutes travel time loss for a bus traveler sharing the same road. About one third of the marginal external cost of road congestion in Rome are borne by bus travelers.

Our findings support a range of alternative policies. For example, the high relevance of hypercongestion suggests that, even if road pricing instruments were politically acceptable, the use of quantitative measures to curb traffic on heavily congested roads (e.g. through traffic lights) may be welfare increasing. Our findings indicate that *separate* lanes for buses should

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

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, 2016).

Our results also support policies aiming at reducing road congestion through an increased supply of public transit. We find that public transit – which has a modal share of 28% in Rome – reduces travel time of motor vehicles by roughly 15 percent in the morning peak, on average. We further show that the marginal congestion relief benefit of public transit provision does not vary with the level of public transit supply. In light of the significance of the congestion-relief effect, the current level of subsidies, which is about 80 percent of the operational costs in Rome, is justified and should possibly be even increased.

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Appendix A1: Figures and Tables

Figure A1 – Strikes by month

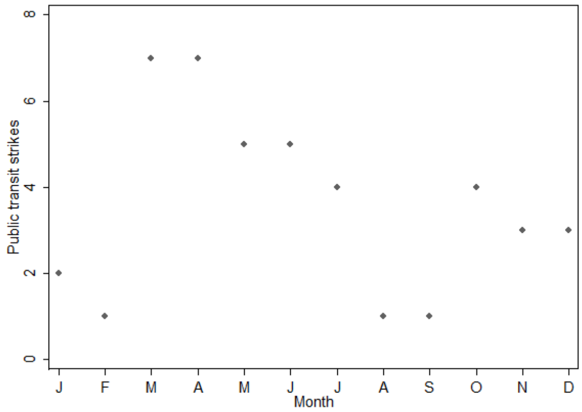

Figure A2 – Strikes by weekday

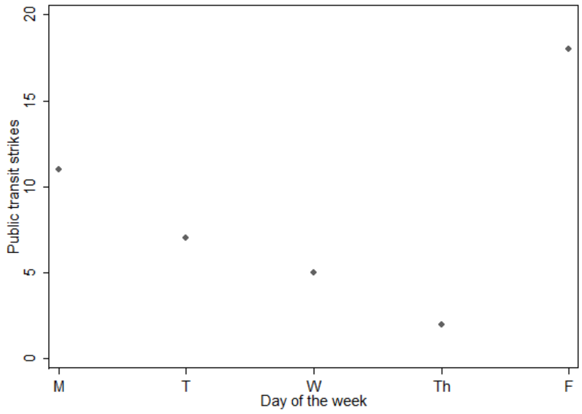

Figure A3 –Public transit share by company

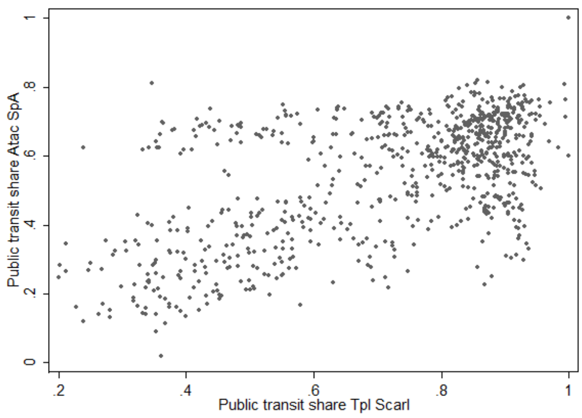

Figure A4 – Public transit on non-strike day

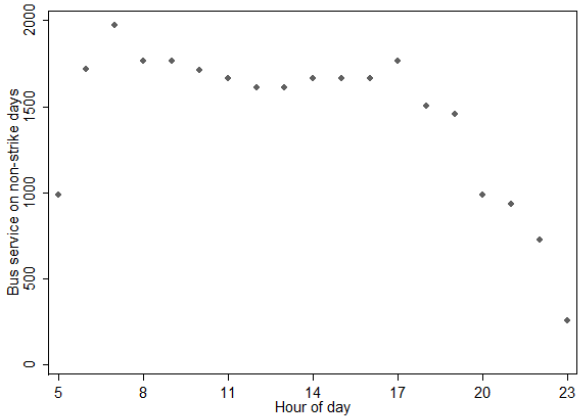

Figure A5 – Rome

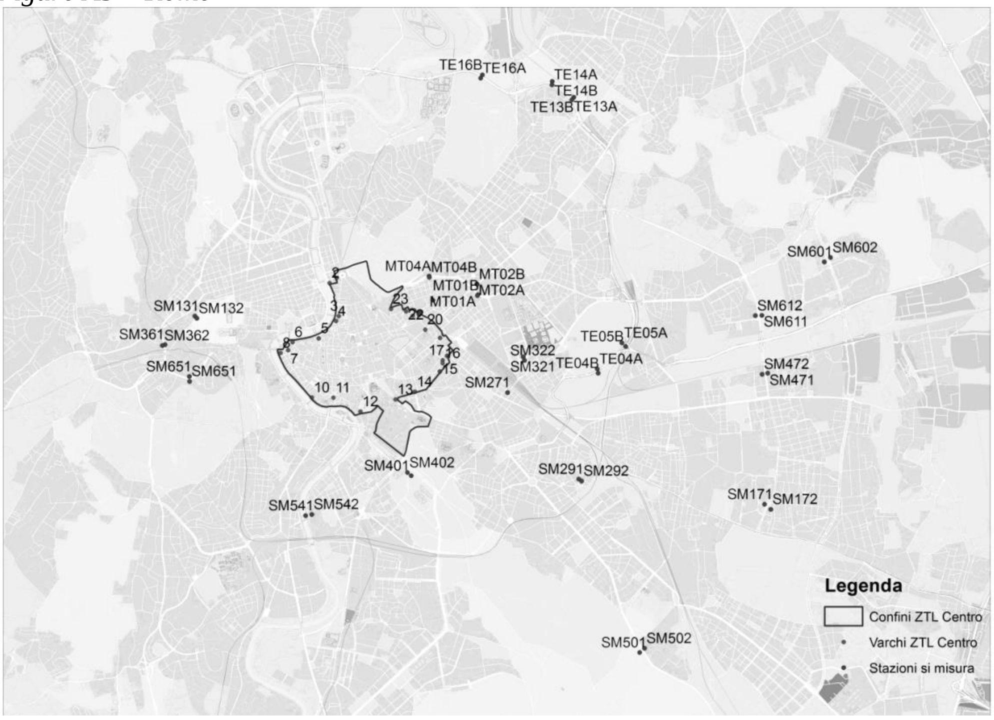

Figure A6 – Public transit service on strike days

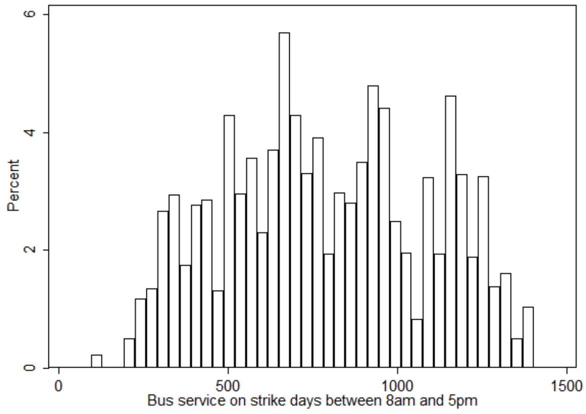

Figure A7 – Travel time histogram

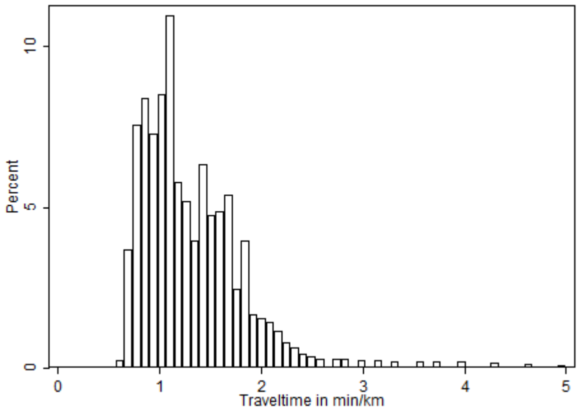

Figure A8 – Vehicle density histogram

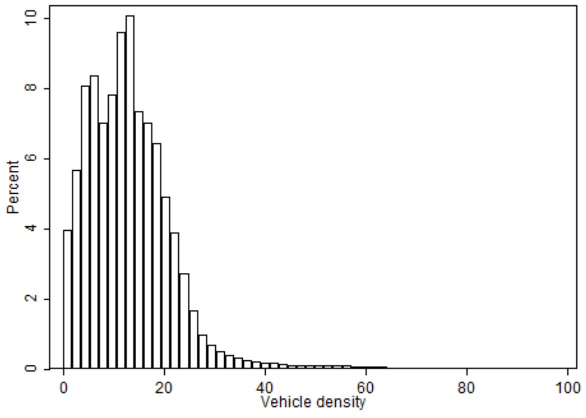

Figure A9 – Vehicle flow histogram

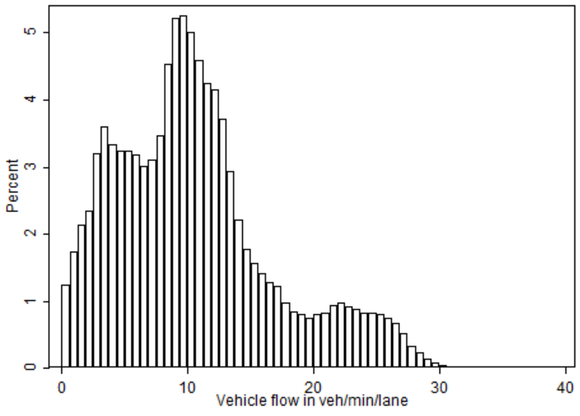

Figure A10 – Vehicle flow by hour of the day

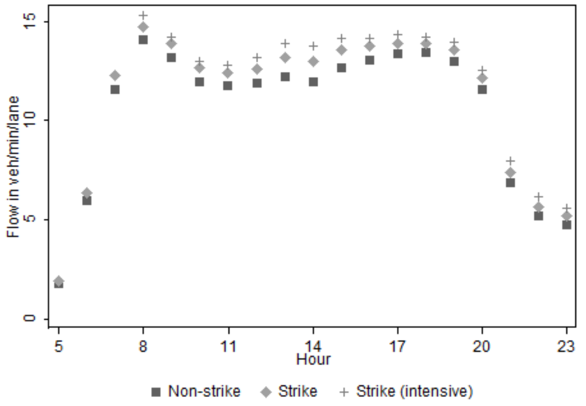

Figure A11 – Heavy congestion by hour

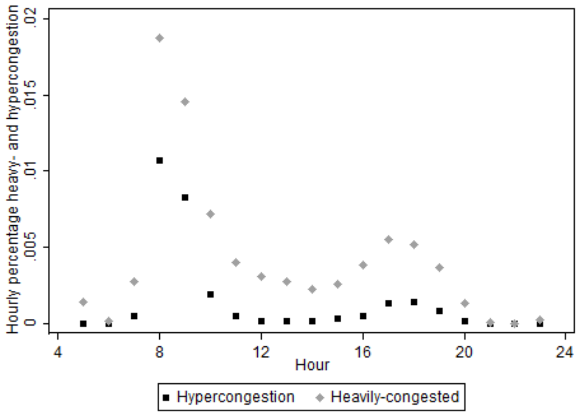

Figure A12 –Travel time-density

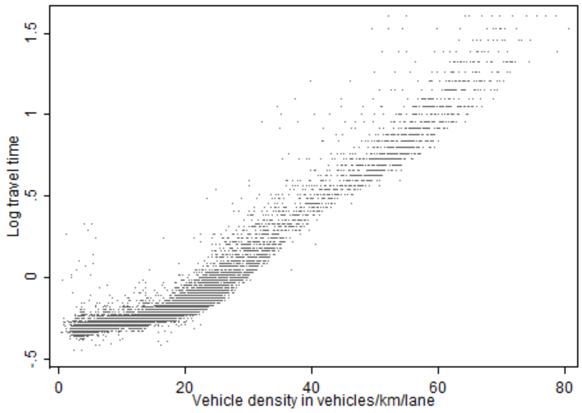

Table A1 - Logarithm of travel time

	(1) All roads (33)	(2) Heavily congested (10)	(3) One-lane (12)	(4) Arterial roads (7)
Density	0.0238***	0.0251***	0.0110***	0.0290***
	(0.000101)	(0.000121)	(0.000128)	(0.000932)
N	422691	117,790	158,427	81,981
R^2	0.925	0.927	0.945	0.9163

Note: The dependent variable is the logarithm of travel time. Controls are included but not tabulated.

Table A2 – Public transit effect on motor-vehicle density

	All roads (33)		Heavily congested (10)		One-lane (12)		Arterial roads (7)	
Morning peak: Public transit share	-5.15	***	-9.16	***	-3.78	***	-9.17	***
	(0.67)		(1.40)		(0.51)		(1.56)	
Afternoon peak: Public transit share	-2.68	***	-4.56	***	-2.27	***	-2.60	***
	(0.35)		(0.74)		(0.36)		(0.78)	
Off-peak: Public transit share	-1.71	***	-2.69	***	-1.68	***	-1.69	***
	(0.16)		(0.32)		(0.16)		(0.35)	
Observations	422,691		117,790		158,427		81,981	
R^2	0.5445		0.4760		0.6814		0.5431	

*Note: The dependent variable is density. Controls are included Standard errors (in parenthesis) robust and clustered by hour. Significance levels indicated at 1%, ***, 5%, ** and 10%. *. The number in parenthesis in column titles indicates the number of roads.*

Appendix A2: Sensitivity Analysis of the effect of public transit share on travel time

We conduct a range of sensitivity analyses to verify the effect of public transit share on travel time to various specifications. In column (1), we show results with day fixed effects. Our results appear very robust. In column (2), we cluster standard errors by road and week-of-year.[71] Standard errors become only slightly larger. In column (3), we add additional interaction effects for national strikes and semi-cancelled strikes as well as a white strike dummy.[72] The estimated sizes of these interaction effects are very small. For example, during the white strike, travel time increases slightly by 0.032 min/km.

Table A.2 – Travel time: alternative specifications

	(1)		(2)		(3)	
	Travel time		Travel time		Travel time	
Morning peak: Public transit share	-0.244	***	-0.249	***	-0.210	***
	(0.070)		(0.075)		(0.038)	
Afternoon peak: Public transit share	-0.095	***	-0.096	***	-0.061	***
	(0.028)		(0.025)		(0.021)	
Off-peak: Public transit share	-0.064	***	-0.073	***	-0.038	***
	(0.016)		(0.018)		(0.012)	
Public transit share × National strike					0.028	**
					(0.011)	
Public transit share × Semi-cancelled strike					0.029	*
					(0.013)	
White strike (dummy)					0.032	**
					(0.014)	
Day-fixed effects	Yes		No		No	
Clusters of standard errors	Location		Week-of-year and location		Day	
Observations	422,691		422,619		422,691	
R^2	0.5865		0.0005		0.5865	

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

[71] 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.

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

Appendix B: Public transit fares and motor-vehicle demand

The effect from a change in public transit prices – fares – is another supply side function aspect we investigate. Rome`s public transit operator adjusted fare prices on May 25th of 2012, most notably for single tickets from €1 to €1.5.[73] Fare prices are thought to affect demand for public transit and therefore its main alternative, private motor-vehicle use. Annual single ticket sales declined from 2011 to 2013 by 11% (ATAC 2011; 2013). This suggests that the price elasticity of public transit is -0.22, so public transit demand is rather inelastic, in line with Litman (2015).

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 window of about six months on both sides of the boundary, and we use the same control variables as in Table 4, while including third-order polynomial time trends before and after the boundary rather than week fixed effects. For results, see Table B1.

We find that the fare hike increases flow by 30 vehicles (about 5% of the mean). The cross price elasticity of motorized vehicle travel with respect to transit prices is then about 0.10. This estimate is similar to long-run effects estimated for other (see Litman, 2015). 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 B.1 – Travel time and flow as a function of public transit fare changes

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

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

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

We have investigated the robustness of these results in several ways. In particular, we have estimated models controlling for linear trends while reducing the window size around the boundary. Given a six-months window (on both sides) but with linear controls, the results are identical. Given a five months or four months window the estimates increase to 0.06 and 0.10. Given a three-month window, the estimate is again 0.04, and still highly statistically significant.

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

Table C.1– Aggregate model, parameters and results

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