The economics of roads

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Congestion, public transit and accident management

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The economics of roads
Congestion, public transit and accident management

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Preface

Candid reader,

I want to congratulate you on picking up such a fine piece of scientific work. Before diving into the jolly world of transport economics, allow me to extent thanks and give praises to those who have made this possible.

My promoter Jos has been vital to the success and his support cannot be overstated. Over these last years, he has always been immediately responsive to any request for help, stoic in the communication of knowledge, and fully supportive of me becoming a better scientist. With his sharp comments and often refreshingly unconventional solutions to the many problems of empirical research, he is an inspiration and has made my PhD the most joyful experience. A fond memory are our many meetings we had together. In the beginning, we were fortunate to have Piet with us in these. His incredible academic talent was only outmatched by his ability to provide a lighthearted environment in combination with wise and effective communication. Instead of attacking the work of others he would rather compliment the effort and make suggestion for exploring improvements. Due to loosing Piet, Erik took over the stewardship of the faculty and became my promoter. While less directly involved, he was unequivocally supportive of my PhD, and I am thankful for the chance to discuss transport issues with him. With hindsight, it is hard to imagine having taken a better decision to embark on a PhD under the circumstance I encountered. It's been a great PhD.

Next to my promoters there are two people who have supported me throughout – my parents. Their unflinching parental devotion demonstrates that investment in children is a high growth strategy. My wife Korina deserves equal praise. She gives exceptionally good advice in all matters of life. For instance, in the first months of my PhD, she got me a coffee mug decorated with the repeated statement: "I will finish what I start". Many mornings these last years this has provided inspiration.

There are two persons that will join me on stage during the defense that have some responsibility for my PhD as their earlier advice led to this moment. In 2003, Florian took me on a trip to Bayreuth where I got introduced to concept of Philosophy and Economics, my later choice for a Bachelor. Seven years

later, during a library study session at Utrecht University, Ramon recommended me to apply for a PhD position at the VU with known outcome. It is a great honor and an even greater pleasure to continue shaping the world with the two of them. An honor was also bestowed upon me by Martijn, Harry and Alexandros for allowing me to join their defense as Paranymph myself. Thank you for these instructive and pleasant moments. In general, I was tremendously lucky in terms of people I got to meet at FEWEB. Sharing the office with Sergejs, Jessie and Chris, and on the 5th floor with Hans, Yuval, Stefanie and Ceren. Likewise, colleagues became friends once the department moved to the 9th floor and I shared an office with Maria, Hugo and Ioannis. Gratitude go also to Eric and Vincent whom I joined in teaching, Thomas, Jesper and not to forget Jenny and Elfie. Many more colleagues deserve mentioning such as Or and Ilias and the newer PhD generation around Gerben and Francis. To work together with all of you (also those of you not explicitly mentioned) has been inspirational, instructive and joyful. It would be my pleasure to work with any of you in future.

To Marcus and Sheryl, I am deeply indebted for proof reading countless pages and Hagen, Matt and Agustin for the many scientific discussions over the years. Special thanks and credit go the reading committee for their time, effort and valuable advice.

Martin, Amsterdam 2019

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1 Introduction

1.1 Motivation

Transportation is essential. It allows us to meet, exchange ideas and trade; all activities that are integral parts to our evolutionary-cognitive advantage.[1] Transportation is however not effortless. From this perspective, the obstacles associated with distance, such as the time it takes to travel between locations are a limit to our capabilities. Clearly, this limit changes over time and many of us travel faster and cheaper than ever before.[2] But even today, travel is associated with substantial costs to ourselves and to others. This dissertation measures some of the costs that are associated with land-based transportation and we suggest policies to reduce these.

Modern, land-based transportation requires substantial individual and collective investments. Collectively, we finance the construction and maintenance of transport infrastructure as well as public forms of transportation (e.g. rail and bus).[3] On an individual level, we require a mode of transport (e.g. car, bus or bicycle) and an energy source (e.g. gasoline) as inputs. Arguably the most valuable resource necessary for individuals to travel is finite, scarce and cannot be produced – it is time. All forms of personal transportation require travel time of its users. Under perfect transport conditions, travel time is reduced to an optimum.[4] However, travel conditions are usually not perfect and travel time is not at its optimum because of, for example, peak-hour traffic or road accidents.

Road congestion is an immense, global problem. The European Commission (2011) speculates that about 1% of GDP (€130 billion) is lost in travel time and fuel due to congestion each year in the EU-28 alone. It is especially urban areas that have problems with congestion.[5] For example, in London,

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[1] Transport of goods and services allows for the specialization in human activity and increased labor productivity. Transport is essential to progress. The limits of transport define the size of the market and in general, the development-level of society. (e.g. Plato, 430BC; Hume, 1738; Mumford, 1961).

[2] The price of transport has decreased by more than 90% in the last 50 years for goods (Glaeser and Kohlhase, 2004; Hummels, 2007) and more than 50% for passengers (The Economist, 2000; Lawyer, 2007).

[3] The collective investments towards the public road infrastructure networks provide the basis for regional economic developments from travel and trade (Baum-Snow et al., 2015; Adler et al., 2018a).

[4] Apart from travel time, other characteristics such as safety and monetary cost also play a role in the optimal travel decision. Despite improvements in travel time over the years, the average amount of time spend on commuting is relatively constant-known as Marchetti's (1994) constant. Improvements in travel efficiency are used to travel more frequently and further, a case of Jevons paradox where resource savings through efficiency gains are used for an increase in consumption.

[5] Human agglomeration in urban areas increases congestion due to travel demand. Already ancient cities experienced road congestion, for the case of Rome around the time of Julius Cesar, see, Cary (1929) and Van Tilburg (2007). Progressing urbanization throughout the last millennia have meant a steady increase in externalities such as road congestion (Falcocchio

one-fifth of commuters spend more than two hours a day for travel from and to work (Transport for London, 2014). Outside of Europe, residents of Los Angeles lose on average €5,700 to traffic jams each year (The Economist, 2014). While these costs are already staggering, in addition to the fuel and time costs there are unaccounted cost to public health and the environment that further increase the burden.[6] Following current trends, congestion is going to increase under pressure of continued urbanization and car ownership in the developed world, but even more so, in the developing world (Schafer & Victor, 2000; TomTom Traffic Index, 2017). The advent of autonomous vehicles in the near future is predicted to lend even more urgency to this issue as the interaction between regular cars and autonomous vehicles as well as an increase in mobility might substantially increase congestion whereas sensible policy choices have the potential to dramatically reduce it (Ranft et al., 2016; Calvert et al., 2017).

We aim to contribute to the on-going discussion on how to measure road congestion and examine the cost and benefits of the main policy remedies, such as road pricing and public transit provision. Road congestion and transportation in general are important subjects and henceforth receive attention by academic disciplines from engineering to healthcare and psychology.[7] While we rely on this knowledge, our analysis is rooted in economics.

1.2 Transport in economics

The importance of transportation in economics is increasing. In the past, economists abstracted from the implications of distance, space and the complexities of transport for the reasons of simplicity. Then, notably, in 1826, Von Thünen introduced transportation into his explanation of the distribution of human activities over space. His assessment that transport costs are essential to this distribution motivated urban economics, economic geography and transport economics.[8]

Transport is still highly relevant to the distribution of human activity from housing to production. For example, when we would like to analyze the determinants of household locations, the

and Levinson, 2015). Actually, congestion is one of the main counterbalances to agglomeration forces driving urbanization (Brakman et al., 2009).

[6] The additional costs to offset one-year carbon-dioxide emission from congestion alone would be €45 million for Los Angeles (The Economist, 2014). The health cost still debated but might exceed the other costs.

[7] See, for examples of transportation in the engineering literature (Chakroborty & Das, 2017), healthcare (Fournier, 2017), mathematics (Carrillo et al., 2012), sociology (Kaufmann, 2017), and politics (Dunn, 2015).

[8] Von Thünen argues that economic activity centers around a core, usually a city center, which is supplied by resources from the surrounding areas – the 'hinterland'. Spatial economics and regional economic also greatly benefited from his contribution for similar reasons.

distance and implicit travel time to work and family matters (Alonso, 1964; Eliasson and Mattsson, 2000; Gubins and Verhoef, 2014; Mulalic et al., 2014).[9]

As a starting point to an economic investigation into transport, one might want to assume that a rational individual – epitomized by *the homo economicus* – optimizes his travel according to his preferred travel time, transport mode, level of comfort, departure and arrival time.[10] Sets of preferences containing these travel specifics can be bundled up to one utility benchmark so that alternatives can be compared. For example, a trip can be done either by car or train, each with their own advantages in comfort, speed and costs. For the comparison of alternatives, it is the most convenient to 'monetize' all preference aspects. For example, extra travel time can be expressed as an Euro-equivalent (Becker, 1965; Small et al., 2005; Koopmanns et al. 2013; Peer et al., 2014).

Table 1.1 – Thesis chapter content

	Chap. 2	Chap. 3	Chap. 4	Chap. 5
Road congestion	+	+	+	+
Road cost curve	+	+		
Marginal external cost	+	+	+	+
Road pricing	+	+		
Second-best policies	+		+	+
Welfare analysis	+	+	+	+

The place where individuals with a demand for travel encounter the supply in transport possibilities is the transport market. The (short-term) supply of road transport is directly measured and discussed in Chapter 2 and 3 and indirectly in the rest of the Chapters. In a perfect 'theoretical world', market mechanisms lead to the most efficient outcome. However, in the real world, market frictions and the unregulated use of common resources can result in suboptimal outcomes.[11] A situation where an individual's action creates costs that are borne by others are a negative externality, given that there are no other market transactions (e.g. compensation payments). Traffic externalities are far reaching and also encompass road accidents, air- and noise pollution (De Borger and Proost, 2013). This thesis

[9] The proximity to amenities such as green space and landmark buildings also plays a role (Brueckner et al., 1999; Koster et al., 2016).

[10] The concept of the homo economicus where individuals take decisions to maximize their utility is crucial for the evaluation of policy alternatives. For an early discussion of the concept see Smith (1776), Rau (1826), and Mill (1874).

[11] The abuse of a common good due to missing regulation is a reoccurring theme in many areas from pollution to land ownership, healthcare and also transport. Such a t*ragedy of the commons* can often, but not always, be solved with allocating ownership of the public resource to an authority (Hardin, 1968).

focuses foremost on the economics of road congestion – one of the main problems concerning road transport - important in all chapters of this thesis, visible in Table 1.[12]

1.3 Road congestion

An individual's decision to use a car increases travel time of all road users in proximity and this is unaccounted for by that individual. This 'time loss' can have various causes. For example, traffic jams from cars waiting to pass a bottleneck obstruction that reduces road capacity (Vickrey, 1969) are a form of *nodal congestion*. Even without bottlenecks, an increase in traffic density, e.g. on a highway, can result in *link congestion.* Vehicles waiting to pass through a link or queuing at a bottleneck (e.g. intersection) are referred to as *stock congestion* while cars passing through a section are a form of *flow congestion*. In reality, a mix of these types of congestion is plausible. In Chapters 2 and 3 we make use of *static* (i.e. *stationary-state*) models in our theoretical section as opposed to *dynamic congestion*. These models differ in the assumptions they make as well as to what specific real-world applications they can be prescribed to. The coexistence of competing explanations to congestion has resulted in continued empirical interest (see Helbing, 2001).

Empirical studies on road congestion have a long history and it is possible to distinguish these by the source of the underlying data, the study location and the applied research methodology (Small and Verhoef, 2007, p.69ff). Traffic data can be sourced from fixed measurement infrastructure at the road-side: such as pneumatic tubes, induction loops embedded in the road surface and license plate recognition cameras. Alternative data sources are from in-vehicle 'floating-car' data such as specific test-vehicles in traffic and from mobile devices such as phones or navigation systems as well as trip information from travel surveys. Roads are vastly different in characteristics and so the source of the data often defines the scope of the work. Due to their importance and discernible traffic patterns, most applied research focuses on highways. In comparison to inner city roads, highways have a higher speed limit, sometimes more lanes and on- and off-ramps instead of intersections. However, the delineation is sometimes not easy, as in the case of arterial roads and highways that lead through densely populated areas. Research interest for inner city roads is steadily increasing. Except for Chapter 5, we

[12] Externalities also apply to other congestible facilities, such as for university computers (Kobus et al., 2011) and airports (Czerny & Zhang, 2014). Externalities can also be positive, when a benefit occurs to others as an unintended consequence of an action.

focus on both inner city roads and highways, relying on pneumatic tube and induction loop data as data sources. We use highway loop data in Chapter 5.

Corresponding to these various data sources, a wide-array of methodologies exists. There is an ongoing debate whether to consider travel time a function of vehicle flow, the ratio of vehicle flow to road capacity or of vehicle density. In chapters two to four, we add to this debate by proposing novel empirical strategies for the measurement of road congestion. Policies to reduce congestion are as varied as the data sources and research methodologies.

1.4 Policy remedies

Remedies to road congestion are difficult to find and hard to implement. The first thing that comes to mind is to increase road capacity by building new roads so that more cars can travel. However, most urban centers already have densely built infrastructure. Reducing building density to accommodate new roads would decrease the benefits of density (Jacobs, 1961; Ciccone and Hall, 1996; Glaeser, 1998).[13] Even then, new road capacity would only produce medium-term congestion relief as in the long-term induced demand for travel would increase road congestion to similar levels, a circumstance known as the law of highway congestion (Downs, 1992; Duranton and Turner, 2011).

Perhaps, the "best" (i.e. cost effective) and certainly most direct strategy is marginal cost pricing. This concept is also sometimes referred to as first-best pricing, where each traveler is confronted with their own marginal social cost of travel (Walters, 1968; Hotelling, 1983). For roads, the same principle applies, and there are several applications to highways (Pigou, 1920; Knight 1924; Vickrey, 1963; Dewees, 1979; Fosgerau and Small, 2012) and to urban areas (Keeler and Small, 1977; May and Milne, 2001; De Palma et al., 2006).[14] For dynamic models see Vickrey (1969), Chu (1995); Arnott et al. (1993), Verhoef (2003), Van den Berg and Verhoef (2011). Most often practical constraints, other market distortions and the political process prevent first-best optimization and instead second-best pricing is applied in practice, see Small and Verhoef (2007) for a review.[15]

There are several road tolls that were designed to reduce road congestion over the last decades. Tolls vary substantially from a few cents per kilometer in Singapore to more than €10 for

[13] A reduction in agglomeration would reduce the agglomeration benefits of the location.
[14] Apart from the empirical work by Keeler and Small, articles on the road pricing for cities are based on simulations due to the complexities inherent in road networks.
[15] Constraints to first best pricing are for example the lack of information, the inability to vary tolls over time and over space and the political process (Milne et al., 2000).

access to the inner city of London. With electronic road pricing, the price depends on the distance driven, whereas for the cordon toll entry is charged for an entire area. Using traffic models for Cambridge, Milne et al. (1994) find that congestion zoning is inferior to congestion specific charges, nonetheless, congestion zones are technically easier and continue to be frequent.

For most cities, tolls vary between peak and off-peak hours. In line with higher traffic demand, peaks have usually higher tolls and off-peaks are often not tolled at all. Road tolls reduce travel demand and redistribute peak travel demand to off-peak travel, see Arnott et al. (1988). Afternoon peak pricing reduces especially discretionary trips in the afternoon (Eliasson et al., 2009). In Hong Kong, pricing the peak direction would be at least as important as choosing the 'optimal' cordon zone area (Harrison, 1986). For the Randstad area in the Netherlands, a cordon toll on the highway network was projected to result in a time gain of 0.1 min/km (Small and Gomez-Ilbanez, 1998). We address highway travel time gains in the Netherlands in Chapter 3, 4 and 5, and optimal congestion tolls for highways and inner-city roads in chapter 2 and 3.

Road tolls differ substantially due to the differences in consumer prices, the value of time, travel demand at the location but also the aim of and methodology it is based on. For example, in Singapore road pricing is based on the evaluation of various pricing regimes since 1975 where price effects on travel time are posteriorly evaluated and adjusted. For Hong Kong, road pricing is based on a simulation by Harrison (1986), similarly to the proposed road tolls for Cambridge, based on economic evaluation of marginal user costs. Often the intended impact of road pricing is expressed as an intended flow reduction instead of a travel time improvement. For example, Small and Gomez-Ilbanez (1998) conclude that cordon road tolls of €2.65 to €3.95 for peak traffic reduce flow by approximately 20%. This makes travel time gains (actual and intended) hard to compare as also gains from off-peak pricing are either not recorded or sometimes reported combined with peak-benefits as total travel time benefits.

Some tolls do not result in long-term travel time gains on the road as in the case of London where changes in the traffic composition have led to resurgence in congestion (Financial Times, 2016). This is connected to the setup of the toll and suggests that a future increase of travel demand through, for example, autonomous vehicles without tolls might result in even more congestion (Ranft et al., 2016; Citymetric, 2017).

The basis and implementation of road tolls continue to be actively debated. Inner city cordon tolls usually are borne to a considerable extent by car-owning suburban households. The effectiveness of cordon tolls depends on the size of the toll area. Smaller cordon areas have a larger traffic distribution effect and so the range for the optimal price level is smaller than for larger areas (Fowkes et al., 1993). Also, the use of the toll revenue is a contested issue. After the deduction of the operational cost, up to 90% of revenue is still available. It is apparently this use of revenue that plays a key role for social acceptability and hence for the successful implementation of road pricing (Verhoef et al., 1998; Lindsey, 2006). Political, economic and practical considerations have made road tolling for reasons of congestion uncommon and contested. By comparison, second-best pricing alternatives are omnipresent.

Under the umbrella of second-best pricing alternatives, there is the possibility to charge for parking or to reduce the cost of transport alternatives, for example, public transit and bicycle use. It is even possible to put a price on car use (e.g. through road tolls) and then use the revenues to finance second-best congestion policies. Studies that evaluate second-best policies are complex because of indirect and secondary market effects, e.g. on the housing market and focus in scope on a set of second-best alternatives (Verhoef et al., 1995; Parry and Bento, 2002; Tikoudis, 2015). These studies rely on the measurement of congestion costs and knowledge of the benefits from second-best policies.

Transit helps alleviate congestion and reduce other traffic externalities when it is a susbstitue for car travel (Litman, 2017). We measure the congestion relief benefit from public transit in chapters 3 and 4. Additional economic arguments for public transit provision are that since an increase in the use of public transit leads to a higher public transit frequency and shorter waiting times, public transit exhibits increasing returns to scale (Mohring, 1972). Efficient and affordable public transit provision is supposed to provide fairer access to mobility and jobs (O'Regan and Quigley, 1991; Glaeser et al., 2008). Lastly, cities with public transit are usually denser and therefore have a larger agglomeration benefit (Graham, 2007).

Public transit management and finance varies substantially across the globe. North American public transit is heavily subsidized and only accounts for a smaller number of trips outside the urban centers. In Asia and Europe, public transit can account for a large share of urban trips. The optimal level of subsidies to public transit are widely debated (e.g. Nelson et al., 2007; Parry and Small, 2009; Anderson, 2014; Basso and Silva, 2014). The effects from changes in subsidies and transit supply might vary over time (Duranton and Turner, 2011; Litman, 2015). In the short-run, an increase of transit supply or lower ticket prices might motivate substitution between transport modes. In the long-run, decisions about individual car ownership, household and firm location choices are relevant. We contribute to the debate about the benefits of public transit and economic justification of subsidies in chapters 2 and 4.[16]

Road accidents are another major source of economic and personal losses. Accidents kill 1.25 million people annually and reduce gross domestic product by 1.3% and even 2.5% when taking reductions to the the quality of life from injuries into account (Elvik, 2000; WHO, 2017). A large body of scientific literature addresses the causes and the prevention of accidents. For some recent examples, see Hauer (2010), Smolensky et al. (2011), and Otte et al. (2012). One of the factors increasing accident severity is the weight ratio of the vehicles involved (Van Ommeren et al., 2013). Insurances help internalize risk factors such as vehicle weight (Dementieva and Verhoef, 2016). The risk of vunerable, non-motorized travelers is fundamentally impacted by the weight of vehicles, speed and level of car ownership in society (Adler and Ahrend, 2017). Accidents also affect non-involved parties. We consider the external cost of traffic accidents and incidents in terms of road congestion in chapter 5. Hereby, we also contemplate the benefits of accident and incident management toward congestion reduction in a welfare framework.[17]

[16] There are other solutions that also have a long track-record. Another viable alternative is to reduce inner city parking space similar to increasing parking prices (Van Ommeren et al., 2011). Improvements in internalizing driving externalities by indirect means, such as fuel taxation can result in consumers changing behavior in unintended ways, such as switching to smaller cars and driving marginally less with consumer behavior rebounding in other energy intensive consumer products (De Borger et al., 2016). There are several transport alternatives that are only briefly mentioned such as bicycle use, see, e.g. Rietveld and Daniel (2004); Van Wee and Börjesson (2015). Our research addresses short distance travel in an urban setting, for longer distance travel and intermodality see, for example, Behrens and Pels (2012). Innovative use of underutilized infrastructure can be an alternative (Marrades and Segovia, 2013).

[17] We largely ignore other traffic externalities such as pollution which are highly important for pricing (e.g. Koelbl et al., 2014; Dimitropoulos et al., 2016; Sonnenschein und Mundaca, 2016).

2 Road congestion and public transit

2.1 Introduction[18]

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

[18] This chapter is based on Adler, M. W.; Liberini, F.; Russo, A.; van Ommeren, J. N. (2017). Road congestion and public transit. *ITEA Conference Working Paper*. We thank Rome's Mobility Agency (Agenzia per la Mobilita) and the Italian regulator for public sector strikes (Commissione di Garanzia per gli Scioperi) for kindly providing data. We also thank Alex Anas, Richard Arnott, Gilles Duranton, Dan Jaqua, Ken Small and Erik Verhoef for insightful comments. We are grateful to audiences at UC Irvine, University of Toronto, Newcastle University, London School of Economics, VU Amsterdam, Brno University of Technology, Vienna University of Economics and Business, Institut d'Economia de Barcelona, the Urban Economics Association meeting in Minneapolis, the IIPF conference in Lake Tahoe, the International Trade and Urban Economics workshop in St Petersburg, the Verkehrsökonomik und –politik Conference in Berlin and the meeting of the Italian Society for Transport Economics for useful comments and suggestions. All errors are our responsibility. We acknowledge financial contribution by the European Research Council-OPTION program.

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).[19] The latter literature estimates the causal effect of density on travel time without accounting for fundamental endogeneity issues from measurement error and omitted variables. Common unobservable shocks, e.g. road accidents, may affect density and travel time, 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.[20] 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 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 allowing for hypercongestion. We emphasize here that hypercongestion is present in only about 2 percent of the observations. Our welfare calculations apply to other 98% of congested traffic. 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 (possibly due to political constraints), it may be possible to achieve some gains by reducing 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 requires considering how *all* road users are affected. Congestion imposes travel time losses not only 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 they deliver clear

[19] 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).

[20] We ran some simulations – available upon request – indicating that measurement error in travel time is a fundamental issue: 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 the density parameter α in equation (2.3) is about 30 percent. Note also that, in presence of measurement error in flow, one would expect a standard attenuation bias (Wooldridge, 2002, p.75). However, our simulations indicate that measurement error in flow produces an almost negligible downward bias.

policy implications. Specifically, our results provide an empirical 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.[21] Yet, little is known about the 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 exploit one fundamental data novelty: we observe strikes that vary at the *intensive* margin, i.e. the reduction in public transit service per strike. To be more precise, we have information about *hourly* reductions in public transit supply during strikes – measured 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. Moreover, when we estimate the congestion relief benefit, we also include bus travelers, which previous literature ignored.

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. We find evidence that the efficiency of transit can be further increased through a range of policies that reduce congestion such as bus lanes and fare reductions.

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. Geroliminis and Daganzo (2008) use similar road level data to estimate a speed-density curve for the city of Yokohama.[22]

[21] In most OECD countries, subsidies to public transit range from 30% to 90% of operating costs (USDOT, 2011, Kenworthy and Laube, 2001). In addition, capital costs are also frequently subsidised. 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).

[22] They do not focus on estimating external costs and welfare losses.

They also demonstrate that the fundamental diagram with a backward bending supply curve under hypercongested conditions also exists as a macroscopic fundamental diagram for entire neighborhoods with heterogenous road infrastructure. 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 Bogotá, 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 a few roads are jammed at a certain moment), the implied welfare losses it produces are relevant in the aggregate.[23]

The standard way of measuring the marginal external cost of congestion uses directly postulates a positive relationship between travel time and flow in order to derive the optimal road tax, as suggested by Pigou (1920). However, this assumption is violated in presence of hypercongestion causing underestimates of the marginal external cost and welfare gains of policies that reduce demand (Fosgerau and Small, 2013). Nonetheless, the assumption is widely 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 to estimate the welfare losses of road congestion while acknowledging endogeneity in the estimation of the travel time-density function. Our paper also contributes to the literature on the costs of congestion by providing evidence on the spillover effects of congestion on bus travelers.[24] To our knowledge, we are 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,

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

[24] See also Small (2004) who finds that reductions in road congestion induce substantial reductions in travel time for public transit travelers.

showing that the congestion-relief benefit is significant.[25] 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 empirical 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. 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 externalities.

The paper proceeds as follows. In section 2.2, we introduce the theory that underlies our empirical identification strategy. Section 2.3 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 2.4 and describe the data. Section 2.5 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.[26] In section 2.6, we examine the welfare effects of public transport subsidies while adjusting public transit supply. Section 2.7 concludes.

2.2 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. Our approach considers an *isotropic* road in a stationary steady-state. There is a debate in the literature about whether hypercongestion may provide a stable equilibrium given this setup (Small and Verhoef, 2007). Assuming a linear demand function and a homogenous

[25] 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.

[26] 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.

spatial distribution of vehicles, Arnott and Inci (2010) show that the equilibrium is stable but it is not clear to what extent this holds in our data. Without spatial homogeneity, a bottleneck, for example, in the form of a downstream parking facility is a necessary condition for the occurrence of a stable hypercongested equilibria (Verhoef, 1999, 2001). We will demonstrate that our data suggest that multiple equilibria are seldom. The presence of multiple equilibria however does not invalidate our approach, as in the welfare analysis we will compare the observed equilibria to the optimal equilibrium, which we will see is unique. As an alternative approach, one may assume roads that have bottlenecks (Arnott, 2013; Fosgerau and Small, 2013). We will also interpret our empirical results assuming roads with bottleneck and focus our welfare calculations on non-hypercongested observations. 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}.

2.2.1 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 per kilometre is an increasing and convex function of the *density* of motor vehicles on the road, D:

$$T = h(\mathrm{D}), \tag{2.1}$$

where $\partial T/\partial D > 0$.[27] Using (2.1) and the fact that density is defined as $D \equiv FT$, where F denotes the flow of motor-vehicle travelers we can rewrite (2.1) as $y(T,F) = T - h(\mathrm{FT}) = 0$, we find through the implicit function theorem that:

$$\frac{dT}{dF} = -\frac{\frac{\partial y}{\partial F}}{\frac{\partial y}{\partial T}} = \frac{\frac{\partial h(FT)}{\partial F}}{1 - \frac{\partial h(FT)}{\partial T}} = \frac{\frac{\partial T}{\partial D}T}{1 - \frac{\partial T}{\partial D}F}, \tag{2.2}$$

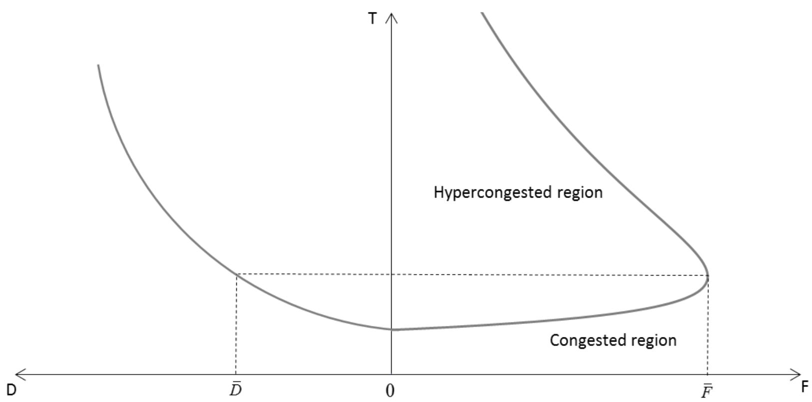
which describes the relationship between T and F.[28] To understand this relationship, note that when density is zero, flow is zero as well. Higher density raises travel time and, given (2.2), flow if $\partial T/\partial D < 1/F$. However, as density increases, the point where $\partial T/\partial D > 1/F$ is reached, so $dT/dF < 0$

[27] 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.

[28] 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.

and $dF/dD < 0$.[29] 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 2.1 provides an illustration.

Figure 2.1 − 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 $\alpha, \beta > 0$, as proposed by Underwood (1961). We adopt this functional form in the empirical analysis, because it provides an accurate description of the travel time-density relation for roads in our sample (we test it against more general statistical relationships).[30] In this case, we have

(2.3) $$\frac{dT}{dF} = \frac{\alpha T^2}{1 - \alpha D} \Longrightarrow \bar{D} = \frac{1}{\alpha}$$

Hypercongestion thus occurs when $D > \bar{D}$.

[29] Convexity of *h(.)* is crucial for this argument: if the function is linear, hypercongestion does not occur.

[30] The literature on highways supports our assumption that travel time is an exponential function of density above a certain critical value, called the critical density. Below this critical value there is no relationship between travel time and density. Typically, the critical density is about 8 motor vehicles per kilometer on a 120 km highway. In our data, only about a quarter of density observations are below 8. Within cities, however, the critical density is likely lower. Our results do not change when we exclude observations with a density below 8.

2.2.2 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, or not travel at all, and are heterogeneous in their reservation utility of travel by each mode. Aggregate travel demands for private motor vehicles and transit are negatively sloped and have positive cross-price elasticities. The generalized price of public transit travel, 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 equilibrium, there are N_{PT} public transit travelers, F motor-vehicle travelers and N_P non-travelers, per hour ($N \equiv N_{PT} + N_p + F$). The generalized price of motor-vehicle travel is equal to T, so we put the value of time at unity and ignore all other trip costs. We have

$$N = N_{PT}(p_{PT}, T) + F(T, p_{PT}) + N_P(p_{PT}, T), \quad (2.4)$$

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.

2.2.3 The effect of public transit strikes

We normalize the supply of public transit (veh-kms), assuming fixed seat capacity, 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 is 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.[31] 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

[31] During a strike, 'demanded flow' is higher but throughput at the measurement location is temporarily lower because of hypercongestion. See footnote 30 for stability considerations.

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.

2.2.4 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.[32] Second, we assume that the demand function is linear with a time-invariant slope: any temporal variation in demand occurs because of shifts in the intercept.[33] Furthermore, any temporal variation in the demand function is *exogenous* to traffic conditions (e.g., workers must 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. In addition, we assume that demand functions are independent per link so that serial link interactions are ruled out.[34]

2.2.5 Welfare analysis

The total cost for society of private motor-vehicle travel equals $F \cdot T$ (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 a measure of the marginal external cost, denoted MEC. Total differentiation of the social costs and subtracting the average cost T shows that:

$$MEC = \frac{d[FT(D)]}{dF} - T = \frac{dT}{dF}F + T - T = \frac{dT}{dF}F = \frac{\frac{\partial T}{\partial D}D}{1 - \frac{\partial T}{\partial D}F} \tag{2.5}$$

[32] This might lead to underestimates of the welfare losses of congestion (and the pervasiveness of hypercongestion). This can be shown by noting that travel time is a convex function of density, and therefore that travel time is a convex function of flow, when density is in the hypercongested range. For hypercongested hours, traffic inflow exceeds outflow for the early phases where the queue grows, and reversely where it declines so that supply might not necessarily exactly equal demand for these hours.

[33] Our results, shown in the Appendix Figure 2.A3, also hold when we assume that demand has a constant elasticity per hour and road.

[34] When hypercongestion is a result of serial link interactions the potential welfare gains might be lower.

where the final step follows from (2.2).

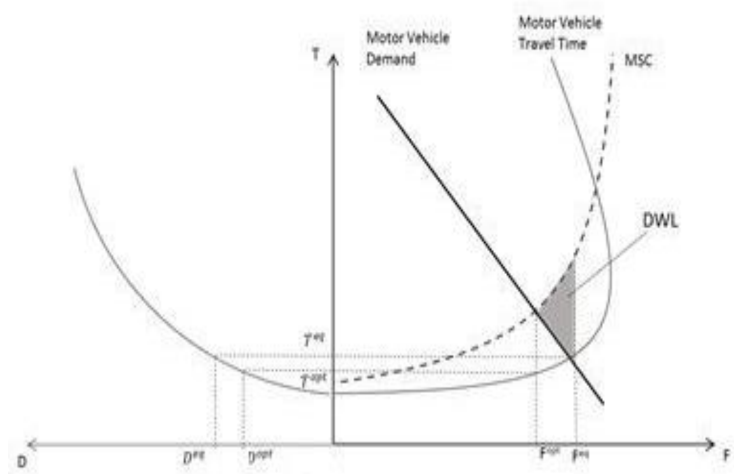
Let us focus on equilibria where the road is *not* hypercongested, so $1-\frac{\partial T}{\partial D}F$ is positive and less than one.[35] An increase in density, e.g. due to an upward shift in the demand for motor vehicle travel, causes an increase in the steady-state flow. It follows that MEC is positive. Assume again that $T = \beta e^{\alpha D}$. Then $MEC = \alpha D\, T/(1 - \alpha D)$.

We use 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* (evaluated at the optimum). The tax will then induce an optimal flow below the equilibrium one (assuming the road is initially not hypercongested). The welfare gain (i.e. the eliminated deadweight loss) 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 is exactly equal to optimal flow times the ensuing reduction in travel time. By contrast, if demand is vertical, the welfare gain is zero (because there is no reduction in travel time). See Figure 2.2, where we show the average cost function – 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 *T*.

In principle, governments may prevent hypercongestion by imposing tolls on vehicles entering the parts of the road network where density exceeds the level associated with maximum flow. Pricing instruments alone may not be well-suited to control hypercongestion. 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. Governments can intervene by adopting *quantity* restrictions (possibly in combination with pricing instruments). These include (second-best) policies such as adaptive traffic lights. Traffic-engineering studies 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 but potential welfare losses from waiting at traffic lights (Kouvelas et al., 2017).

[35] Equation (2.6) 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.

Figure 2.2 − Deadweight loss (DWL) from congestion with horizontal and vertical demand



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 buses share the road with other vehicles, the travel time of buses is strongly correlated with the travel time of 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 private motor vehicles:

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

Hence:

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

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.[36] For sufficiently small μ, so that public transit speed is proportional to motor-vehicle speed, the marginal effect is a constant:

(2.8) $$\frac{\partial T^{PT}}{\partial T} \approx \frac{1}{\theta}.$$

[36] The intuition is that smaller motor vehicles such as motorbikes receive a lower travel time penalty from congestion than larger public transit buses that are more easily blocked.

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

(2.9) $$MEC\ on\ bus\ = \frac{dT}{dF}\frac{N_{PT}}{\theta F}.$$

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 totally differentiate T^{PT} $w$ith respect to flow. It can be shown that:

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

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.

2.3 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. Given hypercongestion, the relationship between T and F is not an injective function. Therefore, one cannot apply standard econometric techniques to estimate it. We therefore proceed as follows: we first estimate the effect of density on travel time using (2.1) and then combine this estimate with (2.2) to derive dT/dF. Given estimates of *h*, denoted by $\hat{h}$, for each observation of D, we calculate the predicted travel time $\hat{T}\ =\ \hat{h}(\mathrm{D})$, as well as the predicted flow $\hat{F}\ =\ \mathrm{D}/\hat{T}$. We show that the travel-time flow relationship obtained using $\hat{T}$ and $\hat{F}$ accurately predicts the observed travel-time flow relationship.[37]

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

[37] Keeler and Small (1977) address this issue by estimating flow *directly* as a quadratic (and therefore possibly non-monotonic) function of travel time and then invert the estimated function. There are two difficulties with this approach. First, it usually does *not* provide the causal effect of flow on travel time. Second, even if the goal is to obtain the best fit between flow and travel time, this approach has a worse fit, at least for the data of Rome, although it includes more parameters compared to our approach which estimates time as a function of density. The latter result is intuitive, because the relationship between (log) travel time and density is monotonic, and almost perfectly linear, and therefore "easy to estimate", whereas the relationship between flow and travel time is nonmonotonic, and therefore "difficult to estimate".

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:

$$logT_{i,t,D} = \tau_i + \alpha D_{t,D} + \kappa' X_{t,D} + u_{i,t,D}. \tag{2.11}$$

Road fixed effects capture time-invariant differences in road supply such as lane width, the speed limit as well as the distance of the measurement point 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 works which only occur during certain periods). We emphasize 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.[38]

One econometric difficulty with estimating (2.11) 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 overestimate of the effect of density.[39] Measurement error is not the only source of endogeneity. For example, unobserved supply shocks (e.g. road closures, accidents…) may simultaneously affect density (directly or indirectly measured) and travel time.[40] 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 (2.11) 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 (as buses disappear), which may invalidate the assumption that bus strikes are valid instruments of motor-vehicle density. This is a minor issue

[38] Hence, each cluster contains a number of observations equal to the number of road segments observed.
[39] See footnote 19.
[40] That unobservables might shift the supply function by affecting density and travel time simultaneously is not problematic for our estimation as long as the shock to the supply function is not correlated with our instrument. The weather can also be a factor that affects both travel time and density. We control for weather conditions in our empirical analysis, see below.

however, because on average 1 percent of all vehicle flow in Rome refers to buses (specifically, only six buses pass a road per hour). 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 (2.11) may be a restrictive specification. To deal with this issue we specify log travel time as a quadratic function of density and apply control functions approaches to instrument density. Finally, 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.[41]

Given estimates based on (2.11), we can estimate MEC using (2.2). 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 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:

$$var(\text{MEC}) \approx \frac{var(\partial T/\partial D)\, D^2}{\left(1 - \frac{\partial T}{\partial D} F\right)^4}. \tag{2.12}$$

The denominator of this expression contains a power of *four*. Combined with (2.2), 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 (2.8), which allows us to calculate (2.9). Furthermore, we can

[41] A further minor issue is that an increase in demand may have an ambiguous effect on density due to the presence of multiple equilibria when the road supply curve is backward-bending. Nevertheless, as we demonstrate below, hypercongestion happens seldom in our data and multiple equilibria are unlikely.

estimate the effect of log motor-vehicle density on bus travel time, σ, which allows us to calculate (2.10).

We also estimate the effect of public transit supply on private motor vehicle travel time, exploiting variation during strikes. The underlying mechanism is that public transit supply reduces motor vehicle density (which we intentionally *not* control for in this model) and thereby travel time. We follow the literature by relying primarily on linear models (Anderson, 2014). 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 (2.11), so that:

$$T_{i,t,D} = \tau_i + \varphi S_{t,D} + \rho' X_{t,D} + \epsilon_{i,t,D} \quad (2.13)$$

where the coefficient φ captures the marginal effect of public transit share, $\partial T/\partial S$.[42] We estimate (2.13) using weighted regression where the weights are proportional to the (hourly) flow per road to make the estimated φ representative for the average motor-vehicle traveler in our sample and cluster standard errors by hour.[43] In a sensitivity analysis, we will examine to what extent φ depends on the level of public transit supply S. In a similar way, we estimate the marginal effect of public transit share on motor-vehicle travel flow $F_{i,t,D}$, hence, $\partial F/\partial S$. [44]

[42] 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.
[43] In the sensitivity analyses, we demonstrate that our results do not depend on the way we cluster standard errors.
[44] 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.

2.4 Data

2.4.1 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).[45] 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 2.1 – Descriptive statistics 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).

[45] 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 assume 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).

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 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, called ZTL (Zona a Traffico Limitato).[46] 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 the inflow and outflow of vehicles for this zone, but have no information about traffic within the zone.[47]

2.4.2 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 2.1. 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.

Table.2 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.

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

[46] 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).

[47] 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.

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.[48] See Table 2.2.

2.4.3 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.[49] 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.[50] We do not distinguish between which providers are affected by the strike.[51] 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 2.A). An additional three announced strikes were fully *cancelled* shortly before taking place. We will refer control for the cancelled strike days.[52]

Italian law does not allow full transit service shutdowns during strikes, mandating a high minimum service level during peak hours. Consequently, the strikes we observe are *partial*, in the sense that a positive share of service is always provided. Moreover, regulation forbids (with rare exceptions)

[48] 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.

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

[50] 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).

[51] Strikes of different public transit providers usually coincide see Figure 2.A3 in the Appendix (possibly 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.

[52] 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. However, because our identification is based on public strike hours, and we include day fixed effects, the placebo test is redundant.

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 2.A1 in Appendix 2.A). Most strikes take place on Mondays and, in particular, Fridays (see Figure 2.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 exclude nighttime hours because there is no public transit service between midnight and 5am.[53]

Figure 2.3 – Public transit share for strikes

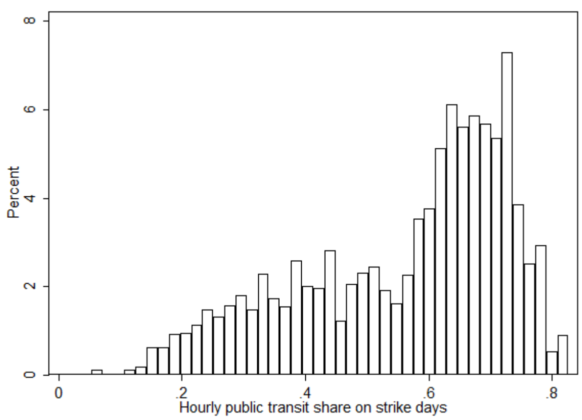
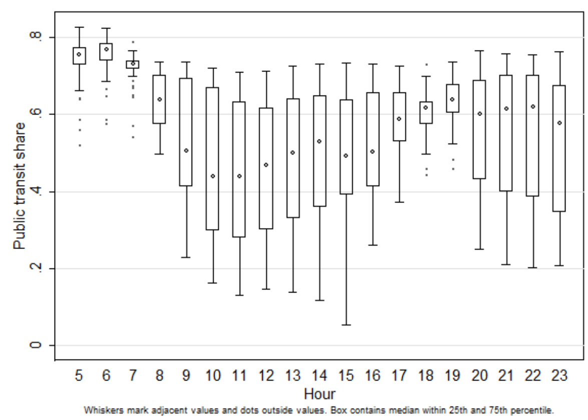


Figure 2.4 – Public transit share per strike hour



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.[54]

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

[53] 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.

[54] 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.

available during strikes, as can be seen in Figure 2.3. This share varies between 0.05 and 0.83, the average being 0.56. Note that we observe relatively few strike (peak) hours with low intensity due to the regulatory scheme mentioned above. In Figure 2.4, we provide the range and three quantiles for the distribution of transit available share distribution over 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 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.[55] 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 2.A4 and 2.A6 in Appendix 2.A), supporting the use of strikes as a way of identifying the effects of public transit supply.

2.4.4 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.[56] 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).

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

[56] See Figure 2.A5 in the Appendix for a map of the measurement locations. We also have information on eleven additional measurement locations. However, we ignore them because they are either too close to traffic lights (hence provide unreliable information on flow) or present *extreme* variation in flow over the period observed. This variation is likely due to malfunctioning of loop detectors or road supply shocks (e.g., closure of lanes).

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 per lane. We exclude extreme outliers.[57] In total, we have 422,691 hourly observations for motor vehicle flow, density and travel time.[58] We give descriptive information in Table 2.3. 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 2.A7 to 2.A9 of Appendix 2.A.[59]

Table 2.3 – 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 2.5 and 2.6, 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 2.A10). These figures indicate that on average travel time, density and flow are higher during strikes.[60] 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 2.5 also shows clearly that during peak hours the increase in travel time is substantially larger, implying

[57] 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.
[58] 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.
[59] We weigh all descriptive statistics for travel time by flow, as we are interested in the travel time *per motor-vehicle*.
[60] It is possible that the composition of motor vehicles changes during strikes, which causes additional welfare losses. Anecdotal evidence suggests that public transit users in Rome tend not to have access to motorcycles/scooters (which are mainly used by relatively young travelers, independently of traffic conditions). However, most transit users do have access to cars, so the increase in flow is likely predominantly due to cars.

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. Several of the effects we measure below, e.g. the congestion relief effect of public transit may differ between roads because of differences in their congestion level. Hence, it is useful to classify the road in our sample accordingly. 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 2.7 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.[61] On average, these 10 roads are heavily congested three hours per day.

Figure 2.5 – Travel time by hour of the day

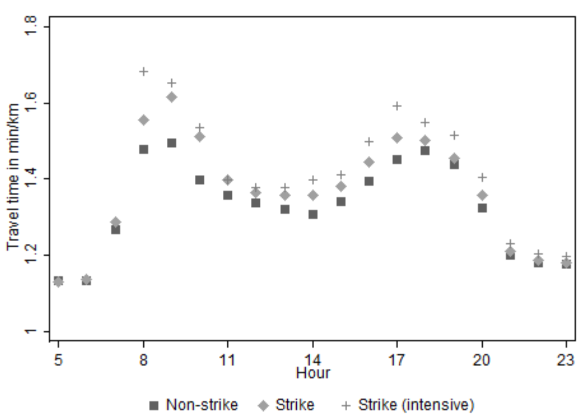
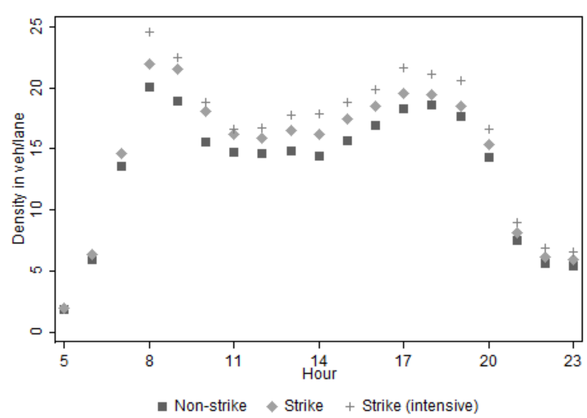


Figure 2.6 – Density by hour of the day



In theory, a road is hypercongested when, for given flow, the travel time lies on the backward bending portion of the supply curve. In Figures 2.8 and 2.9, we depict the travel time-flow curve for,

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

respectively, a road that clearly shows signs of hypercongestion and for one where hypercongestion is absent. However, in practice it is not always clear for each hourly observation whether the road is congested or not. To illustrate, consider the road in Figure 2.8 – 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 average cost (supply) curve. It is a priori unclear whether these observations refer to hours where the road is congested or hypercongested.

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 (2.3) in Section 2.2.1). 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 2.7 – Daily number of heavily congested hours per road (33 roads)

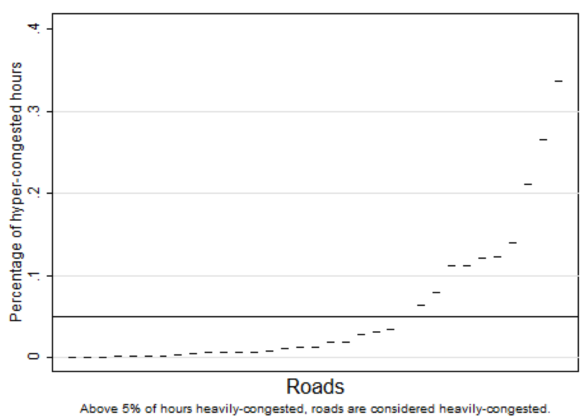


Figure 2.8 – Hypercongested road

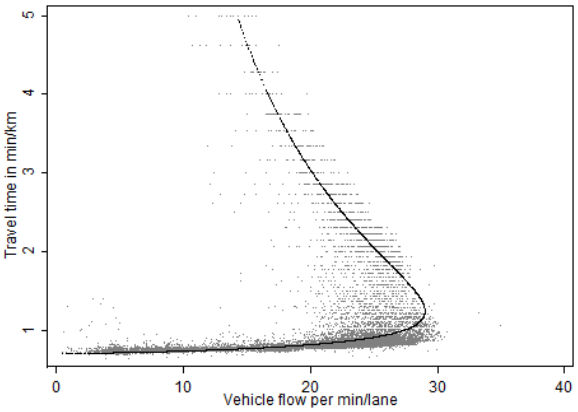
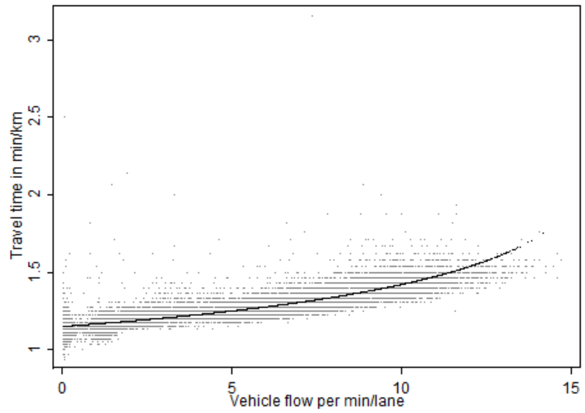


Figure 2.9 – Congested road



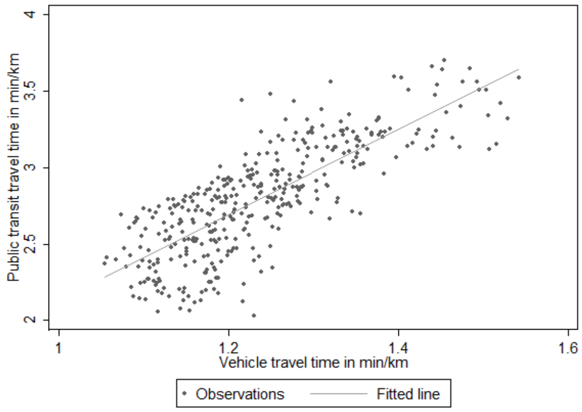
Finally, note that we estimate specifications which assume that the logarithm of travel time is a linear function of density. In the Appendix (Figure 2.A12) we show this relationship for the same road depicted in Figure 2.8. The figure indicates that this assumption is reasonable. A similar conclusion applies for the other roads in our sample.

2.4.5 The effect of road congestion on bus travel times

The Rome Mobility Agency provided us with information on the in-bus travel time (i.e. excluding boarding times). 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).[62] We have a total of 380 hourly observations.

[62] 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.

Figure 2.10 – 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 private 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 2.10, 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 time of 2.8 minutes.[63] 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.

[63] 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*.

2.5 Empirical Results

2.5.1 Welfare 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 2.4, 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 2.3.

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 2.4 – 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. Weather and time controls in equation (2.11) are included but not tabulated. The hourly strike intensity is the instrument for IV. Robust standard errors clustered by hour-of-day in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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 2.5 reports the average results. In the OLS specification, for each road, the effect is positive, with an average effect of 0.024 (see Table

2.5). Note that the standard deviation of this effect is about 0.01, supporting the idea that the estimated effects differ between roads.

Table 2.5 – 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.[64] 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 (recall that this ratio is about 1 percent).

The second column of Table 2.5 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 to 0.015). Again, the OLS estimates are severely upward biased, by about 30 percent.[65] This upward bias is also statistically significant for most

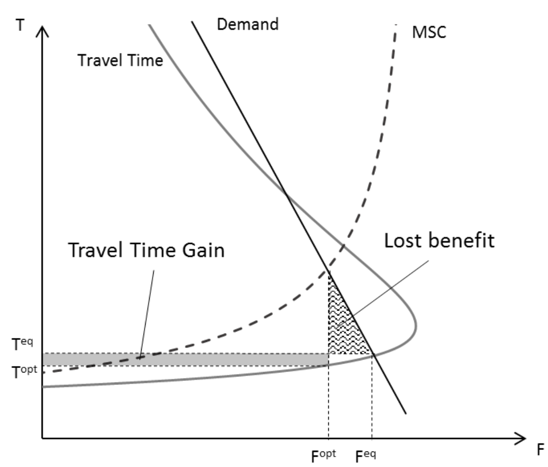
[64] See the discussion in Wooldridge (2002, page 105). For the roads where the instrument is weak, the test is equal to 1, 2, 4, 6, and 8 respectively. For these five roads, the Hausman *t*-test (Wooldridge, 2002, page 120) is less than two (in absolute value) suggesting that the OLS and IV estimates are statistically equivalent.
[65] This conclusion holds even more if we include all 33 roads. The IV effect is then about 33% lower.

roads: for 20 of the 25 roads, the Hausman t-test exceeds two (in absolute value). As discussed in Section 2.3, measurement error in travel time is most likely one of the main reasons for this bias.[66]

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 2.11 provides an example of such prediction for one road. The predicted travel-time flow relationship is backward-bending, in line with empirical traffic studies (Helbing, 2001; Geroliminis and Daganzo, 2008).[67]

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/α, where α is the estimated effect of density on log travel time (see expression (2.3) above). Our estimates imply that hypercongestion occurs in about 2 percent of the time, on average. Given our observation (see Section 2.4.4) 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 2.A11).

Figure 2.11– Deadweight loss avoided when moving from congested (left panel)



[66] 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.
[67] These results are also in line with simulation studies (e.g., May et al., 2000; Mayeres and Proost 2001; Newbery and Santos, 2002).

Table 2.6 summarizes the main results of this section.[68] The first column reports the main measures describing the observed traffic conditions. These are averages over all road-hour pairs in our sample and include the MEC (computed only for the hours where roads are not hypercongested). This measure is useful for defining policies to make small incremental reductions in traffic. It shows that the marginal external time cost of a motor-vehicle travelling one km is about 0.53 minutes on average.[69] Assuming a value of time equal to 15.59€/h,[70] this external cost is €0.137 (0.53*15.59€/60).

We now describe how we compute the welfare losses of 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 travel-time – corresponding to each observed equilibrium (per hour and road).[71] 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 2.5. Optimality requires that marginal benefit equals marginal social cost. Hence, in the optimal equilibrium, $\tau_r + \varphi \mathrm{F} = T + MEC$ 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:

[68] For computational reasons, we perform these calculations based on a 10% random sample of our set of observations.

[69] We report here the weighted average of the marginal external time cost for a road, using the flow per road as weight. The ratio between each road's marginal external cost and private cost (i.e. travel time minus free flow travel time) allows the comparison with the power of BRP congestion functions. The ratio of MEC/(value of private delay) is equal to the power of the BPR. See Appendix Figure 2.A13 and Small and Verhoef (2007, 76f). Higher BRP powers correspond with more severe congestion, e.g. the road of Figure 2.8 has a BPR power close to 8. Our computations produce the same ratio and are thus validated against widely used powers for this function.

[70] This is the median value of time for car users in Milan, the second-largest city in Italy, reported by Rotaris et al. (2010). We did not find a corresponding value for Rome.

[71] 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 2.11). 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.

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

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

Finally, we calculate the welfare improvement of inducing a shift from the observed congested equilibrium to the optimum. This improvement can be decomposed in two parts: the change in total consumer benefits (the area under the inverse demand function and above the equilibrium travel time) and the change in total cost for the remaining optimal flow (optimal flow times the difference between average time in the optimum and in the equilibrium). Figure 2.11 provides an illustration for a downward-sloping demand function, given an initial equilibrium where the road is not hypercongested. We refer to Adler et al. (2017) for a calculation of the welfare losses from hypercongestion which are at the high end of the marginal external cost.

In Table 2.6 (columns 2 to 5) we report the results for different values of φ. On top of the quantities describing traffic conditions in the optimum (rows 1 to 3), we report the marginal external (time) costs of one additional motor vehicle-km. We also report the overall welfare gain of a policy intervention that eliminates excessive congestion (thereby moving to the optimal equilibrium), expressed in vehicle-minutes per kilometer per road lane. Note that these are average values for all roads-hour pairs in our sample. We decompose the above welfare gain into the change in consumer benefits and in travel time costs.

Table 2.6 – Welfare changes: observed and optimal equilibria

	Observed	Optimal φ=0	Optimal φ= - 0.1	Optimal φ= - 0.3	Optimal φ= - 2
Density (veh/km-lane)	13.49	6.71	10.38	11.71	13.06
Flow (veh-km/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
MEC (min/km)	0.53	0.18	0.29	0.36	0.49
Welfare gain (veh-min/km-lane)		*1.14*	*0.68*	*0.47*	*0.19*

Note: These are averages for all roads and all hours in our sample. The welfare gains are expressed in vehicle-minutes per kilometer of road lane.

For brevity, we discuss the results in detail only for the case where $\varphi = -0.1$. As shown in Table 2.6, 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 per km per road lane (that is, about 25 percent). Average travel time falls from 1.33 to 1.26 min/km, i.e. about 5 percent. This reduction may seem small, but the drop is very substantial on some roads. For example, for the road depicted in Figure 2.8, average travel time falls from 0.96 to 0.81 minutes/km, i.e. about 15 percent. In addition, we see from Table 6 that the average flow decreases by about 15 percent. The induced welfare gain (per minute lane-kilometer) is equal to 1.05 vehicle minutes. This value equals roughly twice the marginal external cost as measured in the observed equilibrium, i.e. about €0.26. This welfare gain comes into existence because travel time costs fall by 3.68 vehicle minutes, whereas the consumer benefits fall by about 2.63 vehicle minutes. Finally, the average MEC computed in the optimum is equal to 0.18 min/km, i.e. about three times smaller than in the observed equilibria. In monetary terms, the MEC in the optimum is equal to €0.046 per km (0.18*15.59€/60). This value is indicative of the optimal road toll. Quite intuitively, it depends on the slope of the demand function: for example, when demand is almost perfectly inelastic ($\varphi = -2$) the MEC in the optimum is close to 0.5, i.e. almost equal to the average MEC in the observed equilibria. We find similar welfare gains from removing congestion and hypercongestion when we assume constant demand curve elasticities instead of linear demand curves (see Figure 2.A14 and Table 2.A3 in the Appendix).

To complete the picture, we show the marginal external cost for the observed in Figure 2.12, as well as the welfare gain of optimal policy per hour of the day, when $\varphi = -0.1$ in Figure 2.13. 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 2.12 – Marginal external cost

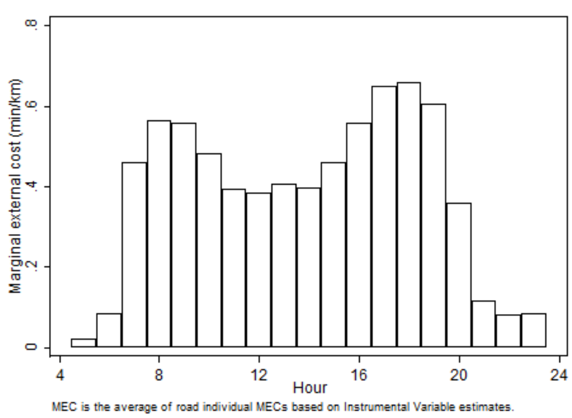
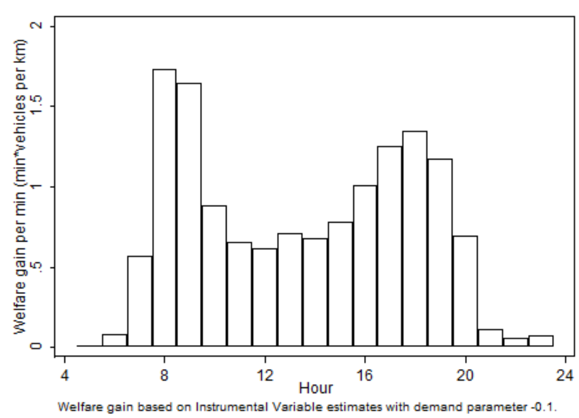


Figure 2.13 – Welfare gains



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, 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.[72] 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.

2.5.2 Travel time losses of bus travelers

We now estimate the external cost of congestion of private motor vehicles on bus travelers. We start with the approach based on (2.9). 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 flow of motor-vehicle travelers, which is roughly 0.4 in Rome[73], 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 private motor-vehicle travelers.[74] Then the marginal external cost to bus travelers is in the order of 40 to 50

[72] Akbar and Duranton (2016) provide citywide estimates of supply and demand functions for Bogota', using information from travel surveys and Google Maps.
[73] According to data provided by the city of Rome (PGTU, 2014), the average occupancy of buses is 42 passengers per veh-km. Given the average hourly motor-vehicle flow of about 600 and occupancy of 1.3, this value implies a flow of about seven buses per hour per road (0.4*600*1.3/42).
[74] Focusing on the city of Milan, Rotaris et al. (2010) report a median value of time of €9.54/h for bus travelers and €15.59/h for car travelers.

percent of the marginal external cost to motor-vehicle travelers. Consequently, the marginal external cost to bus travelers is quite large.

Table 2.7 – 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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We also estimate the time losses to bus users via an alternative approach, based on (2.10). 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. We find that this marginal effect, given controls, is about 0.0188, see column 3 of Table 2.7. 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 (column 4), so if we assume that σ =α, we obtain a conservative estimate.[75] Given that, on average, in-bus travel time (i.e. excluding time for boarding at bus stops), 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 (2.10).[76] Hence, our alternative approaches provide similar results. The marginal external cost through

[75] This effect is somewhat smaller than the effect presented in column (1) of Table 2.4, 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.

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

travel time delays of bus users is about 0.05€/veh-km, i.e. roughly 30% of the overall marginal external cost (0.137+0.05 = 0.187€/veh-km).

2.5.3 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.[77] We include controls for location, weather conditions and hour of the weekday, week of the year and month of the year.[78] 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 2.8 – Vehicle flow and public transit share

	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 2.8) facilitates the interpretation, because

[77] 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.

[78] 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).

hypercongestion might diminish the effect of strikes on flow (as flow might increase when public transit supply reduces hypercongestion). 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 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 2.8). That is, about 9.6% of the average flow.[79] 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 public transit can have both a positive effect on flow (by removing hypercongestion) and a negative effect (by removing congestion), the effect of public transit on flow in heavily-congested roads is statistically insignificant (Anderson, 2014, Small and Verhoef, 2007).[80]

Table 2.9 reports the results of the estimation of the effect of transit supply on travel time, estimating (14).[81] 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 2.5. These are our main estimates that we will later use in the welfare analysis of Section 2.5.3. 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 and 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. Therefore, public transit in Rome is a relatively unattractive alternative for travelers, suggesting that supply shocks due to strikes are likely to have a smaller effect on modal choice than in other cities.

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

[80] We have excluded observations at night. During the night time, travel times and flows are essentially identical on strike and non-strike days, which can be interpreted as a placebo test of strike exogeneity (see Anderson, 2014).

[81] 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.

Table 2.9 – Travel time and public transit share

	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.*

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 on roads that are prone to hypercongestion (as there is little evidence of higher flows, see Table 2.3). By comparison, the travel time reductions on arterial roads, and in particular one-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).

These results are important, providing support to the main idea of Anderson (2014): the congestion relief benefit of public transit is much larger on congested roads, so studies that aim to estimate the effect of public transit on travel time employing a representative set of motor-vehicle travelers will *strongly* underestimate the economic benefit of public transit when it is supplied in heavily-congested areas.

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 Figures 2.14 and 2.15, 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, again consistently with the importance of hypercongestion.

Figure 2.14 – Travel time

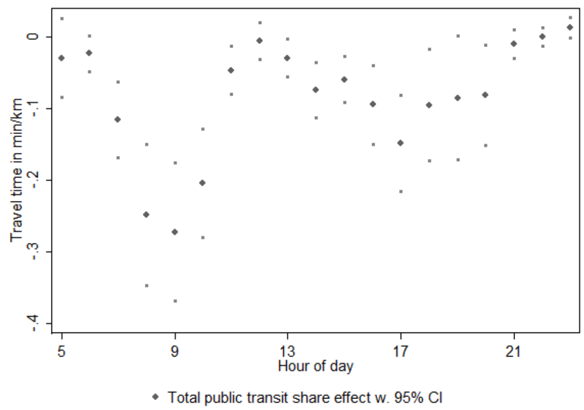
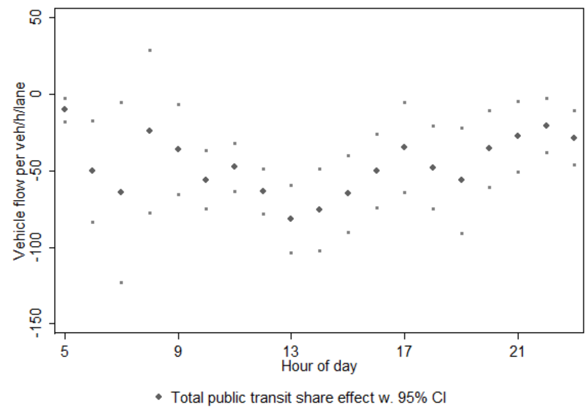


Figure 2.15 – Flow



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 2.8. We find that the effect is negative and equal to - 0.038. Given that, on average, a road in our sample is hypercongested about 2% of the time, this result suggests that removing the current supply of public transit would almost triple the pervasiveness of hypercongestion (to about 6% of the time per road).

Taken together, these results imply that the beneficial effect of public 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 the previous estimates provide a measure of the *average* congestion-relief benefit of public transit. However, to investigate the *marginal* congestion relief benefit, it is relevant to know whether the derived marginal effect is constant, i.e. to what extent the effect of public transit on travel time is linear. To investigate this issue, 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 on travel time is constant.[82] We come to the

[82] 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.

same conclusion when we focus on the effect of public transport on flow. We present here the results using a fifth-order polynomial of the public transit in Figures 2.16 and 2.17.

Figure 2.16 – Travel time

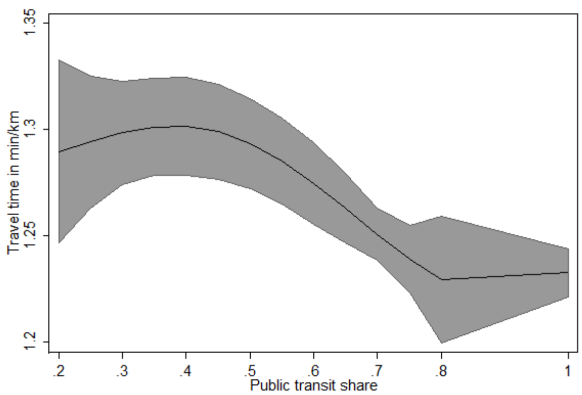
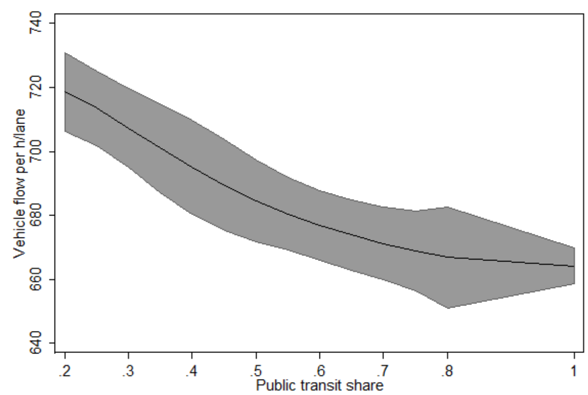


Figure 2.17 – Flow



A possible 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 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, a reduction in public transit supply can be regarded as an implicit increase in the generalized price of public transit travel. In this perspective, one can compare the effect to changes in the fare. In our data, we observe one substantial fare increase (by 50 percent), taking place in May 2012. 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).

2.6 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 2.9, 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.[83] 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 2.10.

Based on the above estimates, we also consider the effect a 1% shutdown in public transit provision. This decrease costs €5.95 million in lost congestion relief benefits to motor-vehicle travelers but also €2.3 million to bus travelers annually.[84] 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 Table 2.10.

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. The marginal reduction in time delay is about 300 minutes per bus. Assuming that the value of time is 9.54 Euros per hour, the marginal external benefit of an additional bus during peak hours is

[83] 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.

[84] 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 annual extra loss of 2.3 million euros.

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 2.10 – 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 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.

2.7 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 2.C1 in Appendix 2.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.[85] Specifically, we assume that $T = \beta e^{\alpha \mathrm{D}}$, with $\alpha = 0.02$ (this is the estimate from Table 4, column 2). Consistently 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, using (10), with $\frac{1}{\theta} = 2$ (as estimated in Table 7, column 2).[86] Finally, we calibrate the fare elasticity of transit passenger-kms using our own estimates and data provided by the city of Rome. This elasticity is 0.22 (see Appendix B for the derivation), which is rather low in comparison to the elasticities assumed by Parry and Small. However, given that transit fares in Rome are much smaller than in comparable European cities, low fare elasticity seems quite reasonable.[87]

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[85] Parry and Small postulate a time-flow relation, whereby travel time is a power function of flow.

[86] We assume 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, according to data provided by the city of Rome.

[87] Our results do not change substantially when we use the elasticities assumed by Parry and Small. Note also that our data suggest an elasticity of private motor vehicle flow to transit fares of 0.1 (see Appendix 2.B). Given that the own price elasticity of transit is 0.22, this value is roughly consistent with a modal diversion ratio from cars to transit between 0.4 and 0.5, as assumed by Parry and Small.

Table 11 reports the results. The top panel reports the marginal external congestion cost per motor vehicle kilometer, which equals €0.33/veh-km in peak hours, and €0.13/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 (€0.12/veh-km in peak hours, €0.04/veh-km off-peak).

Table 2.11 – Parry and Small model for Rome: optimal public transit subsidies

		Peak		Off peak	
Marginal external cost, motor vehicle travel. €/veh-km		0.33		0.13	
of which: on other motor vehicles travelers		0.21		0.09	
on bus travelers		0.12		0.04	
		Rail		Bus	
		Peak	Off-Peak	Peak	Off-Peak
Current subsidy, share of op. cost		0.76	0.76	0.74	0.69
Marginal welfare effects	Weighted Avg.				
Marginal benefit per €cent/pax-km[a]	0.10	0.31	-0.07	0.11	0.21
marginal cost/price gap	-0.24	-0.38	-0.41	-0.34	-0.21
net scale economy	0.12	-0.02	0.21	0.04	0.31
externality	0.15	0.53	0.14	0.31	0.02
other transit	0.08	0.19	0.11	0.10	0.09
Optimum subsidy, share of op. cost		>0.9	0.72	>0.8	>0.9

Notes

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

The bottom panel of Table 2.11 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 welfaregain 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.[88] 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 211).

2.8 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 from measurement error in density and travel time as well as potential omitted variables. 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 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. An intuitive explanation to this is the large share of scooters and motorcycles in Rome which can traverse heavily congested road sections faster than buses. Moreover, if speed delays are similar for cars and buses then travel time delays are disproportionate for bus travelers. 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 presence of hypercongestion suggests that, even if road pricing instruments are available, the use of quantitative measures to curb traffic on heavily congested roads (e.g., through adaptive traffic lights) may provide some welfare gains (Fosgerau and Small, 2013). Our findings suggest that taking into account the

[88] The marginal congestion relief benefit is comparable to the average benefit obtained in the previous section (see Table w2.10), 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 2.10 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.

shadow cost on road capacity, separate lanes for buses might 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 75 percent of the operational costs in Rome, is justified and should possibly be even increased.

Appendix 2.A1: Figures and Tables

Figure 2.A1 – Strikes by month

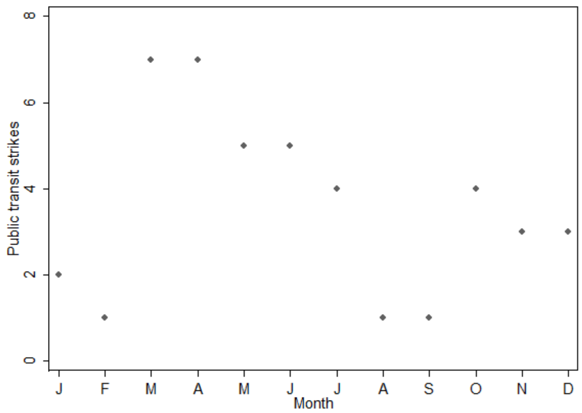


Figure 2.A2 – Strikes by weekday

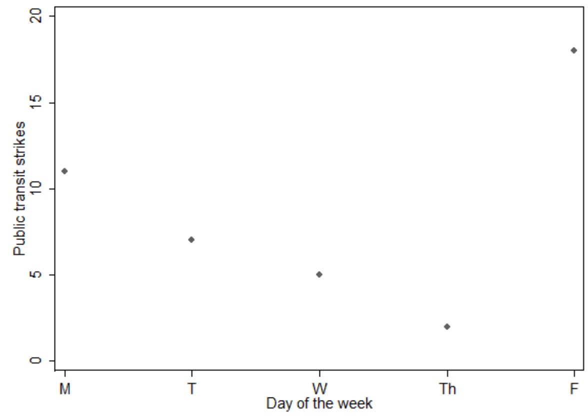


Figure 2.A3 –Public transit share by company

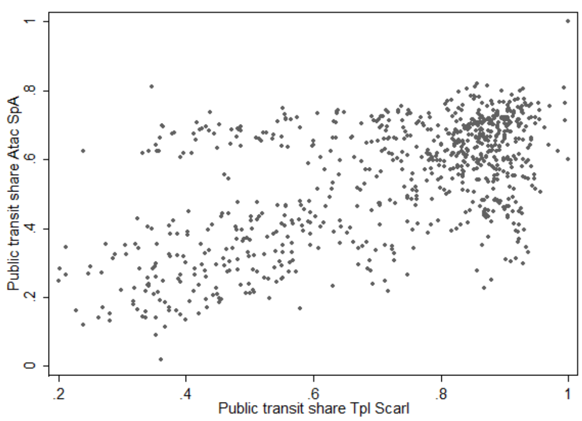


Figure 2.A4 – Public transit on non-strike day

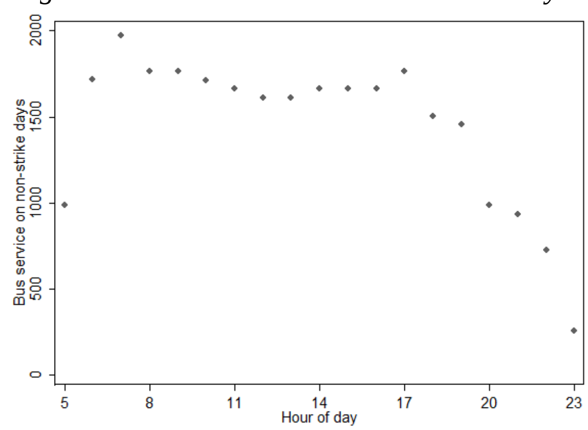


Figure 2.A5 – Rome

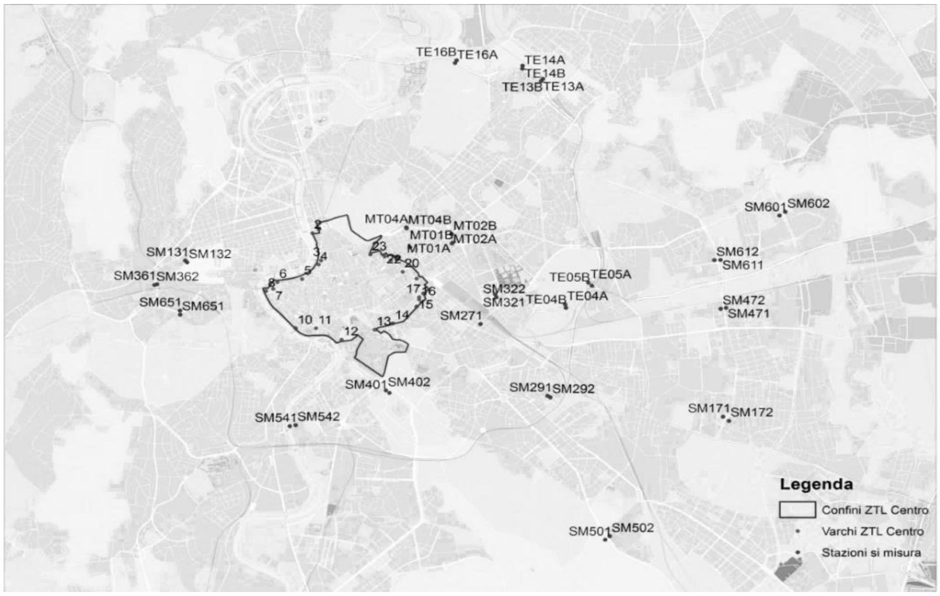


Figure 2.A6 – Public transit service on strike day

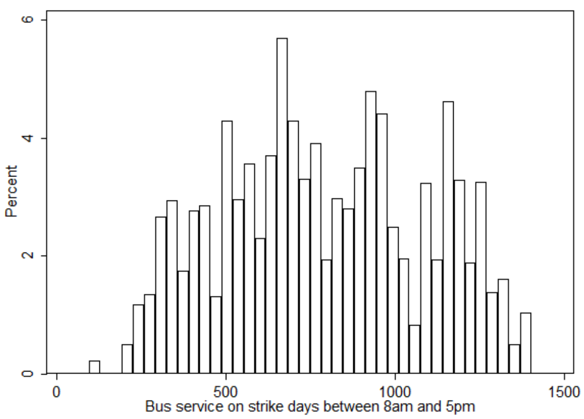


Figure 2.A7 – Travel time histogram

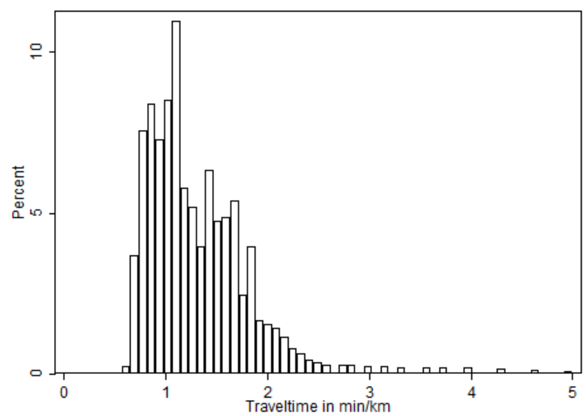


Figure 2.A8 – Vehicle density histogram

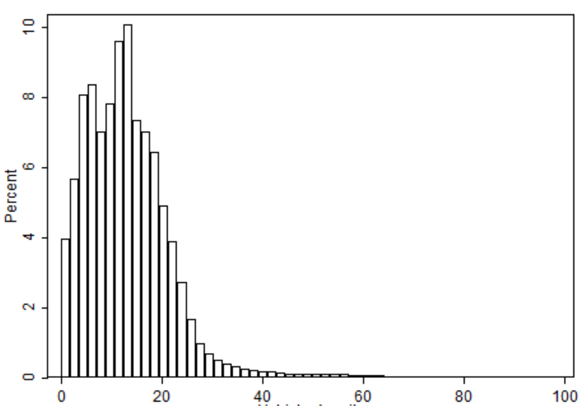


Figure 2.A9 – Vehicle flow histogram

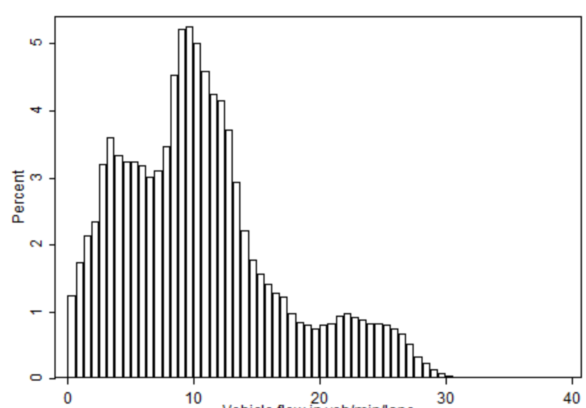


Figure 2.A10 – Vehicle flow by hour of the day

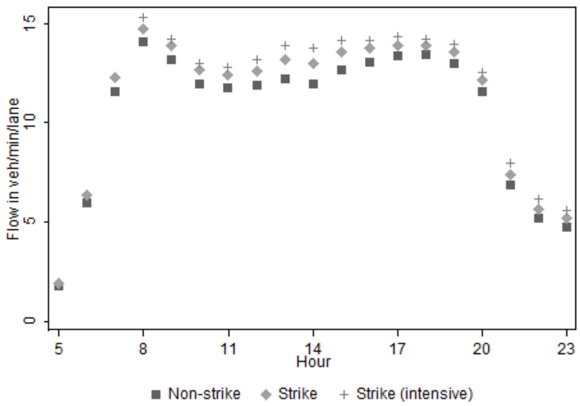


Figure 2.A11 – Heavy congestion by hour

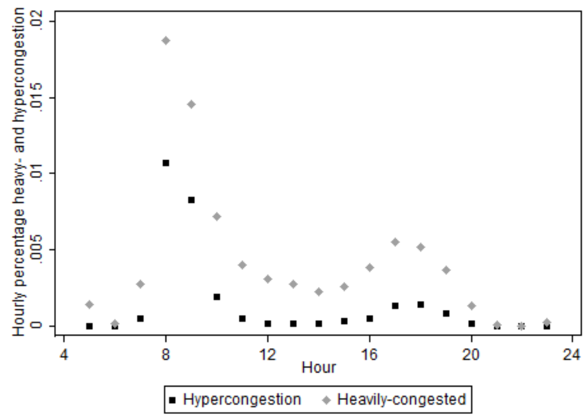


Figure 2.A12 – Travel time-density

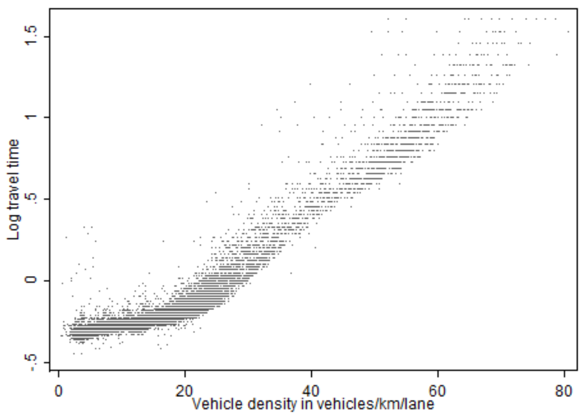


Figure 2.A13 – Power of BPR congestion functions

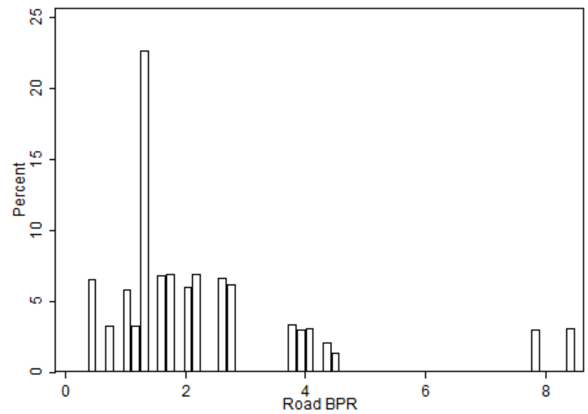


Table 2.A1 - Logarithm of travel time

	(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 2.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	

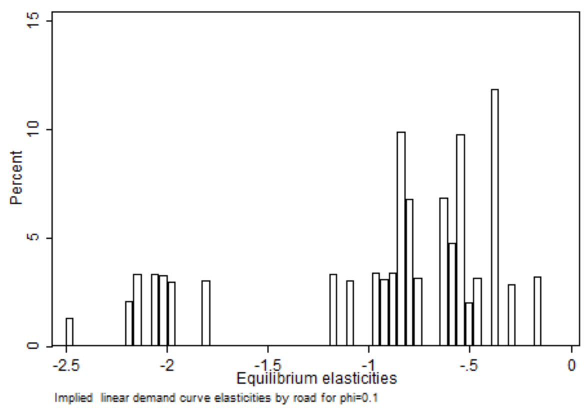
Note: The dependent variable is density. Weather and time controls are included but not tabulated. *Standard errors (in parenthesis) are robust and clustered by hour. Significance levels indicated at 1%, ***, 5%, ** and 10%. *. The number in parenthesis in column titles indicates the number of roads.*

Table 2.A3 – Welfare changes: observed and optimal equilibria with constant demand elasticity

	Observed	Optimal ψ= - 0.1	Optimal ψ= - 0.3	Optimal ψ= - 2
Density (veh/km-lane)	13.84	12.52	11.80	9.54
Flow (veh-km/min-lane)	10.66	10.12	9.73	8.33
Travel time (min/km)	1.31	1.30	1.28	1.22
Hypercongestion	0.02	0	0	0
MEC (min/km)	0.53	0.06	0.06	0.04
Welfare gain (veh-min/km-lane)		*0.44*	*0.66*	*1.24*

Note: These are averages for all roads and all hours in our sample. We assume a constant demand elasticity (ψ) per hour and road. We compute the MEC for times when a road is *not* hypercongested. The welfare gains are expressed in vehicle-minutes per kilometer of road lane.

Figure 2.A14 – Implied demand elasticities



Appendix 2.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.[89] 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.[90] 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 2.A2.2 – Travel time: alternative specifications

	(1) Travel time		(2) Travel time		(3) 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.*

[89] 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.

[90] 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 2.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.[91] 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 2.4, while including third-order polynomial time trends before and after the boundary rather than week fixed effects. For results, see Table 2.B1.

Table 2.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%, *.*

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

[91] 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.

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.

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

Table 2.C.1 – Aggregate model, parameters and results

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

3 Road supply curve estimation and marginal external congestion cost

3.1 Introduction[92]

Car congestion is a large problem. Policy makers everywhere are under immense pressure to remedy the externalities that arise from road congestion. For example, in Europe, congestion reduces GDP by 1% annually (Leineman, 2011). For dense urban areas, this problem is even larger. In London one-fifth of the workers commute each week an equivalent of one working day (Transport for London, 2010). Large economic gains are possible from reducing congestion. For example, by reducing congestion in California by 50%, labor demand, labor earnings and GDP would increase by up to 2% (Karpilow and Winston, 2016).

The 'fundamental law of road congestion' implies that road capacity expansion does not alleviate the problem of congestion because capacity expansion increases travel demand (almost) one to one (Duranton and Turner, 2011). Therefore, congestion pricing is argued to be the best panacea for congestion problems (Downs, 1992; Couture et. al, 2016).[93] Congestion pricing and other second-best policies rely on knowledge of the road supply curve and marginal social cost curve.

The debate about road supply curves - defined here as the relationship between travel time and flow - and optimal road pricing is extensive and unabated. Both, engineers and economists have postulated diverse theoretical and empirical models to identify the causal relationship between travel demand and congestion costs (Helbing, 2001; Small and Verhoef, 2007, 69ff.). One of the key issues is that the 'fundamental diagram of traffic flow' which starts from the assumption that density reduces time implies that one flow level of cars can be associated with more than one travel time (Haight, 1963). Hence, the relationship between travel time and flow is not a function, but a correspondence, and

[92] This chapter is based on Adler, M. W.; Koster, H. R. A.; Van Ommeren, J. N. (Mimeo) Road supply curve estimation and marginal external congestion cost. We thank the seminar audience at the 2015 European Regional Science Association in Lisbon and the German Forum of Regional Science in Innsbruck, 2016, for useful comments.

[93] In most places, public support of first-best congestion pricing is limited. The alternative to first-best pricing are second-best pricing options such as public transit provision, parking regulation and bicycle promoting policies that also rely on knowledge of the supply curve. Potential future externality reductions from autonomous vehicles are currently speculative (Karpilow and Winston, 2016; Ranft et al., 2016; Calvert et al., 2017).

cannot be interpreted as a causal effect of flow on time.[94] One may distinguish between a 'congested regime' where travel time increases because travelers restrict each other use of road space and a 'hyper-congested regime' where travel time continues to increase but the number of travelers declines because of inefficient 'production of travel'. The latter is usually a result of travel demand exceeding road capacity either because of increased travel during peak hour traffic or because of a (temporary) reduction in capacity due to something such as an accident or a downstream bottleneck. Whereas 'congestion' is more frequent than 'hyper-congestion', we provide indicative evidence that the latter is substantially costlier.

We are interested in finding the marginal external cost of travel by estimating the marginal effect of vehicle flow on travel time in the Dutch city of Rotterdam. The function we estimate is a road cost curve, sometimes also referred to as (short-run) road supply curve. With the supply curve, we determine the marginal external congestion cost, welfare optimal road use and tolls.

We obtain a backward-bending road supply curve by estimating travel time as a function of vehicle density, as is standard in the engineering literature (and which is a monotonic function). There are endogeneity issues from simultaneity and measurement error when estimating travel time as a function of density. Simultaneity occurs when drivers reduce their speed because of an increase in proximity from other cars and as a result car density increases and vehicle flow might decrease. That the measurement error in vehicle flow, vehicle density, speed and travel time are positivity correlated with travel demand is well documented in the engineering literature (e.g., Smith et al., 2002; Herrera and Bayen, 2007). To deal with endogeneity we make use of an instrumental variable approach. This is common for supply curve estimations in economics but to our knowledge a novelty in the transport economics and engineering literature (Angrist and Krueger, 2001).[95]

There are several suitable instruments that are exogenous to vehicle travel time (and have a high correlation with density). One suitable instrument is bicycle volumes near the roads of interest; a highway ring road and an inner-city road. An alternative instrument are hour-of-weekday dummies.

[94] The lack of a causal interpretation holds for static models. Static (i.e. stationary-state) models define a direct relationship between car flow and car speed but require a number of assumptions, such as a homogenous road, homogenous users and constant inflow and outflow. Dynamic congestion models use more realistic assumptions, specifically for flows to vary over time but are therefore also more complex (see, for example, Fosgerau and Small, 2012).

[95] In the literature, endogeneity problems are avoided by using the effect of car density instead of flow as the main effect of interest (e.g. Else, 1981; Hall, 1996; Helbing, 2001; Rauh, 2010) or travel time as a right-hand side variable (e.g. Keeler and Small, 1977). We do not follow the first approach because it makes the welfare interpretation less convincing and do not follow the second approach because it minimizes the sum of squared errors for the independent variable instead of the dependent variable.

The use of this instrument produces results that are statistically not distinguishable from the results using bicycle volumes as instrument, and which can be used for locations where other transport modes are not available as an instrument (the latter has the disadvantage that it requires additional assumptions).

The methodology we propose has two main advantages. First, we demonstrate that instrumentation allows us to estimate an unbiased road supply curve. Hereby, travel time is a monotonic function of vehicle density but backward-bending function of vehicle flow. The estimated functional form we obtain is in line with theoretical predictions of stationary-state congestion models.

A second advantage is that it allows us to calculate the optimal toll which depends on the marginal external congestion cost. In an earlier work, Keeler and Small (1977) discuss optimal road pricing for highways in and around San Francisco and find that tolls should be largest for peak-hours in proximity to the city center.[96] Indeed, we find somewhat larger optimal road tolls for the town of Rotterdam.

There are two additional minor advantages. In our approach, we account for unobserved shocks to road supply, for example from accidents, and obtain costs that are independent of such occurrences. Road-side shocks to the supply curve such as accidents and incidents are hard to observe and affect flow and travel time simultaneously. Another advantage is the broad applicability both to inner city roads and highways. We show that the method is usable both for single measurement points and for connected measurement points representative of a trip. In general, we show that it is possible to estimate supply curves with readily available time-aggregated (hourly) data from snapshot measurement points. Thereby our research supports the formulation of cost-efficient and sensible pricing strategies by local authorities.[97] Further, we demonstrate that our methodology is also suited to data that are aggregated in terms of time and space.

The paper proceeds as follows. In Section 3.2, we explain the empirical framework. Then we introduce the dataset according to descriptive statistics in Section 3.3. Afterwards, in Section 3.4, we present the empirical results that are used for a brief welfare analysis in Section 3.5. The last Section concludes.

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[96] According to them, the optimal toll during rush hours close to the city is €0.77 per km (in 2017 prices).

[97] One major problem of congestion pricing, taxes and zoning is that it is often ad-hoc and based on trial and error (Small and Verhoef, 2007). Our research is based on data that is often already available to decision makers and allows for an a priori pricing strategy.

3.2 Empirical strategy

We are interested in estimating the marginal external effect of travel quantity on travel time on a road of a given length.[98] The inverse of vehicle speed is travel time T, in minutes per kilometer, which itself is an F, the number vehicles passing a lane per minute, so that $T \equiv D/F$. With the implicit function theorem, we obtain the implied relation of travel time and flow: $\frac{dT}{dF} = \frac{\partial T}{\partial D} T \times (1 - \frac{\partial T}{\partial D} F)^{-1}$ (see Adler et al., 2017). We assume that travel time is an increasing convex function density, $T = \mathrm{T}(D)$ where $\frac{\partial T}{\partial D} > 0$ and $\frac{\partial^2 T}{\partial^2 D} > 0$. Let us assume that travel time is an exponential function of density and controls X so that $T = e^{\beta + \alpha D + \theta X}$. This can be rewritten so that the logarithm of travel time at road *i*, hour *t* depends on density $D_{i,t}$, controls $X_{i,t}$ and an error term $\varepsilon_{i,t}$, so that:

$$\log T_{i,t} = \beta_i + \alpha D_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}, \tag{3.1}$$

where we aim to estimate the coefficient α, the effect if density and the intercept β which can be interpreted as the natural logarithm of free flow travel time. We include the controls: weather variables (i.e. wind speed, temperature, precipitation intensity and duration), their squares, hour-of-day fixed effects and 365 day-fixed-effects to control for day specific unobservables that may affect road supply.[99]

Let $f(D_{i,t})$ be a flexible function of density:

$$\log T_{i,t} = \beta_i + f(D_{i,t}) + \theta X_{i,t} + \varepsilon_{i,t}. \tag{3.2}$$

In the empirical application, we estimate $f(D_{i,t})$ by a second-order polynomial function (which we motivate from our descriptive statistics). Before we can estimate equation (3.2) we need to acknowledge that density $D_{i,t}$ might be endogenous. There are three possible sources from endogeneity present; measurement error, reverse causality and omitted variable bias. Error in the measurement of flow, density and travel time is a well-documented problem and increases at higher levels of these three variables (Bennett et al, 2006). Reverse causality is particularly a problem when

[98] As a basis to our empirical strategy, we assume an *isotropic* road in a stationary steady-state. In the literature there is an ongoing debate about whether hypercongestion may provide a stable equilibrium given this setup (Small and Verhoef, 2007). Assuming a linear demand function and a homogenous spatial distribution of vehicles, Arnott and Inci (2010) show that there is a stable hypercongested equilibrium using the stationary steady-state assumption. As an alternative without the spatial homogeneity assumption, one may assume roads that have bottlenecks (Verhoef, 1999, 2001; Arnott, 2013; Fosgerau and Small, 2013).

[99] In our application, it is not possible to include hour-of-weekday fixed effects, because of the high correlation with bicycle use and the resulting lack of identifying variation in our instrument.

estimating travel time as a function of flow, because reductions in travel time also lead to lower flows. Because flow measurements are used to determine density (as direct density measures are not available to us), measurement error and reverse causality are also present in our estimation with density as independent variable. Furthermore, infrequent and often unrecorded road-side incidents such as accidents constitute an omitted variable bias. The instrumentation we propose reduces the bias from these endogeneity issues.

Since density $D_{i,t}$ might be endogenous, ordinary least squares estimates might be biased and because equation (3.2) is a non-linear model, we cannot use a standard two-stage least squares approach that plugs in first-stage fitted values (Blundell and Powell, 2003). Instead, we account for endogeneity with a control function approach (see Holly and Sargan, 1982; Blundell and Powell, 2003; Yatchew, 2003).[100] We use bicycle flow and hour-of-weekday as our instruments $z_{i,t}$ which are arguably uncorrelated with $T_{i,t}$ but correlated with density $D_{i,t}$. Bicycle and motor vehicle travel, as derived demands, are based on the same motivations such as travel to work, and as such follow a clear pattern over the course of the day and week. Hence, motor vehicle density is highly correlated with the time and demand for other transport modes that are considered a close alternative. For our estimation procedure to return unbiased estimates it is essential to note that in Rotterdam, roads in the inner city are not shared between bicycles and cars and that bicycle use at traffic lights does not affect car speed.[101] Hence, bicycle use cannot affect travel time directly. It is possible that travelers switch from car use to bicycle use because of road congestion. This is not a reverse causality problem in our case because we measure vehicle density and hence our instrument is valid, given car density. For each observation, we use as instrument the mean bicycle flow at hour t and weekday (Monday through Sunday) of the observation but excluding the bicycle flow of the observation we instrument for.

[100] Apart from the reverse causality concern for car flow, the control function estimation technique also conveniently accounts for other endogeneity problems: measurement error and omitted variable bias. There is measurement error for car flow at the highway through the transformation from actual to virtual induction loop data. Inner city car flow observations also have some measurement error, because pneumatic tube measurements perform less well at higher densities. The bicycle flow observations also have measurement error for the same reason. For peak densities, flows might be up to 10% larger than observed, for a discussion see e.g. Bell and Vibbert (1990).

[101] We can think of alternative instruments for car flow at a hyper-congested location: travel demand from another transport mode with large capacity limits (i.e. metro use, number of pedestrians); car flow at an uncongested location. Car flow at an uncongested location still might not be exogenous as car inflow could be limited due to lower car outflow at the hyper-congested location. A potential reason why bicycle use as an instrument might not be exogenous at other locations is that traffic lights are often set to accommodate all road uses and thereby affect the flow, capacity and speed of cars. A circumstance that can be accounted for by using time of the day as a control variable or in our case the availability of data where traffic lights are not in close proximity.

A suitable alternative to bicycle flow as an instrument is the use of hour-of-weekday time dummies as instruments. These are exogenous given controls. Especially hour-of-day controls and day-fixed-effects are necessary to ensure that changes in road supply from traffic measures such time dependent signaling and the probability of road supply affecting incidents are accounted for. Hour-of-weekdays are a suitable alternative for locations where high-quality data on an exogenous instrument such as bicycle use is not available.

We use an exogenous shift in demand measured through the instrument to estimate the road supply function. In the first-stage, we regress $D_{i,t}$ on $z_{i,t}$ and $X_{i,t}$:

(3.3) $$D_{i,t} = \Phi\left(z_{i,t}\right) + \vartheta X_{i,t} + \mu_{\ i,t}$$

Then we insert the residual $\iota_{i,t}$ from equation (3.3) as a control function into equation (3.2), so that:

(3.4) $$\log T_{i,t} = \beta_i + \alpha D_{i,t} + \gamma D^2{}_{i,t} + \theta X_{i,t} + \iota_{i,t} + \varepsilon_{i,t}$$

We are in particularly interested in the estimates α and γ for the road supply function and marginal external costs. Standard errors for the control function are calculated with a bootstrap procedure assuming normality and using 1000 bootstrap runs.

Estimates of the road supply curve are relevant for the calculations of the marginal external costs and welfare optimizing road tolls under certain assumptions on demand and in-vehicle time. We make four necessary assumptions. Let us assume that we are on an isotropic road with stationary-steady state congestion.[102] For each hourly observation, demand and supply are in equilibrium and the linear demand curve shifts only in intercept during the day. Furthermore, in-vehicle travel time accounts for all vehicle user travel cost then the cost of travel is the number of travelers multiplied with travel time. More informative for welfare considerations than the user costs are the marginal external cost, the difference between the time cost to society of a marginal vehicle and the time cost to the user of this vehicle. We arrive at the marginal external cost, denoted by MEC through total differentiation of the social costs and subtracting the average cost T so that:

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

When the denominator $1 - \frac{\partial T}{\partial D}F$ is positive, the marginal external cost is positive. For hyper-congested time periods, the denominator is negative, and this must be interpreted that any increase in

[102] This is a conservative assumption with lower costs than when assuming bottleneck congestion (Arnott, 2013; Fosgerau and Small, 2013).

flow constitutes a welfare improvement, see also Adler et al. (2017). From the estimation of a linear equation (3.1), where we assume that $T = \beta e^{\alpha D}$ then $MEC = \alpha \mathrm{D}\, T\, /(1 - \alpha \mathrm{D})$.[103] We determine the road supply curve from the function between travel time and vehicle density. The backward-bending section of the road supply curve occurs when vehicle flow exceeds the capacity of the road, at a level of density we label 'critical density'. We know that when $1 - \frac{\partial T}{\partial D} F = 1 - \alpha D = 0$, flow is at its maximum and with a linear function between travel time and density, 'critical density' is: $\overline{D} = \frac{1}{\alpha}$. Similar for equation (3.4) where $1 - \frac{\partial T}{\partial D} F = 1 - \alpha D - 2\gamma D^2 = 0$, we find the critical density $\overline{D} = \frac{\alpha - \sqrt{\alpha^2 + 8\gamma}}{-4\gamma}$ with $\overline{D} > 0$. All observations with a density larger than the critical density, we consider hyper-congested.

3.3 Data and descriptive statistics

We have traffic data for Rotterdam. The city has a metropolitan population of about 1.2 million inhabitants. About 57% of commuters travel by car, 25% by public transit and 14% by bicycle (De Vries, 2013). By comparison, car use is higher than in other Dutch cities because more space was allocated to roads in the town center during reconstructions following World War 2's large scale destruction. This makes Rotterdam comparable and our results more applicable to cities outside the Netherlands with car-oriented infrastructure and higher levels of car use. Furthermore, Rotterdam is suitable to our analysis as we have data available for cars and for bicycles at the same time which is important to our estimation.

We make use of hourly information about travel time, vehicle flow and bicycle flow in the inner city and on the highway ring road for the year 2011. In the inner city, travel time, vehicle density and vehicle flow as well as bicycle flow are measured with pneumatic tubes.[104] We focus on (motorized) vehicles at one measurement location in the inner city, see Figure 3.A1 in the Appendix. This location is an important, two-lane, southbound street named Maastunnel in the city center connecting the city through a tunnel beneath the river Maas.[105]

[103] For equation (3.4), the marginal external congestion is $(\alpha \mathrm{D}\, T + 2\gamma D^2 \mathrm{T})/(1 - \alpha \mathrm{D} - 2\gamma D^2)$.

[104] We construct inner city travel time from data of hourly speed intervals that distinguish between 0-31, 31-41, 41-51, 51-57, 57-61, 61-71, 71-81, 81-91, 91-101, and above 101 km/h. Density is not directly measures but we obtain vehicle density through the identity that relates flow, travel time with density: $F \times T = D$.

[105] We also show the validity of our results for the northbound direction and another location − s'Gravendijkswal − in the sensitivity analysis. The number of lanes and lane width determine the short-term supply curve by setting a capacity limit.

Table 3.1 – Travel time, car flow and bicycle flow

	Inner city	Highway
	Travel time (min/km)	
Average	1.31	0.62
Stand. dev.	0.15	0.14
Maximum	3.83	4.63
Minimum	1.16	0.54
	Vehicle density (vehicles/km)	
Average	12.60	8.69
Stand. dev.	8.68	7.00
Maximum	69.94	56.06
Minimum	0.28	0.20
	Vehicle flow (vehicles/min/lane)	
Average	9.32	13.45
Stand. dev.	5.59	9.41
Maximum	23.74	33.67
Minimum	0.22	0.33
	Bicycle flow (bicycles/min/lane)	
Average	1.35	1.93
Stand. dev.	1.35	1.93
Maximum	8.15	51.78
Minimum	0	0.01
Number obs.	6,112	7,408

Compared to other cities, Rotterdam is not heavily congested. We later estimate that only 0.4% of observations in the inner city are hyper-congested. Average travel time in the inner city (1.31 min/km) shows that for most hours of the day, car users travel at speeds close to the speed limit of 50 km/h (i.e. 1.20 min/km). See Table 3.1 for descriptive statistics. The maximum travel time for a kilometer in the inner city is 3.83 minutes (15.67 km/h) which is rather short.[106]

For the highway, we also observe travel time, density and flow recorded with induction loops for a 7.6 km stretch of the highway ring road that is Southbound in the eastern part of the city.[107] On the highway, travel time is 0.62 min/km, only slightly more than the time it takes to travel at the speed

[106] For the speed interval 0-31 we assume cars to travel 15 km/h on average, so that when for one hour all cars are in this category, the maximum travel time is 4 minutes per kilometer.

[107] For the southbound A16 highway, between the A17 and the A20 intersection, data is per 100m virtual loop for the 7.6km in 5-minute intervals. Virtual loop data is based on the induction loops with a maximum distance of 1km. Due to this high frequency of loops, the underlying variation is well captured. However, these loops have various problems: e.g. malfunction and misreporting. For this reason, the raw data is transformed into 100-meter virtual loop data. Our interest is in the variation of speed and flow over a stretch of representative highway network. So, we aggregate over space and time. The aggregation allows us to avoid over-interpretation of data accuracy as well as to capture the variation of speeds and travel time over distance. We remove 0.7% of observation of outliers above 100 cars/km density.

limit of 100 km/h. The faster, three-lane highway has a lower average vehicle density (8.68) but somewhat higher vehicle flow (13.38 vehicles/min/lane) than the inner city.[108]

For all measurement locations, some observations are missing randomly (e.g. due to malfunction and vandalism of measurement equipment) and so we have a varying number of observations per road. The number of observations for the inner city is 6,112 out of a potential 8,760 hours in a year reflecting the fact that malfunctions of pneumatic tubes can only be observed when manually serviced every couple of weeks. For the highway, no observations are missing but the instrument bicycle use is measured with pneumatic tubes with missing observations and, so we have a total of 7,359 observations.

Bicycles use separate infrastructure from motorized vehicles in Rotterdam.[109] So, vehicle flow and density are independent of bicycle flow. The two modes usually do not share road space and are also measured separately. We have data for 32 one-directional bicycle paths across the city and focus on three of these, all crossing the river Maas in proximity to the car measurement points.[110] For the inner city, we assign the bicycle path that is closest to the location, i.e. in the same tunnel and southbound as well. For the highway, because there are no paths in proximity, we assign the average of three Southbound bicycle paths that cross the Maas river similar in that respect with the highway. The proximity and direction of travel make sure that our instrument bicycle flow is highly correlated with the endogenous variable of interest, vehicle density.

Bicycle flows are less than one-fifth of vehicle flows in Table 3.1. This reflects trip modal split of 14% for bicycle use and 57% car use in Rotterdam. The coefficient of variation is larger for bicycle use than for car use, suggesting a larger variation of bicycle use over the day. However, correlation between hourly car density and bicycle flow is large, above 0.5 (and above 0.8 for flow).[111] We observe bicycles flow exceeding 8.3 bicycles per minute/lane in 2.7% of observations. Peak hours with car congestion correspond to hours with intensive bicycle use.

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[108] For the inner city we show the histograms of flow, density and travel time in the Appendix, Figures 3.A2-3.A4. The histograms of the highways are similar and hence not depicted.
[109] Intersections and traffic lights are shared in Rotterdam by bicycles and cars. However, both are at least 500 meters from our observation locations.
[110] There is high correlation between measurement flows and density across measurement points in Rotterdam that has been demonstrated for other cities, see, e.g. Geroliminis and Daganzo, 2008.
[111] It is important to note that all bicycle paths exhibit flow maximum values much lower than their maximum capacity, this is essential to our claim that these can be regarded as exogenous and representative for travel demand. One-directional bicycles lanes of at least 1.5m width have a flow maximum above 2,500 bicyclists an hour, well above the flows that we observe for the bicycle paths in Rotterdam (Zhou et. al, 2015). Despite the high correlation, bicycle flow has a noteworthy different histogram from vehicle density and flow, see Figure 3.A5.

Figure 3.1 – Travel time and flow

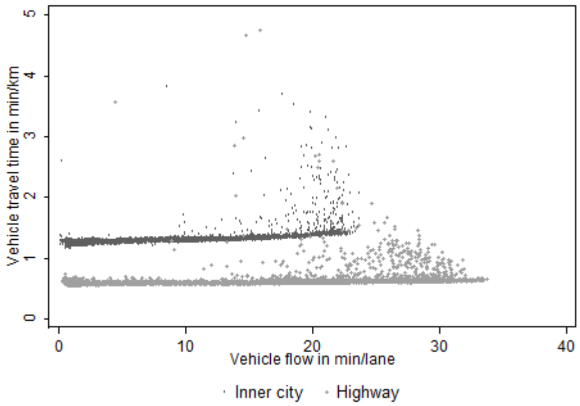
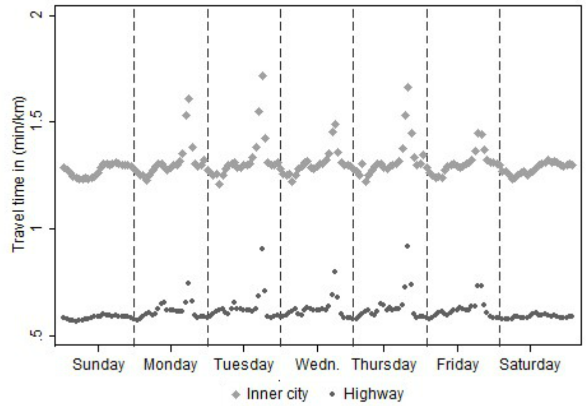


Figure 3.2 – Travel time over the day



The high correlation between vehicle density and bicycle flow in combination with the independence of vehicle travel time from bicycle flow, makes bicycle flow a suitable instrument for our estimations later.

We show the travel time-flow relationships in Figure 3.1. The higher speed limit and the larger capacity of the highway in comparison to the inner city are visible. For both roads, we find that higher travel times also occur at flows lower than the maximum flow – this relationship is usually stylized in the backward-bending cost curve. When comparing the Figure 3.1 with the flow histogram (Figures 3.A2), notice that larger travel times have a much lower observation density because Rotterdam is generally not heavily congested. We are particularly interested in the flows that are associated with the largest travel time losses later on.

Figure 3.3 – Inner city: Car flow and bicycle flow

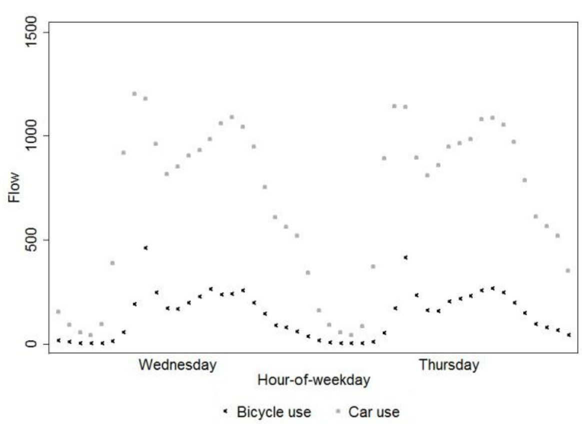
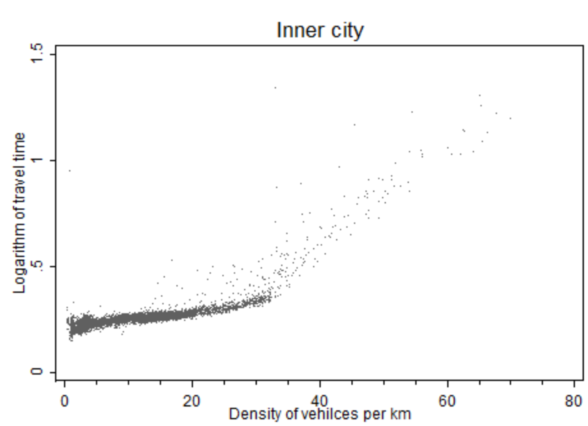


Figure 3.4 – Vehicle density and travel time



Travel time has a clear pattern over the hour and day of the week in Figure 3.2. We find longer travel times on weekdays and during daytime, especially the evening rush hour. On the highway, there is smaller variation in travel times over the day than in the inner city, but for both road types, intra-day variation is much smaller than the absolute variation because very long travel times are not frequent.

The variation in the level of vehicle flow over the day are similar to the variation of bicycle flow; see Figure 3.3 for a more detailed view for Wednesday and Thursday. Not surprisingly, especially morning and evening peak flows are pronounced.[112] Bicycle use has a clear morning peak but a less pronounced evening peak flow perhaps because car use is strongly linked to commuting at specific hours in the Netherlands. Levels of vehicle density change similarly across the day than bicycle flow and vehicle flow, but unlike vehicle flow, vehicle density has a monotonic relationship with travel time, see Figure 3.4. Travel time is increasing in density and in particularly so after about 35 vehicles per kilometer.[113]

3.4 Estimation results

We first estimate the effect of vehicle density on the logarithm of travel time assuming a linear effect. When we ignore the endogeneity issue as well as the non-linearity and estimate an ordinary least squares (OLS), a one car increase in density per km has a positive effect of up to 1.3% travel time (0.017 min/km) in in the inner city and of 2.3% (0.014 min/km) for the highway, see column 1 in Table 3.2 and 3.3.[114]

We also provide the results for the (linear) two-step instrumental variable estimation using bicycle flow and the hour-of-weekday instruments in columns (2) and (3) respectively. By comparison, the travel demand effect on travel times is about one-third smaller for the two-step estimation compared to the OLS estimation.[115] This downward bias is a result of the measurement error in the

[112] The reason why bicycle use is more pronounced than car use at our measurement locations has two reasons, i.e. the lower modal share in general and the more equal spread of bicycle use across the network. We also find this correspondence between car and bicycle flows in Figure 3.A6. Bicycle flow continues to increase over a large interval of "stable" car flows. This is important because bicycle flow is only a valid instrument for car flow if capacity limits are reached for the former and flows continue to increase with travel demand unabated for the latter (where the capacity limit is not reached).
[113] There is a positive, concave correlation between vehicle density and the instrument bicycle use, see Figure 3.A6.
[114] For the estimations using flow as an explanatory variable in which we find comparable results in magnitude, see the Tables 3.A1 and 3.A2 in the Appendix. This similarity in results is expected because hyper-congestion is infrequent.
[115] The size of the bias depends on the size of the endogeneity issue, in other words on the level of congestion. The instrument is globally and locally strong, as indicated by the First-stage F-values that are 1089.6 and 2105.2 for column (2) and (3) in Table 3.2 respectively. The difference between observed density to imputed density increases in density, see Figure 3.A11.

right had side variable, recall that density comprises the product of travel time and flow, where the latter is incorrectly measured at higher traffic volumes. According to column (3), an additional vehicle per km increases travel time by 0.88%, so 0.012 min/km. In other words, an increase in travel time of 0.16% for each 1% increase in density can be substantial, considering that density is 250% larger at 5pm than at 7am. There is however good reason to believe that elasticities estimated around the average might not be representative for all congestion levels.

Table 3.2 – Travel time (log) inner city

	(1) OLS	(2) IV	(3) IV	(4) OLS	(5) Control function	(6) Control function
Density	0.0130***	0.00850***	0.00876***	-0.00149**	-0.002467***	-0.00213***
	(0.000534)	(0.000435)	(0.000351)	(0.000847)	(0.000363)	(0.000358)
Density^2				0.000276***	0.0002478***	0.000258***
				(0.0000116)	(0.0000123)	(0.0000114)
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Hour fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Instruments		Bicycle flow	Hour-of-weekday		Bicycle flow	Hour-of-weekday
N	6112	6112	6112	6112	6112	6112
R^2	0.753			0.881		

Note: We include day-fixed effects, wind speed, temperature, precipitation duration and intensity as controls. Robust standard errors in parentheses. In column (5) and (6) we obtain standard errors by bootstrap procedure (1000 replications). * *p < 0.05,* ** *p < 0.01,* *** *p < 0.001.*

For more severe congestion levels, a quadratic specification (see equation 2) allows a larger flexibility in the effect of density on travel time which is supported by visual inspection of Figure 3.4 earlier. We find that for very low levels of density there is no positive (or even a negative) effect on travel time. The reason is that at low vehicle flow levels, there is no causal relationship between density and travel time. For larger densities and road use, we find a strongly positive effect on travel time, see columns 3 and 4.

On the highway, the road supply curve is similar to the inner city, see column (2) and (3) in Table 3.3. A 1% increase in density increases travel time by 0.8% which corresponds however to a much smaller increase in travel time (0.005 min/km.) than in the inner city. The road supply curve depends on the speed limit as more cars can pass any road segment at higher speeds. With a higher speed limit than the inner city, the highway can accommodate larger flows per lane. However, additional lanes and higher speed limit do not result in a proportional increase in capacity, due to on- and off-ramps and interaction between traffic (Daganzo et al., 2011).

Table 3.3 – Travel time (log) highway

	(1) OLS	(2) IV	(3) IV	(4) OLS	(5) Control function	(6) Control function
Density	0.0232^{***}	0.00789^{***}	0.00864^{***}	-0.00526^{***}	-0.00952^{***}	-0.00876^{***}
	(0.000856)	(0.000586)	(0.000436)	(0.00138)	(0.0024896)	(0.000580)
Density^2				0.000771^{***}	0.000635^{***}	0.000731^{***}
				(0.0000486)	(0.0000751)	(0.0000197)
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Hour fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Instruments		Bicycle flow	Hour-of-weekday		Bicycle flow	Hour-of-weekday
N	7408	7408	7408	7408	7408	7408
R^2	0.668			0.794		

Note: We include day-fixed effects, wind speed, temperature, precipitation duration and intensity as controls. Robust standard errors in parentheses. In column (5) and (6) we obtain standard errors by bootstrap procedure (1000 replications). * *p < 0.05,* ** *p < 0.01,* *** *p < 0.001.*

The specification of the estimation matters for the road supply curve. In Figures 3.5 and 3.6, we depict the OLS estimates (column (1)), the IV estimates (columns (2) and 3)) and the control functions (columns (5) and (6) from Table 3.2 and 3.3). For comparison, we also plot the OLS estimate using flow instead of density as the independent variable in equation (3.1). With flow as the independent variable, we arrive at a linear and positive function of travel time. Notice that for the inner city, the OLS using flow is an overestimate for the congested section and an underestimate for the hyper-congested section of the road supply curve when comparing with the control functions.

The OLS estimates using density are as expected an upper bound and an overestimate due to the endogeneity issues, in particular the measurement error in the right-hand side variable density. While the curve with this specification in increasing in density we do notice the absence of a backward-bending section for the hyper-congestion but rather an almost vertical section for lower than the observed maximum densities.

Figure 3.5 – Road supply curves inner city

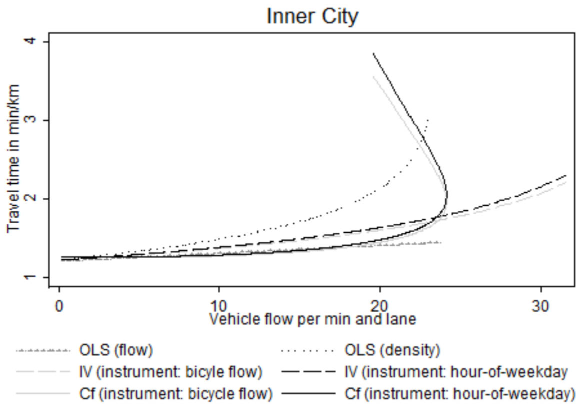
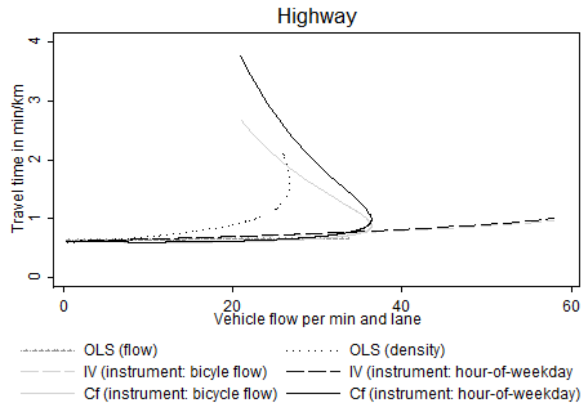


Figure 3.6 – Road supply curves highway



The instrumental variable estimations are above the OLS using flow but below OLS using density. Travel time is somewhat increasing in density but the critical value beyond which the hyper-congested backward-bending section of the road supply curve starts is far outside the range of our data and hence we only see the congested section. Both instruments appear to deliver almost identical results.

We show the estimates of the control function using the instruments bicycle flow and hour-of-weekday in separate estimations. The expected backward-bending section of the road supply curve is well captured.[116] For the inner city, up to a flow of ten cars per minute, we see essentially no effect on travel time. For flows larger than ten vehicles per minute up to a 'critical density' of 47.49 vehicles per km (or a flow of 24.13 vehicles per minute), we find the congested section of the road supply curve where travel time increases both in flow and density. Above the 'critical density, during hyper-congestion, travel time continues to increase past 1.97 min/km but flow decreases as through-put and production of the road is decreasing.

[116] We show results of the OLS estimation using equation (2) from column (4) in Table 2 and 3 in the Appendix in Figure A7 for the inner city and A8 for the highway. The estimation results are significantly different from the estimations using instrumental variable approach. We could use bicycle paths at further away locations as instrument but obtain similar results, see Figure A9).

Figure 3.7 – Control functions inner city

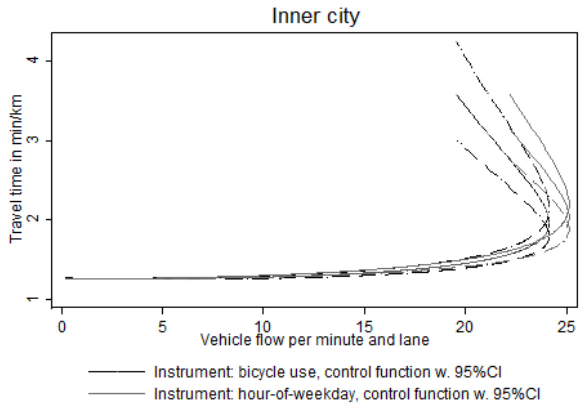
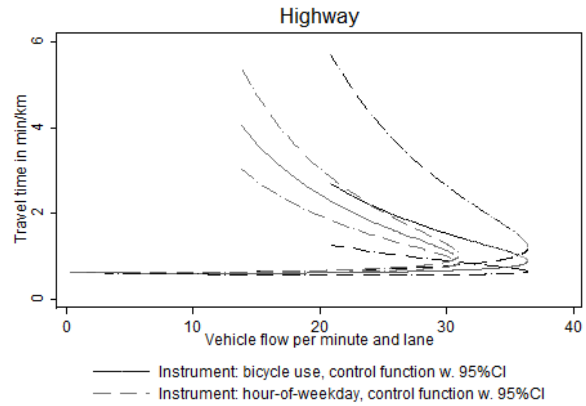


Figure 3.8 – Control functions highway



For Rotterdam, hyper-congestion is rare. In the inner city, 36 hours (0.6%) are hyper-congested and on the highway 57 observations (0.8%). For both instruments, the control function yield statistically indistinguishable results on the 5% significance level, see Figures 3.7 and 3.8. This reassures us of our estimates and that there are several instruments that can be used for the estimation of road supply curves. These general findings apply to inner city and highway alike.

3.5 Sensitivity analysis

We extensively check for robustness of our results using the control function approach. Road supply curves depend on road characteristics and hence can substantially vary between locations. We estimate the road supply curves for three additional locations in the inner city, see Figure 3.9. We have another measurement location at the Maastunnel but where traffic is northbound. We notice that the backward-bending section of the supply curve is shorter due to rarer instances of severe hyper-congestion. For an alternative inner city location (i.e. s'Gravendijkwal), with the measurement section approximately two kilometers north of the Maastunnel, we find a road supply curve with hyper-congestion at lower flows and a steeper backward-bending section. Clearly, this road has a lower capacity than the inner city location Maastunnel and hyper-congestion is more frequent Northbound (3% of observations) but with similar congestion levels for the Southbound direction (0.4%).

For the highway, we use the average of 76 induction loop measurement locations over 7.6 km between highway segment km16.1 and km23.7. When we focus on single measurement locations, at km17, km21 km23 on the highway, we find similar road supply curves in the congested sections, but substantial variation in the frequency of the hyper-congested section (see Figure 3.10). This is expected as variation in road side characteristics and on- and off-ramps has substantial impact on the supply curve. This demonstrates that the use of a combination from various measurement points is to be preferred for two reasons. First, minor variation in road supply across location are less of a problem. Second, and even more important for the economic analysis, aggregated data allows us to infer about the travel time for longer trips or parts of a trip. In other words, the aggregated road supply curve informs us about the travel time given demand for a trip along the aggregated road-segments. This improves on the paper of Adler et al. (2017) by demonstrating that a road supply curve for connected road-segments over a longer distance reflects the road supply curves of the individual road-segments.

Figure 3 9 – Road supply curves inner city

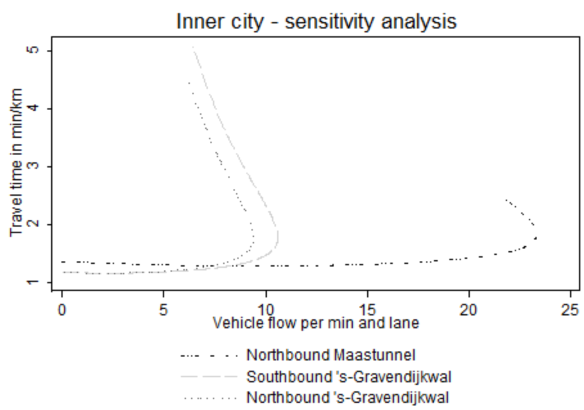
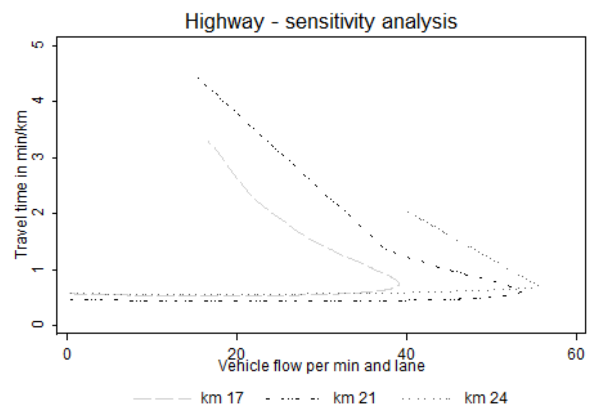


Figure 3.10 – Road supply curves highway



The methodology we propose is also suitable to less aggregated data. For example, we can estimate equation (3.2) for 9.1 million observations of the highway with individual observations by 100m road segment over the 7.6km and 30-minute observation interval. We find almost identical results in the shape of the road supply curve (see Figure 3.A10 in the Appendix). We prefer the main result in Table 3.3 of section 3.4 because the instrument and control variables are available per hour and because of computational efficiency. In general, we also check the sensitivity of our results to the inclusion of night time data and hours that have vehicle density lower than the value ten but find our main results to be insensitive.

3.6 Welfare implications

We can estimate the MEC using the instrumental variable approach using (equation 3.5) when we focus on the positive MEC and tabulate the results in Table 3.3. In the inner city, the marginal external costs are 0.20 min/km per additional vehicle for all hours of the day.[117] For weekdays during working hours, the costs are almost twice as large (0.36 min/km). On weekdays in the afternoon rush hour, the costs are the largest, with four time the average marginal external cost at 0.92 min/km.

Table 3.3 – Marginal external cost in min/km

	Inner city		Highway	
Approach	Linear, IV	Quadratic, CF	Linear, IV	Quadratic, CF
Marginal external cost	0.20	0.18	0.06	0.11
Weekdays 7am to 7pm	0.36	0.43	0.12	0.28
Weekdays 5pm to 6pm	0.92	1.68	0.28	1.02

Note: Instrumental Variable approach (IV), control function approach (CF).

It can be argued that the welfare maximizig toll is equivalent to the marginal external cost in the optimum.[118] For the road toll, we take into account the hourly varation in the number of road users. To express the toll in monetary terms, we assume a value of travel time per car of €21 per hour, so implicitly €14 per person and hour since average car occupancy is 1.5 persons.[119] Our road tolls are based on the quadratic control function approach of equation (3.4). We find that tolls vary greatly over the course of the day, with the highest toll in afternoon rush hours. Between 5pm and 6pm, users would pay €0.50 per km in inner city and €0.40 per km, see Figures 3.11 and 3.12. The average over the course of the day is €0.22 per km in the inner city and €0.16 per km on the highway.

When we are interested in the optimal road-use equilibrium given a linear, elastic demand function and the quadratic supply function estimated in equation (3.4) where: $T = \beta e^{\alpha D + \delta D^2}$. We equate an inverse demand function with a time-variant intercept τ_r and a time-invariant slope φ where

[117] We can compare our results to the power of BPR functions in the literature by calculating the ratio between MEC and the private time loss (i.e. travel time minus free flow travel time). We find a ratio of 1.7 for the inner city and 1.3 for the highway which is lower than for BPR congestion functions with frequent hypercongestion (Small and Verhoef, 2007, 76f).
[118] We assume travel time as the only cost factor and no substitution of trips over time. Without these assumptions our toll is an understimate because of the additional external costs such as polllution associated with travel.
[119] Such a high value of time is supported by Peer et al. (2013) which find value between €35/h to €65/h in the Netherlands during commuter times.

$T = \tau_r - \varphi F$ to the marginal cost curve so that:

(3.6) $$\tau_r - \varphi F = T + MEC$$

This can be rewritten using equation 5 as:

(3.7) $$0 = \tau_r - \varphi \left(\frac{\mathrm{D}}{\mathrm{T}}\right) - T - (\alpha DT + \delta D^2 T)/(1 - \alpha\mathrm{D} - \delta D^2)$$

We optimize for values $\varphi = [0.2; 1]$. The implied corresponding average demand elasticities for the inner city are [-1.4;-7.1] since ∂T⁄∂F=-ϕ F⁄T, and for the highway respectively [-4.3;-21.7] corresponding to values in the literature.[120]

Let us first consider the case of $\varphi = 0.2$ in the inner city. The average optimal density for the inner city is 1.6% lower than the average density. Up to the critical density (50.95), in the congested part of the road supply curve, average welfare gains are 0.12 min/km, see Table 3.4. Above the critical density, welfare gains from reducing hyper-congestion might be substantially larger than those from reducing congestion and always substantially larger than the potential gains in the congested section irrespective of the assumed demand elasticity.

Table 3.4 – Welfare analysis with for various demand functions

	Inner city		Highway	
Φ	0.2	1	0.2	1
Average density (D)	12.60	12.54	8.70	8.70
Optimal density (Do)	12.49	12.53	8.06	8.47
Critical density (Dc)	50.95	50.95	28.71	28.71
Average welfare gain				
Congested: Do>D<Dc	0.12	0.0052	0.26	0.64

There are various forms of first-best road pricing. For example, many large European cities make use of Cordon tolls where road pricing is applied to car users entering the city center as in the case of Stockholm and London. Our estimate could also be used for Cordon tolling. In case of a Cordon toll it would be suitable to price inner city trips on the average vehicle trip length (13km), so around €1.56 per trip. Welfare can be improved by investing toll revenues from first-best road pricing into second-best policies such as investment into bicycle paths and subsidies to public transit.

[120] In an overview study on travel elasticities, Litman (2004) states a short-run elasticity to fuel costs of about -0.2 and for long-run costs about -1.2. The elasticities to generalized costs including also travel time is -0.5 and -1.0 in the short and -1.0 to -2.0 in the long-run (Lee, 2000). When we assume a constant demand elasticity for each hour instead of a linear demand function, we find comparable results in terms of optimal density and welfare gains to Table 3.4.

With a back-of-the-envelope calculation it is possible to determine the additional revenue from road pricing using the marginal extrenal welfare costs per vehicle and summary statistics of Rotterdam. In the metropolitain region 1.2 million inhabitants conduct 804.000 car trips each weekday with an average distance of 13km of which 62% take place in the inner city and 38% on the highway. Furthermore, we make the assumption that the road supply curve for the inner city and highway are representative and that inhabitants exclusively travel in Rotterdam whereas no travel of Rotterdam outsiders takes place inside of Rotterdam.[121] This amount to €158,000 per working day and €40 million annually.[122]

Figure 3.11 – Toll inner city weekday

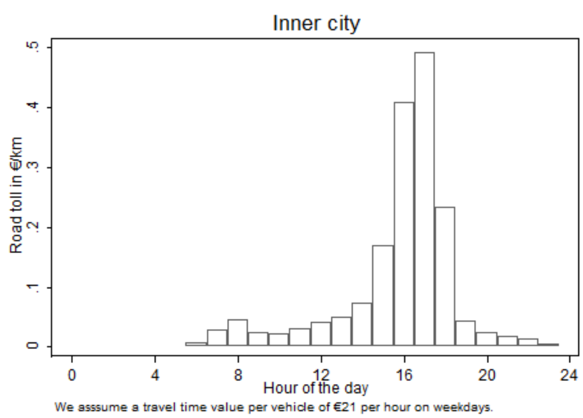
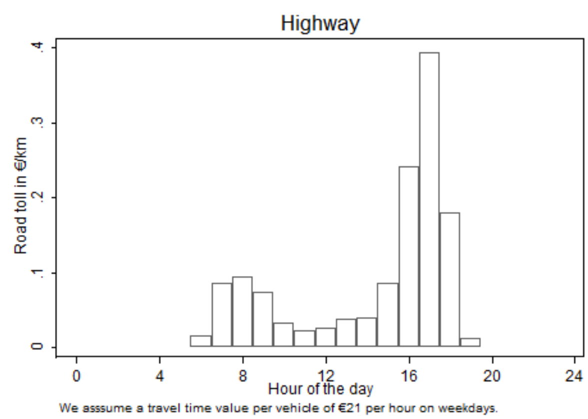


Figure 3.12 – Toll highway weekday



To what extent these findings have external validity for other cities of the size of Rotterdam depends strongly on how representative the here estimated road supply curves are as well as how closely the cities match in terms of travel characteristics such as modal split. It is also important to note that Rotterdam already has second-best congestion relief policies in place, such as comparably high parking fees in the city center, extensive bicycle infrastructure and substantial public transit provision, so that welfare losses are lower than in a comparable situation without such measures.[123] Since we

[121] This is a strong assumption as traffic flows and road supply curves seem to vary somewhat at least for the inner city as shown in the sensitivity analysis. However, we base our assumption on the Wardrop principle (1972) where car users optimize route choice according to the travel time. Also, Geroliminis and Daganzo (2008) show that there is high correlation between travel times at the neighborhood level. We might over-estimate the congestion cost as part of each car trip takes place on tertiary roads in neighborhoods where congestion might be less of an issue.

[122] 804000*0.62*0.22+804000*0.38*0.16. We assume 252 working days. This is about 20% of subsidies to public transit and 110% of public bicycle investments.

[123] Parking pricing can serve as an alternative or additional road pricing mechanism (Arnott and Inci, 2006,2010; Van Ommeren, 2011; Fosgerau and De Palma, 2013).

focus on external welfare losses in travel time we do not account for other external losses from congestion such as environmental and accident losses, hence the welfare loss from congestion based on travel time is an underestimate.[124]

3.7 Conclusion

We estimate the effect of vehicles flow on travel time. Since this effect can backward-bending during hours when high demand for car travel exceeds road capacity, we estimate travel time as a function of vehicle density. This is a monotonic function and relates through an identity to vehicle flow on travel time. However, vehicle flow and density are not necessarily exogenous because of reverse causality and measurement error. Therefore, we demonstrate that the use of exogenous, highly correlated instruments such as bicycle flow or the hour-of-weekday are suitable to account for endogeneity.

We demonstrate that our methodology allows to obtain consistent and unbiased estimates of the road supply curve. The method is well suited for inner cities, highways as well as suitable for various levels of temporal and spatial data aggregation. Instrumentation and the inclusion of day-fixed effects controls substantially reduce the impact of unobservable occurrences such as road works and road incidents on our estimates.

To capture the infrequent (less than 2% of observations) presence of hyper-congestion in our road supply curve, we use a more flexible quadratic specification and a control function approach to address endogeneity. This combination yields a supply curve that closely mimics the data and provides a functional form in line with the fundamental diagram of traffic and stationary-state congestion theory. The quadratic control function is also superior in the precision obtaining the level of vehicle flow where congestion transforms into hyper-congestion, i.e. the ‘critical density’.

We are the first to demonstrate how these unbiased estimates of the road supply curve can be used to obtain the marginal external time cost of vehicle travel. We find large variation in patterns of marginal external cost between the inner city and the highway and across the hours of the day.

We find marginal external congestion costs of 0.16 min/km for the inner city and 0.10 min/km for the highway. Marginal external costs can be by a factor ten larger during afternoon rush hours.

[124] When fuel costs are €0.10 per kilometer and additional external cost such as pollution about €0.02 then peak external cost exceeds the user costs for peak hours. A road supply curve and optimal tolls that are based on behavioral explanations supports the idea that congestion cost is more relevant to the travelers than accident and fuel costs (Verhoef and Rouwendal, 2004; Anas and Lindsey, 2011).

Hence, optimal tolls are between 40 to 50 cents during rush hours and 10 to 20 cents over the course of the day.

Appendix 3.A

Figure 3.A1 – Measurement points Rotterdam

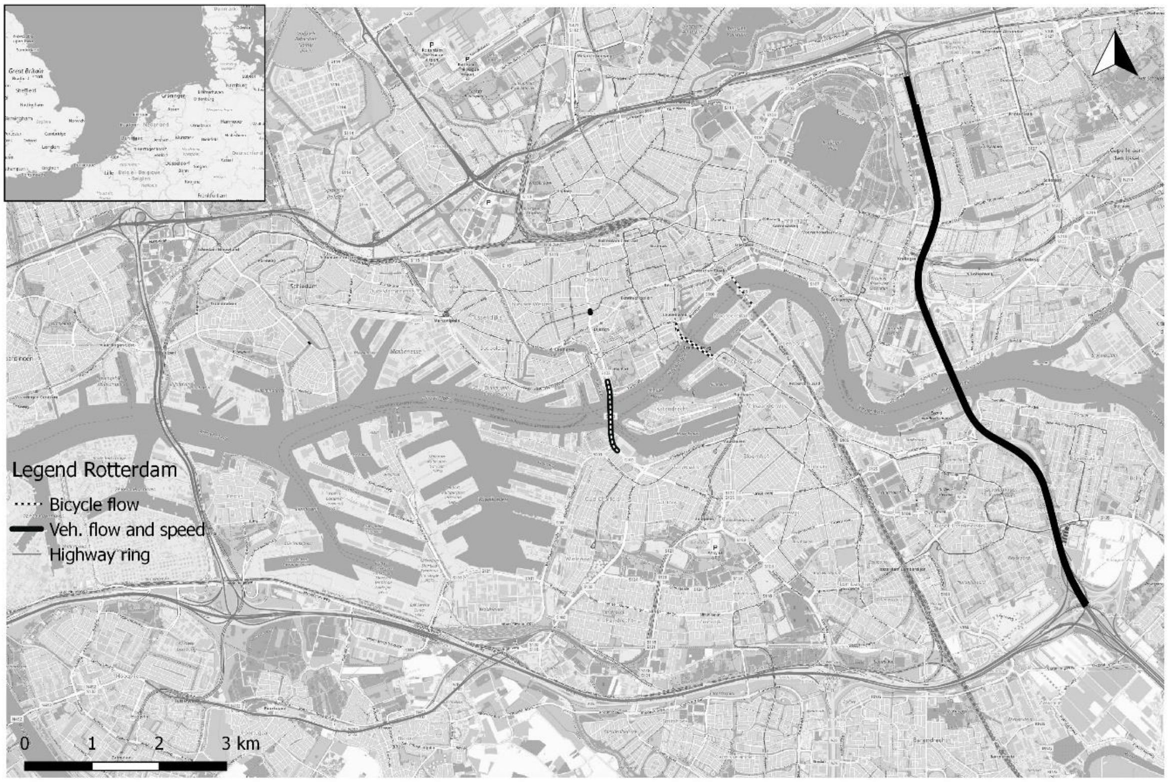


Figure 3.A2 – Vehicle flow

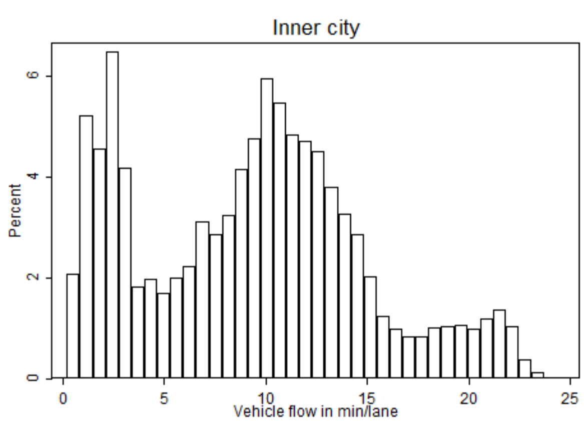


Figure 3.A3 – Vehicle density

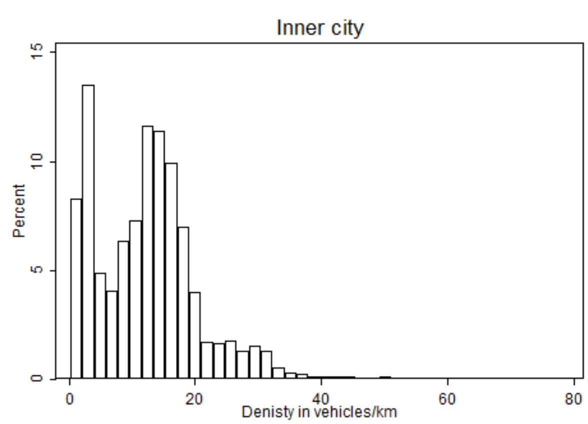


Figure 3.A4 – Travel time

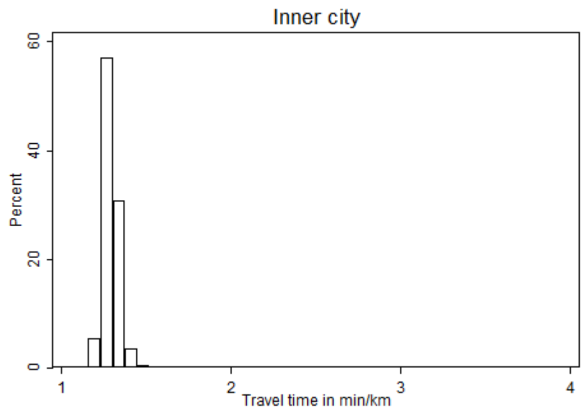


Figure 3.A5 – Bicycle flow

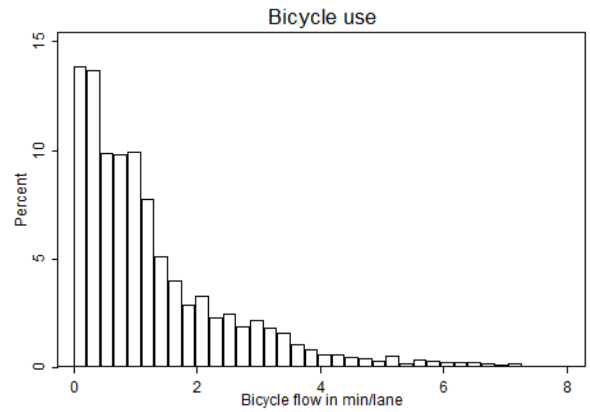


Figure 3.A6 – Bicycle flow and vehicle density

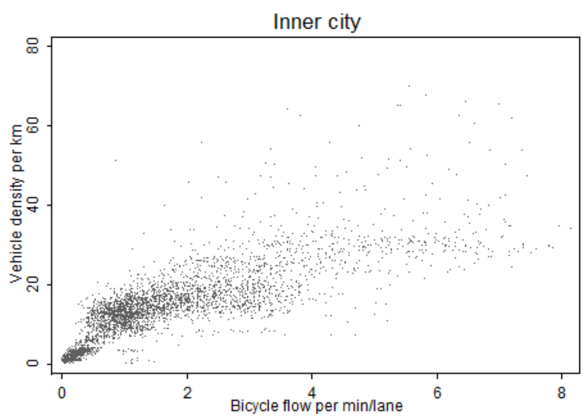


Figure 3.A7 – Road supply and confidence interval

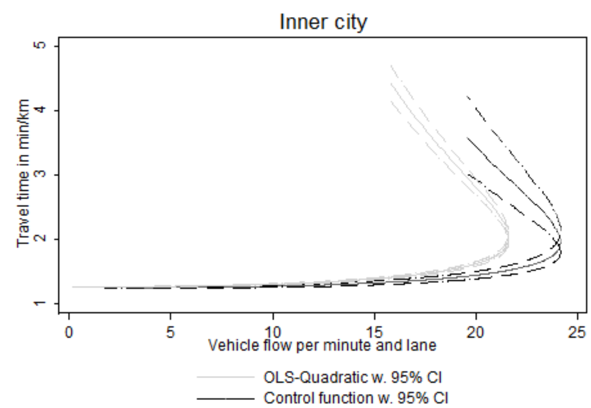


Figure 3.A8 – Road supply and confidence interval

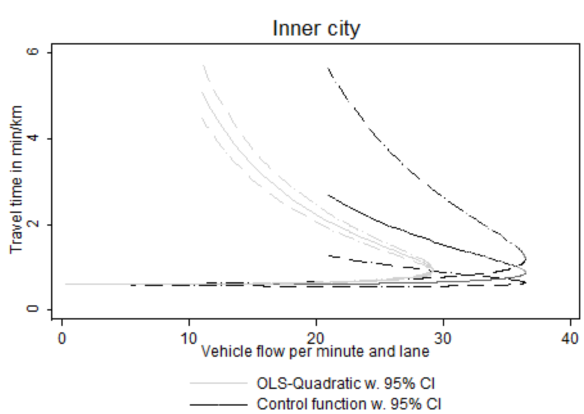


Figure 3.A9 – Road supply curve

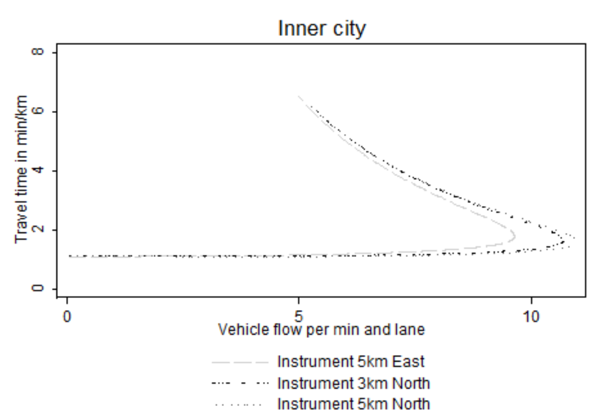


Figure 3.A10 – Data aggregation sensitivity

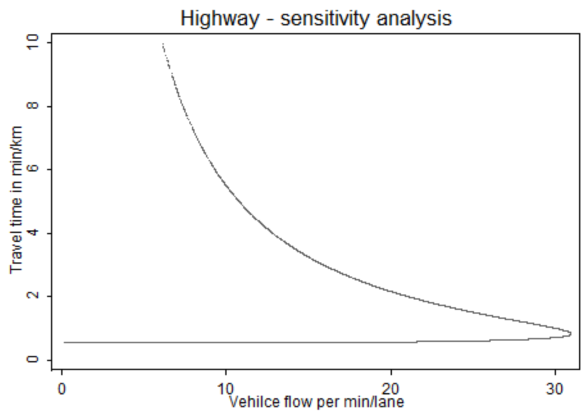


Figure 3.A11 – Imputed and observed density

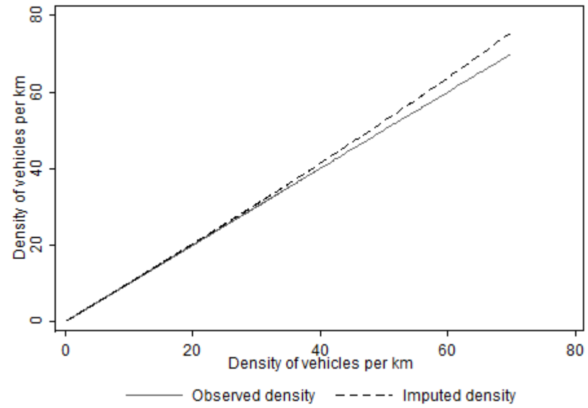


Table 3.A1 – Travel time (log) inner city

	(1) Linear	(2) IV	(3) OLS-Quadratic	(4) Control function
Flow	0.0076***	0.0152***	-0.00348***	-0.00131*
	(0.000409)	(0.000696)	(0.000839)	(0.000536)
Flow squared			0.000541***	0.000488
			(0.0000359)	(0.0000241)
N	6112	6112	6112	6112
R^2	0.45		0.47	

For the controls variables that are included see Table 2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.A2 – Travel time (log) highway

	(1) Linear	(2) IV	(3) OLS-Quadratic	(4) Control function
Flow	0.00153***	0.00566***	-0.00160*	-0.00107*
	(0.000151)	(0.000593)	(0.001080)	(0.0006012)
Flow squared			0.0003408***	0.0002408***
			(0.0000198)	(0.0000198)
N	7408	7408	7408	7408
R^2	0.33		0.33	

For the controls variables that are included see Table 2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4 Does public transit reduce car travel externalities? Quasi-natural experiments' evidence from transit strikes

4.1 Introduction[125]

The provision of public transit is thought to reduce travel time losses and other negative car externalities that are due to car congestion. For this reason, it may be economically justified to subsidise public transit from a welfare perspective as it creates a congestion-relief benefit.[126] Car use and public transit use are not perfect substitutes. Hence, subsidies to public transit provision might be interpreted as a second-best policy. Public transit provision is not the only alternative for policymakers to address negative car externalities. For example, we will provide evidence that bicycling-promoting policies might be another cost-effective way to realise congestion-relief benefits.

The main goal of this paper is to quantify the congestion-relief benefit of public transit for Rotterdam by analysing travel time changes due to public transit strikes.[127] Arguably, strikes can be interpreted as exogenous transit supply shocks and therefore as a quasi-natural experiment as argued by a series of studies (Crain and Flynn, 1975; Van Exel and Rietveld, 2001; Aftabuzzaman et al., 2010; Marsden and Docherty, 2013). We are aware of two other papers that use a similar idea. Lo and Hall (2006) and, more recently, Anderson (2014) analyse the effect of a *single* transit strike lasting 35 days on highway speed for Los Angeles. Anderson (2014) finds a substantial congestion relief benefit of public transit provision with a decrease in time delays experienced by car drivers of 0.12 minutes per

[125] This chapter is based on Adler, M. W. and Van Ommeren, J. N. (2016). Does public transit reduce car travel externalities? Quasi-natural experiments' evidence from transit strikes. *Journal of Urban Economics*, 92, 106-119. We would like to commemorate our colleague Piet Rietveld who was involved in the early stages of this paper but who passed away on 1st of November, 2013. This paper is funded by Kennis voor Klimaat. We thank Taoufik Bakri from TNO Delft, Peter Schout from Rijkswaterstaat, Jos Streng and Roel Rijthoven from Rotterdam municipality for support in data acquisition and constructive remarks. Furthermore, we thank Hugo Silva and seminar audiences of the Amsterdam Tinbergen Institute, Toulouse ITEA 2014 and St Petersburg ERSA 2014 conference for useful comments. Jos van Ommeren is a fellow of the Tinbergen Institute.

[126] Other reasons for public transit subsidies are that public transit's average costs are lower than its marginal costs because of the presence of fixed costs and the 'Mohring (1972) effect'. Car congestion is the main externality of car travel in addition to air pollution and road accidents.

[127] Up to the 90´s, strikes received a lot of attention in the economics literature, which shows that the majority of strike days are public sector strikes. For example, 86% of UK strike days are in this sector (ONS, 2014). In many countries, a large share of public sector strikes is with public transit firms. These firms have market power, and are unionized, which are both key strike determinants.

kilometer traveled.[128] It is unknown to what extent this result can be generalised to other cities where the share of public transit use is much higher or to cities where bicycle use is a viable alternative.[129]

Our analysis differs from Anderson (2014) and Lo and Hall (2006) in a number of ways. First, we focus on a city, Rotterdam in the Netherlands, which, as we will document, is only mildly congested. Second, we analyse the effect of *multiple* strikes of *various* public transit modes (e.g. bus, light rail) that are *citywide*. Third, we examine the strike effect on travel time per kilometer (and flow) for the highway ring road and inner city roads. Fourth, we examine to what extent transit strikes induce public transit travelers to switch into cycling. The latter is particularly relevant, because, as argued by Basso and Silva (2014), public transit subsidies should be evaluated according to other urban policies with a similar aim, such as congestion pricing and bicycling-promoting policies. Finally, by examining heterogeneity in the effect of strikes, we are able to improve our understanding when the public transit relief benefit is particularly pronounced. For example, as one may expect, we find a particularly strong effect during rush hours (but no clear effect during weekends and outside rush hours). In addition, our results suggest that the travel time effect of strikes that lasts a few hours are similar to that of full-day strikes indicating that a continuous supply of public transit during the day is essential for travelers.

We show that the congestion relief impact for inner city roads is by a factor ten larger than for highway ring roads. For the latter we find an effect that is several times smaller than reported by Anderson (2014). It turns out that the congestion relief benefit of public transit for Rotterdam is substantial and about 80% of the current subsidy to public transit. This suggests that even for cities that exhibit mild congestion levels, subsidies to public transit are to a large extent justified by their congestion relief benefit alone.

[128] Lo and Hall (2006) report similar speed reductions of 20% to 40%. However, an earlier strike in the year 2000, not analysed by Lo and Hall (2006) and Anderson (2014) seems to decrease speed by only 5% (The Economist, 2000). Parry and Small (2009) *assume* that public transit provision reduces car travel time by 0.04 minutes per kilometer traveled, substantially less than the results indicated by Anderson (2014). Similar to Nelson et. al (2007), they conclude that subsidies up to 90% of operating cost may be welfare improving. Also Proost and Van Dender (2008) and Basso and Silva (2014) indicate that during peak hours, it may be beneficial when subsidies cover at least 50% operating cost.

[129] As is well known, in comparison to Los Angeles, almost all European and Asian cities provide levels of public transit that are an order of magnitude higher. Because it is likely that the congestion relief benefit is a concave function of the level of transit provision, the marginal benefit might be lower in these cities.

4.2 Data and descriptive statistics

4.2.1 Introduction

We analyse public transit strikes for the period 2001 to 2011 for Rotterdam, a Dutch city with a metropolitan population of about 1.2 million inhabitants. Public transit use is substantial: 21% of residents and 25% of commuters use it each day. Car ownership is low: only 57% of adults belong to a car-owning household, but the proportion of commuters who travel by car is representative for the Netherlands: about half of the Rotterdam commuters travel by car (De Vries, 2013). Average speed for an entire commuter car trip is about 30km/h (Savelberg, 2013). As will be documented later on, in Rotterdam there is mild car congestion, as average speed within the city, as well as on the highway ring road is just below the legal maximum speed limit. Also, as is well known, in the Netherlands, the use of the bicycle is quite common. In line with this, the large majority of Rotterdam residents own a bicycle. Bicycle use in Rotterdam is low from a Dutch perspective: 14 % of commuters bicycle on a daily basis (in Amsterdam this percentage is more than double), but comparable to cities such as Hamburg, Delhi, Barcelona, Tokyo and Berlin.[130]

Within the Rotterdam metropolitan area there is one public transit operator RET which provides inner-city bus, tram, metro and light rail connections. Regional bus connections, between the municipality of Rotterdam and other municipalities, are provided by another (private) company.[131] Within Rotterdam, many roads have separate bicycle paths, which allow us to measure bicycle use over an extensive period.

We will analyse hourly information about bicycle flow, car flow and travel time for the inner city and about car flow and travel time for the highway ring road (see subsections 4.2.3 and 4.2.4) and relate this to the occurrence of strikes (see subsection 4.2.2).[132]

4.2.2 Strikes

Information on public transit strikes is obtained from the Rotterdam municipality, the public transit operator, newspapers and Internet search. We observe 16 public transit strikes between 2001 and

[130] One of the reasons for the low bicycle use in Rotterdam is that it has been rebuilt as a modern ('American') city after its destruction during the Second World War.
[131] Rail is supplied by a semi-public, national rail operator.
[132] Information on inner city traffic is provided by Rotterdam municipality and on highway traffic by TNO.

2011.[133] Table 4.1 lists these strikes by mode, type, date, time and additional information, such as whether they were announced. We focus on 13 *citywide* transit strikes, defined as strikes that affect all inner-city buses, trams and metro, but also consider two national rail strikes and one regional bus strike.[134] Regional buses also operate on routes inside the city, but during citywide strikes do not stop within the city (in order not to break the strike).

Table 4.1 – Public transit strikes Rotterdam, 2000-2011

Type	Date		Time	Information
Citywide strikes				
	Wednesday	08-10-2003	10am to 2pm	
	Thursday	14-10-2004	Full-day	Also rail
	Wednesday	29-06-2005	Full-day	
	Monday	04-09-2006	12am to 1pm	No metro strike, unannounced
	Monday	18-09-2006	8am to 1pm	Unannounced
	Monday	25-09-2006	Full-day	
	Wednesday	15-11-2006	10am to 4pm	No metro strike
	Wednesday	16-02-2011	Full-day	Reduced schedule
	Tuesday	12-04-2011	9am to 2pm	
	Wednesday	11-05-2011	5am - 9am	Irregular schedule
	Thursday	09-06-2011	Full-day	
	Wednesday	29-06-2011	9am to 3pm	
	Sunday	20-11-2011	Full-day	
Rail strikes (only)				
	Thursday	21-12-2000	Full-day	
	Friday	17-06-2005	Full-day	
Regional bus strike (only)				
	Tuesday	20-05-	9am to 4pm, after 7pm	
	Wednesday	21-05-		
	Thursday	22-05-		
Placebo strikes				
Rail strike	Monday	02-04-2001	No strike	Canceled
Citywide strike	Wednesday	06-10-2009	No strike	Canceled
Citywide strike	Sunday	06-11-2011	No strike	Canceled

About half of the citywide strikes last a full day. The other half usually end after four to five hours, and will be labeled partial-day strikes. The majority of strikes include rush hours, defined to be between

[133] In the three years following 2011 there were no public transit strikes in Rotterdam.
[134] About one third of Dutch train users combine train use with bicycle or car use (van Goeverden and Egeter, 1993, and van der Loop, 1997), so a train strike may decrease bicycle and car use for some train travelers.

7am-9am and 4pm-6pm *on weekdays*. All strikes end within 24 hours after commencement except for one regional bus strike that involves strike disruptions on three consecutive days. One citywide strike (in October 2014) coincides with a national rail strike. Importantly, all strikes, except two, were announced (also in national media) well in advance.[135]

Three strikes were first announced and later canceled. We will use these canceled strikes as placebo strikes. Arguably, if the effect of announcements of strikes on switching travel mode is sufficiently small (for which we will provide evidence), then these canceled strikes can indeed be interpreted as placebo strikes.[136]

4.2.3 Inner city traffic

For the inner city, information on the hourly number of cars on the road and bicycle travelers on bicycle paths is collected by pneumatic tubes. We have this information for all directions at 24 locations, equally distributed over the city (see Figure 4.A1 in the Appendix).[137] For 21 out of 24 locations, there is information on either car or bicycle travel. For three locations, two bridges and a tunnel that span the river Maas, information on both car and bicycle travel is available.[138] In total, we have 36 measurement directions for bicycle flow on bicycle paths and 16 for car flow (see Table 4.A1 in Appendix).[139] For two locations, so four directions, we have information on car travel speed. Although we have only four independent speed measurements, these can be thought to be representative for the speed within the whole city as previous studies indicate that within-city speed observations over different locations are strongly correlated (Geroliminis and Daganzo, 2008; Daganzo et al., 2011).[140]

[135] Strike information prior to the strike is not always clear and sometimes even misleading. For example, for the 12th of April 2011 strike, travelers were warned that services would be gradually reduced starting from 9am but actually service provision grinded to a complete halt at this time (Treinreiziger, 2011).
[136] Cancellations occur due to legal challenges and not due to anticipated road conditions. The placebo strike in 2011 was canceled a week before, but the other two only hours before. Because we will show that announced and unannounced strikes have similar effects, it is reasonable to interpret canceled strikes as placebo strikes.
[137] Most locations have two directions. There are is one location with information on one direction and one location with three directions.
[138] The river Maas is a major waterway that divides the city into two parts. The two bridges and tunnel are the only possibility to cross within a span of 5km.
[139] Cycling paths are separated traffic lanes designated for bicycle travel. For most paths this includes a small share of motorized bicycles and small scooters. Negative measurement error for bicycle flow is present because only one bicycle can be recorded every 0.050 seconds. This results in downward bias of 5% to 20% for highly frequented paths (Bell and Vibbert, 1990). Hence, our estimates of strike effects on bicycle travel may be somewhat biased towards zero.
[140] The idea of bathtub congestion, where travel times increase across a city, like water in a bathtub, is based on the notion that within-city speed variation is absent (Arnott, 2013; Fosgerau and Small, 2013).

In our analysis, for a causal interpretation of the strike effect, we aim to compare transport outcomes on strike days with transport outcomes on similar non-strike days. As can been seen in Table 1, during certain periods (e.g. the summer) there were no strikes. Although this may be accidental, it is also possible that strikes were avoided during certain periods for a certain reason (e.g. public transit use is lower during the summer, so a strike may be less desirable according to the strike organizer). Hence, we exclude four months (January, March, July and August) and three years without a strike (2002, 2007 and 2010).[141] Car flow is zero for a few observations and for convenience (as we will use logs) these observations will be excluded. We focus on observations between 6am and 8pm (i.e. 14 hours). In total, we have 88,106 hourly observations of travel time, 338,782 of car flow and 719,661 of bicycle flow.

Figure 4.1 – Travel time

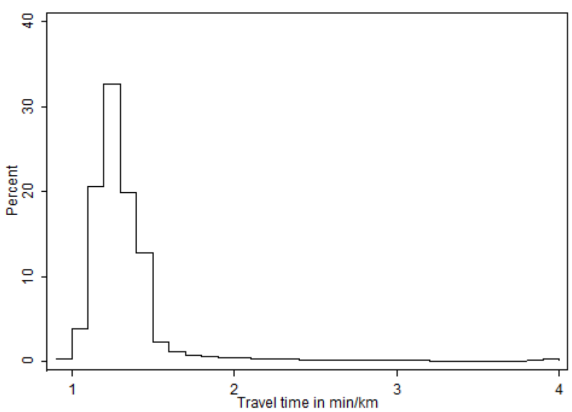
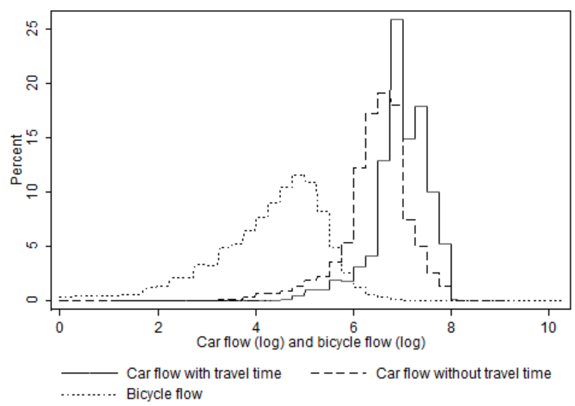


Figure 4.2 – Car and bicycle flows



Our measure of travel time, measured as minutes per kilometer, is based on the proportion of vehicles that travel at a certain speed (during one hour), observed for 11 speed intervals.[142] We construct travel time by calculating the average using the mid-speed value and the proportion of cars per interval.[143] This is potentially problematic, because the lowest interval, below 31 km/h, is quite

[141] Including these observations provides almost identical results as discussed in the sensitivity analysis. About 12.2% of observations are missing, as, due to malfunction and vandalism pneumatic tubes are occasionally not operating. The occurrence of missing observations is independent of the occurrence of strikes and missing observations are excluded from the analysis without introducing selection bias.

[142] To be precise, intervals distinguish between 0-31, 31-41, 41-51, 51-57, 57-61, 61-71, 71-81, 81-91, 91-101, and above 101 km/h.

[143] We construct travel time in minutes per kilometer as the weighted average of the inverse of speed, with weights equal to the proportion of cars in a speed category. For a number of cars, speed is unknown. We ignore these observations initially. In

large. For this speed interval, we assume cars to drive 15 km/h, but we also make other assumptions as discussed in the sensitivity analyses. Hence, travel time is truncated and skewed, see Figure 1, and locations with information on travel time have a similar car flow distribution as other locations, see Figure 2.

Table 4.2 – Summary statistics inner city traffic

	Travel time			Car flow			Bicycle flow		
	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.
Full-day citywide strike	1.55	0.66	294	894.1	508.7	854	188.1	249.6	2,212
Rush hour	1.88	0.86	68	1,090.0	568.7	212	312.4	234.8	506
Non-rush hour	1.45	0.56	226	829.3	470.1	642	151.6	242.1	1,702
Partial-day citywide strike	1.48	0.53	348	911.0	514.9	992	179.5	163.3	2,605
Strike & rush hour	2.00	0.83	12	1165.6	664.5	28	359.6	251.5	83
Strike & non-rush hour	1.32	0.17	94	864.6	426.8	270	146.6	128.6	727
Non-strike & rush hour	1.70	0.74	88	1,060.5	615.7	256	241.9	188.8	664
Non-strike & non-rush hour	1.41	0.42	154	835.9	903.1	438	151.3	138.1	1,127
Rail strike	1.43	0.46	112	875.4	404.1	363	138.0	89.1	517
Regional bus strike	1.56	0.35	164	1,011.8	510.6	465	229.2	847.1	1,256
Placebo strike	1.37	0.35	98	760.9	468.6	363	122.3	121.7	1,201
Non-strike	1.35	0.35	87,146	774.9	465.5	335,772	118.2	117.0	711,878
Rush hour	1.53	0.55	17,828	988.2	557.3	68,545	197.2	150.6	145,525
Non-rush hour	1.30	0.26	69,318	720.1	421.8	267,227	97.9	96.8	566,353
Total	1.35	0.35	88,106	775.9	457.0	338,782	118.9	123.1	719,661

Note: Hourly observations. Travel time in minutes per kilometer.

Table 2 shows mean car travel time for different strike categories. In line with the idea that Rotterdam is a mildly congested city, the mean travel time is 1.35 min/km, close to the time it would take at the 50 km/h speed limit, i.e. 1.20 min/km. Note further that when there are no strikes, travel time during rush hours (1.53 min/km) is only 15% higher than during non-rush hours (1.30 min/km). The table also suggests an effect of strikes: travel time is distinguishably higher during full-day citywide strikes (1.55 min/km) in comparison to non-strike hours (1.35 min/km). The difference in travel time is about 0.20 min/km, so about 15%. At the same time, car and bicycle flows are substantially larger

the sensitivity analyses, we re-estimate models with the proportion of cars with missing speed data as a control variable. Note that by using mid-points we have measurement error in the dependent variable. Because measurement error is likely random, this is not of concern.

during full-day citywide strikes in comparison to non-strike days. During rush hours of full-day citywide strikes, travel time is even 17% higher, on average compared to non-strike days.[144] For most strike categories, the number of travel time observations is high enough to anticipate reasonably precise estimates. For example, for full-day citywide strikes, we have 294 observations about travel time, 854 about car flow and 2,212 observations for bicycle flow.

Full-day strike

Figure 4.3a – Travel time Thursdays June 2011

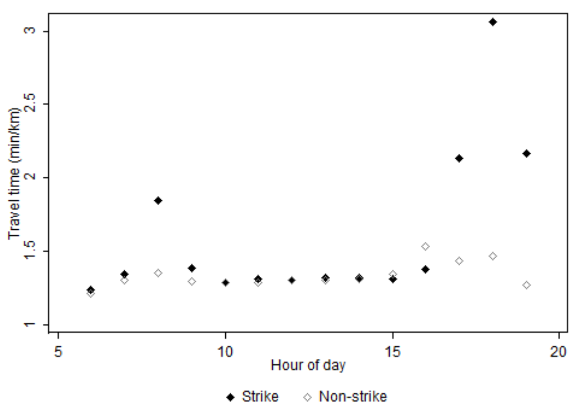
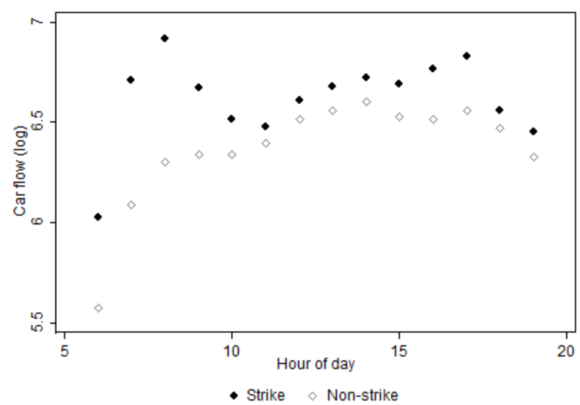


Figure 4.3b – Car flow Thursdays June 2011



Partial-day strike

Figure 4.4a – Travel time Wednesdays May 2011

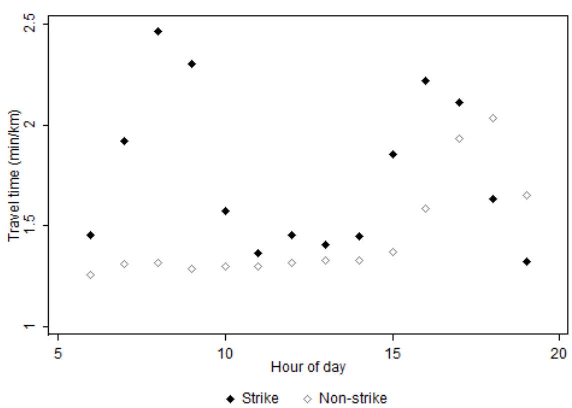
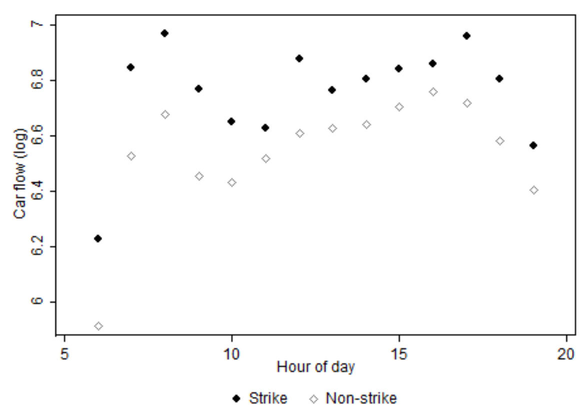


Figure 4.4b – Car flow Wednesdays May 2011



144 For rail and placebo strikes, travel time and flow are similar to non-strike days, suggesting the absence of an effect. For strikes with longer travel time and larger flow, standard deviations of travel time tend to be larger (because of the increase in travel time variation over the day).

A visual examination of how transport outcomes vary over the day on days with and without strikes offers further insights which motivate our estimation methodology later on. Here, we compare transport outcomes on a particular strike day to transport outcomes on non-strike days on the same weekday of the same month of the strike.

Figures 4.3a and 4.3b show travel time and car flow for a strike on a Thursday, on the 9th of June 2011 and for other (non-strike) Thursdays of the same month. During this particular strike, which lasted a full day, car flows are larger and travel time is longer for most hours of the day compared to other (non-strike) Thursdays that month. A similar result also holds for bicycle flow, see Figure A2 in the Appendix.

Figures 4.4a and 4.4b provide information for a partial-day strike - between 5am and 9am - on Wednesday 11th of May 2011 and compare this to all other non-strike Wednesdays in that month. The outcomes of this partial strike appear similar to the full-day strike, suggesting that strikes affect travel time also outside the strike period. Non-strike flow patterns between Thursdays and Wednesdays (see again Figures 3b and 4b) reveal weekday-specific flow patterns. For example, the morning rush hour is more pronounced on Wednesdays. It seems therefore important to control for the interaction of the week-of-the-day and hour-of-the-day fixed effects in the multivariate analysis.

4.2.4 Highway traffic

We also make use of highway ring road data between 6am and 8pm for the year 2011 that is collected using induction loops and transformed to 100 meter virtual loop data (Snelder, 2010; Vukovic et al., 2013).[145] Our data refer to the A16 motorway, east of Rotterdam. We use 15 minute interval data on both directions (that have 3 lanes each) for 7.6 kilometers (between the intersections with the northern and southern part of the ring road, A17 and A20). We aggregate these data to hourly observations of travel time and flow.

We have 771,019 hourly observations, see Table 4.3. Average highway flow is 2,963 cars per hour. At a maximum speed limit of 100 km/h, it takes 0.60 minutes to travel one kilometer. Average travel time in our data is 0.64 min/km, close to the speed limit, with a rather small standard deviation of 0.11 suggesting that congestion is not a major issue on this highway. So, a priori, one does not expect

[145] In the Appendix, we provide results for actual loop detector data for weekdays of the years 2006 and 2011. We prefer to use virtual loop data over actual loop data because detectors experience frequent malfunction with a very high share of impossible outliers.

particularly strong effects of a strike. This is confirmed by the data. During a full-day citywide strike, travel time is similar to that during non-strike hours. However, focusing on averages over the whole day seems slightly misleading because during strike rush-hours, the effect of strikes seems much more pronounced: for example, during citywide strikes, travel times increase by 0.03 min/km and highway flow by about 29%.

Table 4.3 – Summary statistics highway traffic

	Travel time			Car flow		
	Mean	SD	Obs.	Mean	SD	Obs.
Full-day citywide strike	0.64	0.11	6,426	3,033	1,244.0	6,426
Rush hour	0.72	0.17	1,224	4,340	886.4	1,224
Non-rush hour	0.62	0.07	5,202	2,753	1,113.1	5,202
Partial-day citywide strike	0.67	0.17	5,202	3545	957.0	5,202
Strike & rush hour	0.73	0.19	306	3,981	638.6	306
Strike & non-rush hour	0.68	0.15	459	3169	481.9	459
Non-strike & rush hour	0.77	0.26	1,377	4,160	1,123.5	1,377
Non-strike & non-rush hour	0.61	0.03	3,060	3,282	796.7	3,060
Placebo strike	0.64	0.54	1,836	2,288	1,089.2	1,836
Non-strike	0.64	0.29	757,555	2,960	1,150.4	757,555
Rush hour	0.69	0.33	208,903	3,354	1,484.9	208,903
Non-rush hour	0.63	0.27	548,652	2,809	951.7	548,652
Total	0.64	0.29	771,019	2,963	1,151.3	771,019

Full-day strike

Figure 4.5a – Travel time on Thursdays June 2011

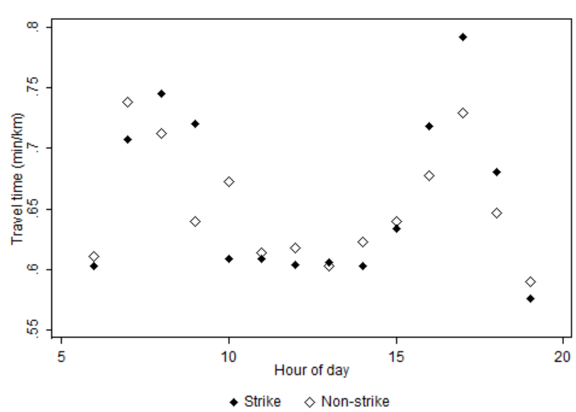
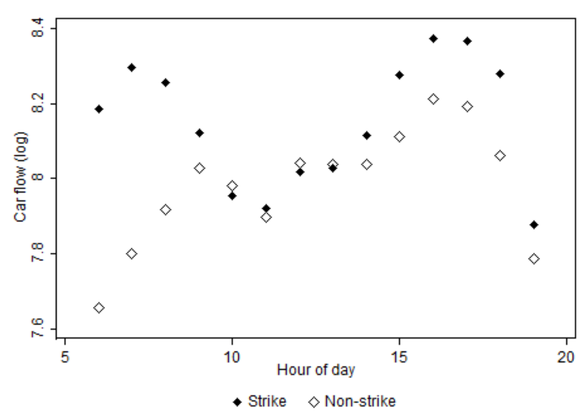


Figure 4.5b – Car flow on Thursdays June 2011



Again, we show car flow for a full-strike and a partial-strike day and compare to car flow on the same non-strike weekdays that month (Figures 4.5b and 4.6b). Similar to inner city roads, highway flows are larger during strike hours, especially for the full-day strike. In Figures 4.5a and 4.6a, it is shown that travel time is higher during strike hours than during the same weekdays that month. These figures also exhibit 'extreme' variation for some hours. For example, on Wednesday the 18th we observe large travel times at 3pm and 4pm in Figure 4.6a, likely caused by an accident.

Partial-day strike

Figure 4.6a – Travel time on Wednesdays May 2011

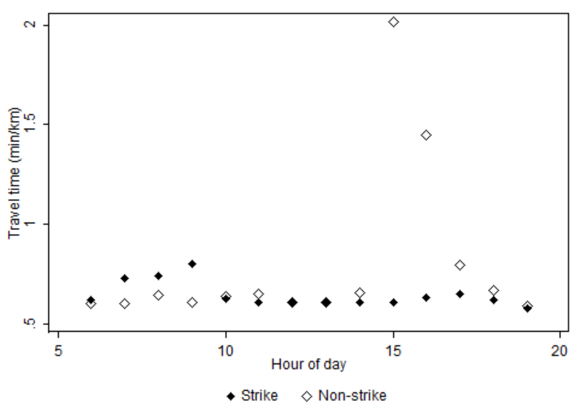
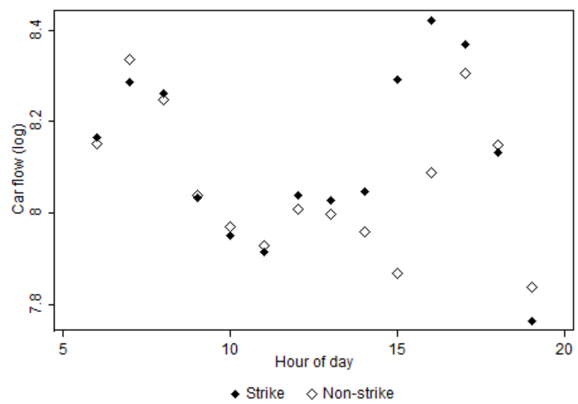


Figure 4.6b – Car flow on Wednesdays May 2011



4.3 Theoretical framework and estimation method

4.3.1 Theoretical framework

In this paper, we use a basic theoretical framework of a transport market to interpret our empirical results. We assume a city that includes car travelers, bicyclists, public transport users and teleworkers (who stay at home). We assume that, within the city, the total number of travelers, including teleworkers, is fixed and denoted by N. Consequently, N includes N_{Pt} public transport users, N_C car travelers, N_B bicyclists and N_T teleworkers. Demand for transport mode *i* depends negatively on the generalized transport mode price p_i (p_{PT}, p_C, p_B and p_T, respectively), which includes travel time loss and positively on the generalized prices of other transport modes p_j, where *j ≠ i*. We normalize the price of teleworking, hence $p_T = 1$. The price of bicycling, p_B, is assumed to be exogenous. This is a reasonable assumption given that bicyclists mainly use bicycle lanes that are not congested. The price of car travel, p_C, is endogenous and an increasing function of the number of car travellers, N_C, so $p_C = p_C(N_C)$. In equilibrium, the following must hold:

(4.1)
$$N = N_{PT}(p_{PT}, p_C(N_C), p_B) + N_C(p_{PT}, p_C(N_C), p_B) + N_B(p_{PT}, p_C(N_C), p_B) + N_T(p_{PT}, p_C(N_C), p_B).$$

On a strike day, public transit is unavailable, so $N_{PT} = 0$ and p_{PT} approaches ∞. As a result, we observe in the new equilibrium:

(4.2)
$$N = N_C(\infty, p_C(N_C), p_B) + N_B(\infty, p_C(N_C), p_B) + N_T(\infty, p_C(N_C), p_B).$$

In the new equilibrium, compared to the non-strike equilibrium, N_C, N_B, N_T and $p_C(N_C)$ will increase. The increase in $p_C(N_C)$ is due the increase in travel time through increased road congestion. It also follows that: $-\Delta N_{PT} = \Delta N_C + \Delta N_B + \Delta N_T$ where Δ denotes changes induced by the transport strike. In the current paper, we have information about ΔN_{PT}, we estimate ΔN_C, and ΔN_B, so we can derive ΔN_T, the number of individuals who decide not to travel, and we estimate $\Delta p_C(N_C)$, which we use to calculate the congestion relief benefit.

For welfare analysis and policy implications, it is useful to distinguish between the marginal and the average congestion relief benefit of public transit. We can express the average congestion relief benefit of public transit as $\Delta p_C / \Delta N_{PT}$, and the marginal benefit as $\partial p_C / \partial N_{PT}$, i.e. the benefit given a small change in the public transport network. By examining the effect of a full public transit shutdown, we estimate the average, rather than the marginal benefit. The latter one is informative for policymakers who aim to adjust the public transport network on a small scale. Given information on traveler's choices, policy makers can, at least in principle, determine which part of public transit generates the highest benefit. Without this information, it is difficult to determine which part of the public transit network has the strongest effect on reducing car congestion. Hence, the policy maker will choose (more or less) randomly which part of the network will be expanded, and for those adjustments of the transit network the marginal benefit is identical to the average benefit.[146]

4.3.2 Estimation method

To estimate the public transit strike effects, we use linear models for travel time and log-linear models for transport flows.[147] We focus on the effect of citywide strikes. For these strikes, we distinguish

[146] However, if policymakers are able to marginally adjust the network based on changes in the congestion relief benefit, it is plausible that the average benefit estimated by us overestimates the marginal benefit. A related issue is whether congestion is a linear function of car flow. Congestion levels are rather mild within Rotterdam, suggesting that congestion is almost linearly related to car flow (Geroliminis and Daganzo, 2008).

[147] Our results are robust to specification. When using speed instead of travel time as the dependent variable, results are similar, but slightly less pronounced, see Adler and Van Ommeren (2015).

between the effect of a full-day strike, the effect of a partial-day strike during strike hours and the effect of a partial-day strike outside strike hours. Because in the previous sections we have seen that the effects of strikes seem to differ for rush and non-rush hours, we also distinguish between rush hours and non-rush hours effects.

To estimate these different strike effects, we assume that the dependent variable $Y_{i,t,D}$ (i.e. travel time, logarithm of car flow or logarithm of bicycles flow), which is observed for a certain direction *i*, of hour *t* on day *D*, depends on a citywide full-day strike dummy F_D, a rush hour dummy R_t, a dummy variable $S_{t,D}$ for strikes at hour *t* of day *D*, control variables $X_{t,D}$, direction fixed effects a_i, and a random error term $u_{i,t,D}$ in the following way:

$$\begin{aligned} Y_{i,t,D} &= \alpha_i + \beta_x X_{t,D} + [\beta_1 R_t + \beta_2(1 - R_t)]F_D \\ &\quad + \big[\big(\beta_3 R_t + \beta_4(1 - R_t)\big)S_{t,D} + \big(\beta_5 R_t + \beta_6(1 - R_t)\big)\big(1 - S_{t,D}\big)\big]P_D \\ &\quad + u_{i,t,D}. \end{aligned} \tag{4.3}$$

The coefficient β_1 captures the citywide strike effect for a full-day strike during rush hours and β_2 captures the same effect but outside rush hours. For partial-day strikes during strike hours, β_3 captures the strike effect during rush hours and β_4 for non-rush hours. The effects during non-strike hours of partial-day strikes are captured by β_5 and β_6 for rush hours and non-rush hours, respectively.

The control variables $X_{t,D}$ include placebo strikes, a regional bus strike, rail strikes and weather condition variables (precipitation, temperature and wind speed).[148] We also control for a range of time controls. We control for ‘special’ days (i.e. Christmas, Queens Day and the annual marathon), hour of the week (i.e. the interaction between hour of the day and day of the week) and week of the year (i.e. the interaction between week and year).[149] These time controls are included because we have seen in the previous section that traffic flows follow certain time patterns during the day, but also to address the possibility that the strike date might be endogenous. For example, negotiating parties (i.e. unions, transport firms and the government) determine when strikes occur and might take the effect on car travel time into account by (not) selecting certain days.[150] So, the occurrence of a strike is likely not fully random with respect to the day of the week. This is also suggested by Table 4.1. For example,

[148] Daily travel demand, and bicycle travel in particular, depends strongly on weather, see, for example Thomas et al. (2013).
[149] Hour of the week contains a dummy for each combination of the hours of the day (14) and day of the week (7), in total 98. Week of the year has a dummy for each week (40) of the year (8), in total 320.
[150] One of the drivers of strikes is the joint costs to firms and employees that bargain about labor, see Franzosi (1989) and Card (1990). In case of public transit, car drivers are outsiders of this bargaining process. It may be then efficient that the government induces public transit firms to accept terms which would have been rejected from a private firm’s consideration alone, in order to avoid car travelers congestion cost (Proost, 2014).

there are no citywide strikes on Fridays or Saturdays. Hence, including time controls is useful for consistency and efficiency reasons. Furthermore, to deal with heteroscedasticity and day-specific unobservables, we choose standard errors that are robust and clustered by day.

4.4 Empirical results

4.4.1 Inner city traffic

We report strike effects on travel time, car flow and bicycle flow based on equation (4.3) in Table 4.4.[151] Our results in the first column indicate that a full-day citywide strike during rush hours increases travel time by 0.36 min/km (about 7 km/h). This travel time increase is in line with a 9% increase in car flow during rush hours, as reported in the second column.[152] This result is consistent with the literature which shows that this effect is usually in the range of 5% to 30% (Van Exel and Rietveld, 2001). During non-rush hours, we find a smaller travel time increase of 0.15 min/km. Hence, one immediate, but maybe obvious, implication is that the benefit of public transit provision in terms of congestion reduction is smaller outside rush hours.[153] Furthermore, as indicated in the third column, a full-day citywide strike increases bicycle flow by 24% implying that a large share of travelers switch to bicycle use (rather than to car use), which presumably reduces the car flow and corresponding travel time increases of a strike. As we have emphasized before, bicycle ownership is high in the Netherlands, so this result is likely specific for bicycle-friendly cities.

Later on, for our welfare calculations, it seems more accurate to use a weighted-average of the full-day citywide strike effects, because we are interested in the average effect for a car traveler. In order to take into account that rush hours occur less frequent than non-rush hours, and that during rush hours, there is a higher flow of cars, we weight the rush and non-rush hour coefficients with their share of hours over the day and their share of vehicle flow.[154] On average, full-day citywide strikes increase car flow by 7.8% and car travel times by 0.224 minutes per kilometer. We interpret the latter

[151] See Table A2 in the Appendix for individual strike effects. These effects are more difficult to interpret given the presence of unobserved day-specific random error. By combining individual strikes into strike categories, any small sample bias due to day-specific random error is substantially reduced.
[152] That we find a substantially smaller strike effect on flow in the estimates than for the raw means in Table 3a demonstrates the necessity to include weather and time controls.
[153] For non-rush hours, travel demand tends to be lower. Moreover, there is a lower share of commuters, so trip rescheduling and trip cancellation is likely less costly to travelers. However, increases in car flows are similar (F-test p-value 0.174) for full-day strike rush and non-rush hours. The same holds for bicycle flows (p-value 0.113).
[154] The share of rush hours of the number of hours included in our analysis is 0.29. The share of car flow during rush hours is 0.57 (see Table 4.3a), so that $((0.36(0.57 \times 0.29) + 0.15(0.43 \times 0.71))/((0.57 \times 0.29) + (0.43 \times 0.71)) = 0.224$.

as a strong effect: for example, the effect is about 60% higher than the value reported by Anderson (2014) for Los Angeles *highways* and several times higher than the value assumed by Parry and Small (2009).

Table 4.4 – Travel time, car and bicycle flow

	Travel time	Car flow (log)	Bicycle flow (log)
Full-day citywide strike			
Rush hour	0.360 ***	0.094 ***	0.244 ***
	(0.126)	(0.021)	(0.057)
Non-rush hour	0.150 **	0.069 ***	0.145 **
	(0.073)	(0.024)	(0.062)
Partial-day citywide strike			
Rush and strike hour	0.541 ***	0.142 ***	0.257 ***
	(0.133)	(0.020)	(0.047)
Non-rush and strike hour	0.013	0.027	0.100 **
	(0.022)	(0.020)	(0.047)
Rush and non-strike hour	0.159 ***	0.014	-0.009
	(0.053)	(0.024)	(0.050)
Non-rush and non-strike hour	0.052	0.010	0.065
	(0.031)	(0.012)	(0.040)
Placebo strike	-0.010	-0.000	-0.023
	(0.041)	(0.013)	(0.050)
Regional bus strike	0.104 **	0.033	0.186 ***
	(0.037)	(0.024)	(0.037)
Rail strike	-0.021	0.068 ***	0.117
	(0.041)	(0.017)	(0.092)
Location fixed effects	Included	Included	Included
Hour of week fixed effects	Included	Included	Included
Month fixed effects	Included	Included	Included
Week of year fixed effects	Included	Included	Included
Year fixed effects	Included	Included	Included
Weather controls	Included	Included	Included
Number of observations	88,106	338,782	719,661
R^2	0.2682	0.7789	0.7474

Note: ***, **, * indicate 1%, 5% and 10% significance levels. Standard errors in parentheses are robust and clustered by day. The rail and placebo strike effects on car speed are based on one and two strikes, respectively.

For partial-day strikes, the point estimate of a strike during rush hours and strike hours is 0.541 min/km. This effect is not statistically different from rush hour full day strikes (p-value 0.3259), likely due to limited number of observations which is only 12. For partial-day strikes, outside strike hours, but during rush hours, travel times increases are substantial (0.159 min/km). These latter two results suggest that a continuous supply of public transit during the full day is essential for travelers. We have also estimated models where we allow for strike effects on days before and after the strike. We find no changes in car flow or travel times that extend to days before and after the strike. We find a very small effect on bicycle flow for the day after a strike but no effect two days after the strike. Apparently travelers hardly change their travel behavior 'permanently' due to a strike.[155]

We find no effect on travel time for the three placebo strikes. This gives us more confidence in the methodology used. As argued above, placebo strikes are defined by us as (announced) strikes which are canceled, so given a large effect of announcement, canceled strikes may not be interpreted as placebo strikes.[156] For this reason, we have tested the effect of announcement by including an announcement dummy. We do not find an effect of announcement on travel time, suggesting that canceled strikes can be interpreted as placebo strikes.

4.4.2 Sensitivity analyses for travel time on inner city roads

To verify the robustness of our results for travel time we conduct a range of sensitivity analyses. We find our results to be robust to various specifications. Table 4.5 shows the main results. For example, it is well known that the pneumatic tube speed measurement techniques, that we use to calculate travel time, perform less well at lower speeds. Consistent with that, we observe that there is a higher proportion of missing observations at lower speeds. Hence, in the first column, we include the proportion of cars with unknown speed as a control variable. We find that strike effects on travel time are somewhat reduced, but not extremely.[157] Note that this control variable is highly endogenous and likely biases the strike effect towards zero, so we interpret the latter specification as an underestimate and prefer the estimates of Table 4.4 without this additional control variable.

[155] The regional bus strike particularly increases bicycle flow (by 19%). This is a relatively large increase, considering the low modal share of regional buses and that the strike took place in non-rush hours. An explanation for this relatively large effect is that the strike overlapped with national school exams, so many students switch to bicycle use. We find no effect on inner city travel time for national rail strikes. We also find no effect on bicycle flow. The latter is not so surprising because bicycle and rail are complements in the Netherlands as about half of travelers use the bicycle as an access or egress mode for rail. Another explanation for these findings is that the share of rail in passenger transport is low in Rotterdam (2.7%), see De Vries (2013). Moreover, there are only two rail strikes, so these estimates are less reliable.

[156] Strike announcement has likely an effect on travel behavior according to Van Exel and Rietveld (2001).

[157] In addition, as expected, we find a positive relationship between the number of cars with unknown speed and travel time.

Table 4.5 – Travel time: alternative specifications

	Travel time		Travel time		Speed share		Travel time		Travel time	
Full-day citywide strike										
Rush hour	0.269	***	0.108	***	0.122	***	0.483	***	0.535	***
	(0.092)		(0.034)		(0.044)		(0.102)		(0.145)	
Non-rush hour	0.101	**	0.047	**	0.049	**	0.190	**	0.109	
	(0.047)		(0.022)		(0.025)		(0.085)		(0.093)	
Partial-day citywide strike										
Rush and strike hour	0.490	***	0.160	***	0.184	***	0.268	***	0.658	***
	(0.120)		(0.028)		(0.051)		(0.034)		(0.176)	
Non-rush and strike hour	-0.001		0.010		0.002		0.018		-0.031	
	(0.019)		(0.009)		(0.007)		(0.021)		(0.030)	
Rush and non-strike hour	0.124	***	0.051	***	0.052	**	0.123	**	0.349	***
	(0.035)		(0.012)		(0.021)		(0.059)		(0.085)	
Non-rush and non-strike hour	0.051	*	0.011	*	0.016		0.072	**	0.060	
	(0.028)		(0.010)		(0.011)		(0.034)		(0.055)	
Placebo strike	-0.009		-0.001		-0.004		-0.010		0.000	
	(0.009)		(0.003)		(0.005)		(0.013)		(0.254)	
Regional bus strike	0.084	***	0.020	*	0.040	***	0.104	***	0.209	***
	(0.021)		(0.009)		(0.013)		(0.037)		(0.021)	
Rail strike	-0.009		0.004		-0.012		-0.051		-0.035	
	(0.028)		(0.013)		(0.015)		(0.043)		(0.083)	
Proportion unknown speed	6.243	***								
	(0.347)									
Time and weather controls	Included		Included		Included		Included		Not included	
Number of observations	88,106		88,106		88,106		87,882		88,106	
R^2	0.5176		0.5786		0.1877		0.2685		0.0041	

Note: In the second column, cars below 31km/h censored at 31. Third column, the dependent variable is the share of cars at speeds beneath 31km/h. Fourth column, we exclude the citywide strikes that were not a complete public transit cancellation. Last column, we do not include controls. See Table 4.4 for control variables. ***, **, * indicate 1%, 5% and 10% significance levels. Standard errors in parentheses are robust and clustered by day.

In the calculation of travel time, we have assumed that cars in the lowest speed interval – less than 31 km/h – travel at an average speed of 15 km/h. To see how much our results depend on this assumption, we estimate a model where all cars in the lowest speed interval are assumed to travel at 31km/h. Now we find that during full-day citywide strike rush hours, travel times increase by 0.108 min/km (see column 2). We interpret this estimate as the minimum effect because this approach strongly biases our results towards zero. To prove this latter point, we estimate a model where the dependent variable is the share of speed observations beneath 31 km/h (see column 3). Reassuringly, the signs of the strike effects are in line with the main results: for example, given a full-day citywide strike, the share of speed observations beneath 31 km/h increases by 0.122 during rush hours.

Four of the 13 citywide strikes are not complete, in the sense that some public transit is still supplied for the metro or that only the time schedule has been reduced (see Table 4.1). Consequently, it is plausible that our estimates are underestimates of complete strikes which are more representative to capture the congestion relief benefit of public transit. We therefore re-estimate the model excluding these four incomplete strikes. The rush hour, full-day citywide strike effect becomes more pronounced and is now equal to 0.483 min/km (see column 4). This result is in line with the idea that complete strikes entail travel time increases. Hence, importantly, it is plausible that using the estimates of Table 4.4 will lead to underestimates of the congestion relief benefit.

There are three competing views on which observations to include in the analysis. As detailed in subsection 4.2.3, we chose to exclude observations for periods entirely without strikes. We also re-estimate the model, including all observations and another where we include only observations of months with strikes. The former specification (with all observations) has the disadvantage of including observations for periods that may not be comparable in terms of unobservables but includes a larger number of observations. The latter specification (only strike months) has the advantage of including only comparable days to the strike but reduces the degrees of freedom. The results which can be provided upon request are essentially identical to those of Table 4.4.

In the fifth column of Table 4.5, we re-estimate the model without any time or weather condition control variable. Not surprisingly, standard errors tend to increase due to a less efficient estimation specification. The effects are identical in sign to those in Table 4.4 but are usually somewhat larger in size.

In a specification similar to equation (4.3), we estimate hour-of-the-day specific effects on travel time (not distinguishing between full-day and partial-day strikes), reported in the first column of Table 4.A3 in the Appendix. We find the strongest strike effect on travel times during morning and afternoon rush hours which provides more confidence in our results. Given the latter specification, we also estimate strike effects for both speed measurement locations (`s-Gravendijkwal and Maastunnel) separately (see last two columns of Table 4.A3). These results indicate that the strike effect on travel time is similar across inner city roads.

4.4.3 Highway traffic

We now focus on the strike effects on the highway ring road. It appears that citywide strikes also have a positive effect on travel times, see Table 4.6. However, in comparison to inner city roads, travel time increases are much smaller. Our result verifies the assumption by Anderson (2014) that car drivers on inner city roads benefit substantially more from public transit through reduced car congestion than car drivers on highways. On the highway, the full-day strike effects for rush and non-rush hours are only 0.017 min/km, and only statistically significant for the latter. Slightly surprising, we find a stronger effect for partial-day strikes, but the effect relies upon few observations and is small in magnitude.[158] For example, during rush hours, the effect is still only 0.056 min/km during partial-day citywide strikes.

Table 4.6 – Travel time and car flow on highways

	Travel time		Car flow (log)	
Full-day citywide strike				
Rush hour	0.017		0.031	*
	(0.011)		(0.017)	
Non-rush hour	0.017	**	-0.017	
	(0.001)		(0.028)	
Partial-day citywide strike				
Rush and strike hour	0.056	***	-0.040	*
	(0.019)		(0.023)	
Non-rush and strike hour	0.065	***	-0.044	**
	(0.015)		(0.021)	
Rush and non-strike hour	0.034		-0.073	***
	(0.054)		(0.024)	
Non-rush and non-strike hour	-0.020		-0.016	
	(0.014)		(0.025)	
Placebo strike	0.049	***	0.002	
	(0.012)		(0.021)	
Time and weather controls	Included		Included	
Number of observations	771,019		771,019	
R^2	0.0727		0.8175	

Note: See Table 4.4 for control variables. ***, **, * indicate 1%, 5% and 10% significance levels. Standard errors in parentheses are robust and clustered by day.

[158] These results are in line with the findings for the actual, but less trustworthy, induction loop data of 2006 and 2011 in Table 4.A4 in the Appendix 4.A.

We use a travel time increase of 0.017 min/km in our welfare calculations later on.[159] We interpret this result as a small effect: it is several times smaller than reported by Anderson (2014) for Los Angeles (and about half of the value assumed by Parry and Small, 2009). We can only speculate about explanations for this difference in the magnitude of the effect. The main explanation is likely that the highways in Los Angeles that are chosen by Anderson (2014) are more congested than those of Rotterdam.

In line with a small strike effect on travel time, we find little or no increase in car flow on highways.[160] This finding is similar to Lo and Hall (2006) and Anderson (2014) and consistent with Duranton and Turner (2011) who do not find an effect of bus supply on highway flow for the United States.[161] Finally, note that the placebo strike effect is statistically significant, but this effect disappears when we use the logarithm of speed as an alternative dependent variable, which suggests that this result is spurious (Adler and Van Ommeren, 2015).

4.4.4 Traffic accidents

So far, we have focused on travel times affected by public transit strikes. However, it is possible that public transit provision affects traffic accidents, because it influences the travel mode of travelers as well as car speed on the road (Aljanahi et al., 1999).[162] Note that in the Netherlands, most traffic accidents occur during bicycling and car use, whereas severe accidents tend to occur at higher car speeds. So, it seems possible that during strikes the number of accidents increases whereas accident severity decreases.

We have police-reported daily traffic accidents data for Rotterdam for the years 2000 to 2009 (except for 2008). Minor accidents are often not reported to the police, and our data therefor over-

[159] Travel time increases are identical for rush and non-rush hours of full-day city wide strikes and jointly significant (p-value 0.034).

[160] We do not find a pronounced strike effect, in contrast to descriptive statistics in Table 4.3b, which is a result of including time controls in the multivariate analysis. Note that for the inner city roads by including time controls, the effect of strikes become more pronounced.

[161] There are very few observations with high travel times and low flow in the inner city (which are likely due to road works, accidents etc.) but for highways these observations are more common. See Figures 4.A4 and 4.A5 in the Appendix, the relationship between flow and speed is shown for the highway as well as the inner city. For more on the fundamental diagram of traffic flow, see Small and Verhoef, 2007, p.84-88. In our data, we have a speed-flow elasticity of -0.07 for inner city roads and -0.03 for highways using a double log specification.

[162] Our travel time measure accounts for that road accidents, especially on highways, often increase travel times by obstructing free flow, see Adler et al. (2013).

represents severe accidents. When we estimate the effect of strike on number of accidents with similar controls as above, the results do not show any strike effect on accidents.[163]

4.5 Welfare analysis

4.5.1 External congestion loss of strikes

We determine the welfare loss due to additional time losses by car travelers given a full-day citywide strike on a weekday using the theoretical framework outlined in 3.1. We will assume an hourly value of time of €14 per person implying an hourly value of time of €20 per car.[164] In addition to congestion losses there are rescheduling costs to car travelers.[165] We do neither include these costs, nor any other external cost of car travel that is likely an order of magnitude smaller than that of congestion.[166]

Table 4. 7 – Number of trips per day for Rotterdam metropolitan area

	Non-strike day	Strike day (% change)	Differences
Public transit	348,000	-100%	-348,000
Car (driver)	804,000	+7.8%	63,516
Car (passenger)	408,000	+7.8%	32,232
Bicycle	588,000	+18.0%	105,840
Trips not replaced by car or bicycle			146,412

In Rotterdam, 1.2 million inhabitants conduct each day 348,000 public transit trips, 804,000 car driver trips, 408,000 car passenger trips, 588,000 bicycle trips and 765,000 walking trips, so in total 2.913 million trips (De Vries, 2013), see Table 4.7. During a full-day citywide strike, public transit is not

[163] The descriptive statistics suggest that there might be a negative effect of strikes on the number of accidents: the average number of traffic accidents on strike days is substantially less than on other days (7.0 compared to 9.2).

[164] In Rotterdam, a car contains on average 1.5 persons (CBS, 2014). We assume that the same occupancy rate applies during strikes. The assumed value of time is slightly higher than the commonly used value of time for commuters based on stated-preference studies for the Netherlands, which is 10 euro. Our assumption of €14 per person can be justified because a substantial proportion of car drivers travel for business for which the value of time is about €30 per hour. Assuming different time values for rush hours and non-rush hours might be more reasonable, but our results are not so sensitive to that. For example, when we assume that the value of time is €25 per car during rush hours and €15 per car during non-rush hours then we obtain almost identical benefits.

[165] We find that the peak hours start earlier and end later for citywide strikes, suggesting that these costs are not zero.

[166] Assuming, that the external cost of CO_2 is €100 per ton, the additional external benefit is only €0.002 per public transit kilometer. For dense western metropolitan areas, Glaeser and Kahn (2008) find that the carbon emission savings from public transit use are about two-thirds of other car emissions. The benefits from public transit to public health in terms of pollution reduction are about €0.02 (Parry and Small, 2009). For higher polluted cities, such as Taipei, these external benefits might be much larger (Chen and Whalley, 2012).

available, so there are no public transit trips. Our estimates indicate that a strike induces car flow to increase by 7.8%, so 63,516 additional car driver trips and 32,232 additional car passenger trips, and bicycle flow to increase by 18%, so 105,840 trips. This implies that the increase in bicycle use is about equal to the increase in persons which travel by car. Furthermore, it means that 201,588 out of 348,000 canceled public transit trips are substituted by a car or bicycle trip. The other 146,412 trips, labeled as teleworking trips in section 3.1, are either rescheduled to another day, made by another mode not observed by us, most likely walking, or fully canceled.[167]

In Table 4.7, column 1, we provide the assumptions which allow us to calculate the external cost of congestion during strikes. In Rotterdam, cars trips have an average length of 15 km of which 62% are driven on inner city roads and the remaining 38% on highways.[168] Given the estimated travel time increase of 0.224 min/km on inner city roads (the weighted-average effect) and 0.017 min/km on highways, a strike induces an additional external cost of congestion of €629,839. The majority of this cost, €601,845, is on inner city roads, and an additional €27,995 on highways.[169]

4.5.2 Congestion relief benefits

Based on the external costs of strikes, we aim to calculate the long-term congestion relief benefit of public transit. We will start from the assumption that this beneficial effect of public transit provision is the same in the long run as in the short run. As discussed in detail later, this assumption essentially implies that the sum of the public-transit induced effects through changes in car ownership, trip cancellations, route choices and relocation decisions by households and firms on car travel demand is zero, but allows some of these effects to be positive or negative. The annual congestion relief benefit is then calculated by annualizing the public transit short-term congestion relief benefit (assuming 252 working days). The annual benefit is then €159 million (see Table 4.8), about €132 per inhabitant. This excludes any benefits of public transit provision on weekends that we assume to be negligible. Given

[167] These descriptive statistics are in line with previous studies which report that during strikes 20% of canceled public transit trips are substituted by walking, 10% fully canceled and 10% rescheduled (PbIVV, 1984; van Exel and Rietveld, 2001). One of the main arguments against public transit subsidies is a low price cross elasticity between public transit and car use. Note that we do not examine changes in public transit prices. However, we find that a third of public transit users substitute to car use during strikes.

[168] The share of car travel distances on inner city roads and highways are about the same for the whole of the Netherlands (CBS, 2014). For cities such as Rotterdam, one expects a higher share of inner city road use. On the highway ring road around Rotterdam we observe 331,744 trips per day, suggesting that 62% of trips are on inner city roads.

[169] The external costs on inner city roads given a trip length of 15km, 866,712 car trips and a €20 per hour value of time is equal to $0.224 \times 15 \times 866{,}712 \times 0.62 \times 20/60 = €601{,}844$. The external cost on highways is then equal to $0.017 \times 15 \times 866712 \times 0.38 \times 20/60 = €27{,}995$.

721 million public transit passenger kilometers (OVPRO, 2014), the congestion reduction benefit per public transit kilometer is €0.22. This benefit is substantial given that the cost per public transit kilometer is €0.46.

The costs of providing public transit in Rotterdam are partially covered by subsidies, about €200 million per year, i.e. €0.28 per public transit kilometer.[170] The congestion relief benefit is then about 80% of subsidies.[171] It is useful to examine this result under different assumptions. For example, if we assume that the specification of complete strikes (reported in Table 4.5, column 4) is more indicative of the congestion relief benefit, then the benefit even slightly exceeds current subsidies (see column 3). In contrast, if we make very conservative assumptions by assuming a trip length of 10 km, an equal split in distance traveled on highway and inner city roads, and that only inhabitants in the city of Rotterdam (and not the whole metropolitan area) are affected by the strike, then the congestion relief benefit is still 22% of the subsidy (column 2).[172] These estimates indicate that the congestion relief benefit alone is substantial but possibly insufficient to justify the current supply of public transit in Rotterdam. Additional gains of public transit provision, such as economies of scale in public transit provision and productivity increases due to decreased car congestion might support current levels of subsidies (Graham, 2007). To do an overall welfare analysis of public transit provision is however beyond the scope of this paper.[173]

It is important to emphasize that there are some reasons to believe that we have either overestimated or underestimated the public transit congestion relief benefit because we have assumed that the long-run effect of strikes is equal to their short-run effect. First, we may then underestimate the long-term congestion relief benefit because during strikes about 20% of trips are canceled (see also PbIVV, 1984; van Exel and Rietveld, 2001). For longer periods without public transit, particularly for

[170] Annual subsidies to operational costs for public transit slightly vary but were €200 million in 2011 (Stadsregio Rotterdam, 2012). That is about €166 per capita, and about 0.3% of average gross salary. By comparison, bicycle infrastructure expenditure by the municipality is only €30 million per year (Savelberg, 2013). Note that bicycle lanes occupy space; hence the social cost of bicycle infrastructure will be higher than the expenditure by the municipality.

[171] Total operational cost of public transit was about €333 million. The farebox recovery for Rotterdam is between 35% to 40% of operational cost, similar to many other cities with extensive public transit in Europe and the United States.

[172] We again employ a weighted average of the strike effect on travel time.

[173] We ignore also other welfare aspects, such as the potential excess tax burden of public transit subsidy generation. When the subsidies are generated through labor taxation they might cause additional welfare losses outside the transport market, whereas the use of congestion pricing revenue might yield a double dividend (see, e.g. Parry and Bento, 2001). Note that we examine the benefits of several transit modes. However, each public transit mode might yield substantially different net benefits, as suggested by Winston and Maheshri (2007). Further, there are egalitarian reasons for subsidies, since public transit disproportionately supports the economically less well-off parts of society (see, e.g. Johnson, 2014, Compton and Pollack, 2014).

commuting, it is unlikely that so many trips are canceled and these trips will contribute to additional car congestion.

Second, we may underestimate the benefit, because for longer periods without public transit, current public transit travelers will increase car ownership and their use, so increasing car congestion. This effect is likely limited and has a clear upper bound. For example, in Dutch rural areas, where public transit is virtually absent, car ownership per household is only 30% higher than in urban areas (CBS, 2014). Note that car ownership in rural areas is also higher because of lower population and employment densities. Hence, a 20% increase in trips seems a more reasonable estimate.

Table 4.8 – Congestion relief benefit

	(1)	(2)	(3)
Assumptions	*Standard*	*Very conservative*	*Full-day strikes only*
Area affected	Metropolitan	City	Metropolitan
Number of inhabitants affected	1.2 million	0.6 million	1.2 million
Car trips weekday	804,000	402,000	804,000
Average trip distance	15 km	10 km	15 km
Value of time per car	€20 per hour	€20 per hour	€20 per hour
Speed benefit inner city	0.224 min/km	0.224 min/km	0.293 min/km
Speed benefit highway	0.017 min/km	0.017 min/km	0.017 min/km
Inner city to highway km ratio	62/38	50/50	62/38
Results			
Weekday public transit benefit inner city	€601,844	€161,786	€787,234
Weekday public transit benefit highway	€27,995	€12,278	€27,995
Overall public transit benefit	€629,839	€174,064	€815,229
Annual public transit benefit (weekdays)	€159 million	€44 million	€205 million
Public transit subsidies	€200 million	€200 million	€200 million
Congestion relief benefit to subsidies	80%	22%	103%

Third, we may overestimate the benefit by ignoring residential and workplace location decisions that are also based on travel times (Kantor et al., 2014; Kok et al., 2014; Johnson, 2014). Without public transit and higher levels of car congestion, some households and firms would re-evaluate their location decision and may move closer to each other, hence reducing car travel. The size of this effect is unknown but must be small because it is a second-order effect. Hence, arguably, the effects of canceled trips and increased car ownership roughly cancel each other, whereas the effect of relocations is small. This suggests that our assumption that the long-term and short-term benefits are roughly equal to each other is not unreasonable.

4.6 Conclusion

Public transit provision is a widely-accepted policy measure to reduce road congestion. The level of public transit provision and therefore the level of subsidies to public transit are subject of debate in many countries (e.g. Parry and Small, 2009; Anderson, 2014). We add to this debate by estimating the effect of multiple public transit strikes on car travel time losses for inner city roads and highways of Rotterdam, which is a rather uncongested city. This quasi-natural experiment allows us to determine the congestion relief benefit, i.e. the monetary value of a reduction in car congestion due to public transit provision.

We demonstrate that during a citywide strike, car travel time within the city increases by about 0.224 min/km. For highways, strikes exhibit a much smaller travel time increase of about 0.017 min/km. Hence, for cities such as Rotterdam, travelers on inner city roads benefit much more from public transit provision than highway travelers. For the city as a whole, the travel time increase for car travelers is about 0.145 min/km. During rush hours, the travel time increase is more pronounced and public transit provision reduces car travel time on inner city roads by about 0.360 min/km travelled. Our main finding is the congestion relief benefit is substantial and about half of the public transit operating cost, equivalent to about 80% of public transit subsidies. Consequently, this indicates that for Rotterdam, and likewise for other cities that are mildly congested, substantial subsidies to public transit are economically justified. This is likely even more true for highly congested cities.

We also show that on a strike day, the increase in bicycle users is about equal to the increase in car travelers. This may be a typical result for a city in a country that is well known to have above-average bicycle use, nevertheless, this finding supports the claim that bicycle-promoting policies (such as bicycle lanes) may be a cost-effective way of reducing car travel time losses.

Appendix 4.A

Figure 4.A1 – Measurement stations

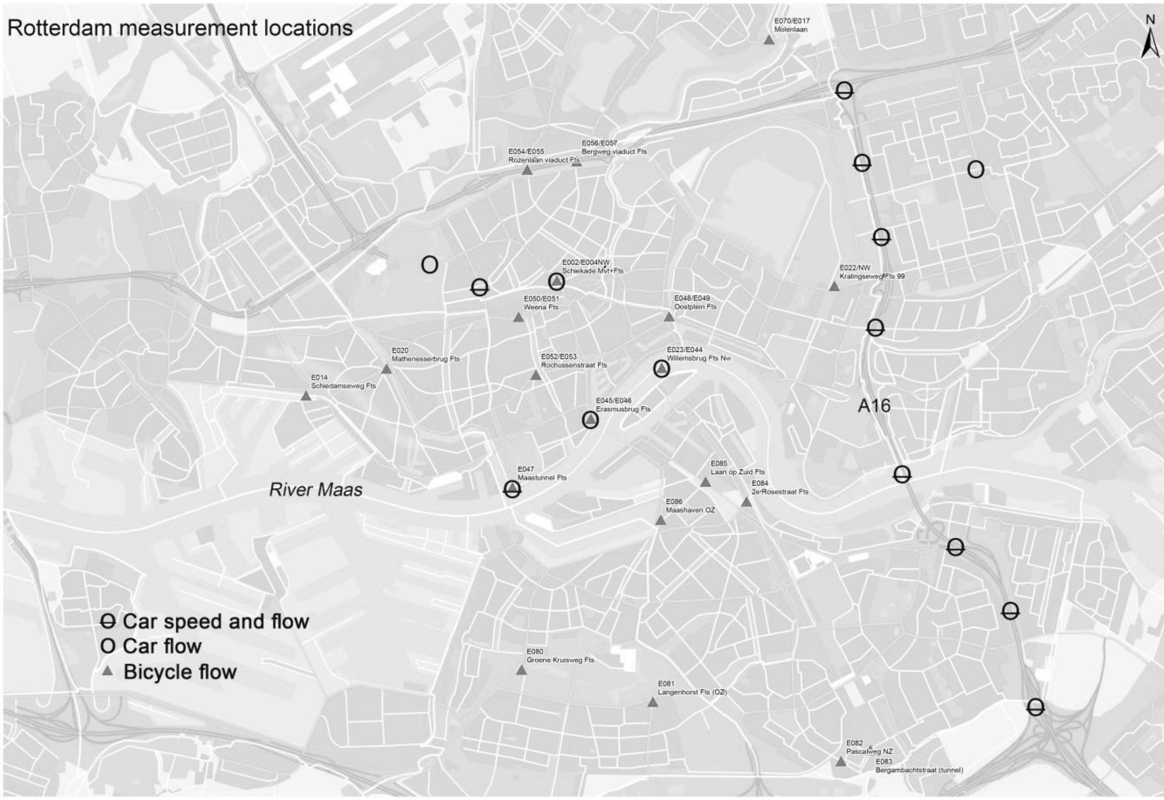


Table 4.A1 – Number of measurement locations and directions

Transport mode	Locations	Directions
Car flow	8	12
Car flow and speed	2	4
Bicycle flow	20	36

Figure 4.A2 – Bicycle flow Thursdays June 2011

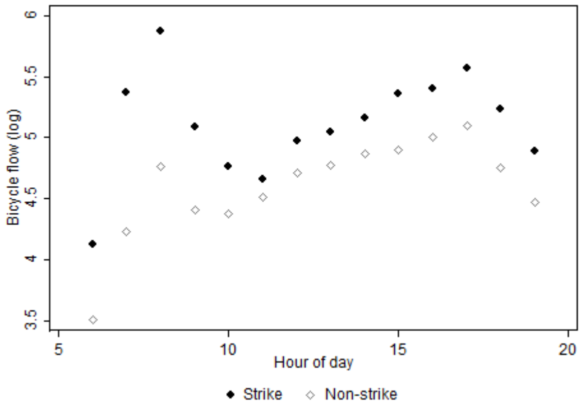


Figure 4.A3 – Bicycle flow Wednesdays May 201

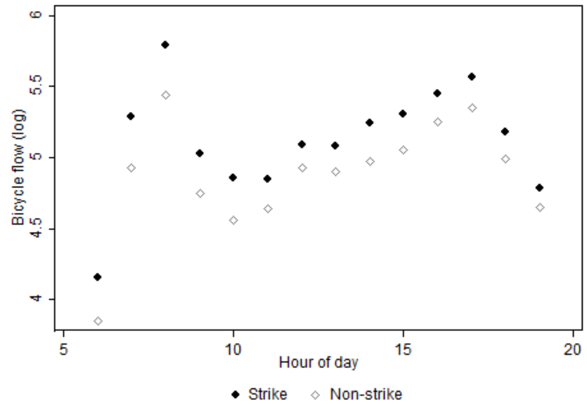


Figure 4.A4 – Speed-flow relationship inner city roads

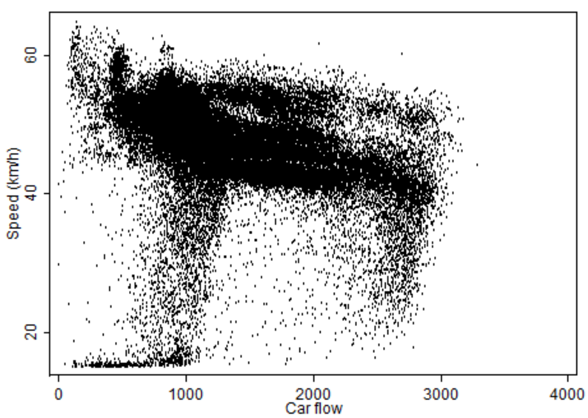


Figure 4.A5 – Speed-flow relationship highway

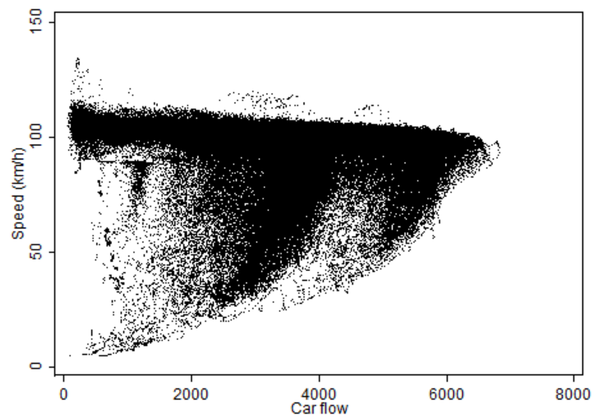


Table 4.A2 – Travel time, car and bicycle flow on inner city roads

Strike mode	Travel time		Car flow (log)		Bicycle flow (log)	
Rail strike 21-12-2000			0.108	***	0.069	**
			(0.028)		(0.035)	
Citywide strike 14-10-2004	0.199	***	0.126	***	0.510	***
	(0.017)		(0.013)		(0.055)	
Rail strike 17-06-2005	-0.028	**	0.059	***	-0.055	**
	(0.013)		(0.016)		(0.022)	
Citywide strike 29-06-2005	0.466	***	0.114	***	0.037	
	(0.047)		(0.024)		(0.051)	
Citywide strike 18-09-2006	0.107	***	0.091	***	0.072	**
	(0.034)		(0.018)		(0.029)	
Citywide strike 25-09-2006	0.404	***	0.162	***	0.167	***
	(0.015)		(0.011)		(0.032)	
Citywide strike 16-02-2011	-0.002		0.039	***	0.191	***
	(0.019)		(0.010)		(0.062)	
Citywide strike 11-05-2011	0.461	***	0.144	***	0.250	***
	(0.067)		(0.014)		(0.046)	
Citywide strike 09-06-2011	0.255	***	0.012		0.306	***
	(0.030)		(0.044)		(0.030)	
Citywide strike 08-10-2003	-0.013		0.031	***	0.245	***
	(0.017)		(0.010)		(0.041)	
Citywide strike 04-09-2006	0.012		-0.028	**	-0.019	
	(0.014)		(0.012)		(0.066)	
Citywide strike 15-11-2006	-0.021		-0.028	*	0.065	
	(0.040)		(0.017)		(0.065)	
Citywide strike 12-04-2011	-0.023		0.060	***	0.022	
	(0.016)		(0.014)		(0.032)	
Citywide strike 29-06-2011	0.049		0.040		0.152	
	(0.033)		(0.048)		(0.084)	
Citywide strike 20-11-2011	-0.027	***	0.019	**	-0.077	***
	(0.006)		(0.008)		(0.020)	
Regional bus strike 20-05-2008	-0.006		-0.014		0.050	
	(0.035)		(0.021)		(0.057)	
Regional bus strike l 21-05-2008	0.273	***	-0.037	**	0.085	
	(0.037)		(0.020)		(0.056)	
Regional bus strike 22-05-2008	0.203	***	0.014		0.027	
	(0.024)		(0.021)		(0.056)	
Placebo Rail 02-04-2001			0.024		0.173	***
			(0.016)		(0.020)	
Placebo Citywide strike 06-10-2009	0.058	***	-0.0227	*	-0.046	*
	(0.017)		(0.0133)		(0.025)	
Placebo Citywide strike 06-11-2011	-0.069	***	-0.007	***	-0.114	***
	(0.020)		(0.008)		(0.023)	
Time and weather controls	Included		Included		Included	
Number of observations	88,106		338,782		719,661	
R^2	0.2687		0.7790		0.7474	

Note: Strike dummies apply for hours when strike is reported. For the 2000 rail and 2001 placebo strike there is no travel time information available. See Table 4 for control variables. ***, ** indicate 1 and 5% significance levels. Standard errors are robust and clustered by day.

Table 4.A3 – Travel time for strike hours by location

Location	Travel time All		Travel Time \`s-Gravendijkwal		Travel Time Maastunnel	
Citywide strike hour						
6am to 7am	0.026		0.056	*	-0.069	
	(0.021)		(0.028)		(0.022)	
7am to 8am	0.101		0.165	*	0.018	
	(0.071)		(0.111)		(0.039)	
8am to 9 am	0.389	***	0.495	***	0.250	
	(0.118)		(0.181)		(0.158)	
9am to 10am	0.136	*	0.228	*	-0.002	
	(0.077)		(0.124)		(0.031)	
10am to 11am	0.024		0.035		-0.006	
	(0.018)		(0.030)		(0.024)	
11am to 12 am	0.004		0.014		-0.011	
	(0.021)		(0.028)		(0.020)	
12am to 1pm	-0.009		0.004		-0.019	
	(0.019)		(0.027)		(0.017)	
1pm to 2pm	0.033		0.083		-0.030	*
	(0.064)		(0.114)		(0.015)	
2pm to 3pm	0.096		0.162		-0.007	
	(0.114)		(0.189)		(0.017)	
3pm to 4pm	0.228	*	0.258		0.189	
	(0.132)		(0.189)		(0.107)	*
4pm to 5pm	0.286		0.410	*	0.114	
	(0.191)		(0.213)		(0.193)	
5pm to 6pm	0.438		0.474		0.354	
	(0.287)		(0.366)		(0.265)	
6pm to 7pm	0.665	**	0.707	**	0.578	
	(0.327)		(0.324)		(0.363)	
7pm to 8 pm	0.325	*	0.386	*	0.240	
	(0.179)		(0.215)		(0.154)	
Citywide non-strike hour	0.090	***	0.141	**	0.025	*
	(0.028)		(0.050)		(0.011)	
Placebo strike	-0.010		0.005		-0.016	**
	(0.128)		(0.032)		(0.006)	
Regional bus strike	0.103	***	0.106		0.103	***
	(0.037)		(0.072)		(0.015)	
Rail strike	0.084		0.110		0.060	
	(0.070)		(0.079)		(0.062)	
Time and weather controls	Included		Included		Included	
Number of observations	88,106		46,441		41,665	
R^2	0.2685		0.2873		0.3399	

Note : ***, **, * indicate 1%, 5% and 10% significance levels. Standard errors in parentheses are robust and clustered by day. The rail and placebo strike effects on travel time are based on one and two strikes, respectively.

Table 4.A4 – Travel time and flow on highways with actual induction loop data

	Year 2011		Years 2006 and 2011	
	Travel time	Car flow (log)	Travel time	Car flow (log)
Full-day citywide strike				
Rush hour	0.037	0.024 ***	-0.003	0.010
	(0.022)	(0.007)	(0.048)	(0.011)
Non-rush hour	0.002	0.009	0.039	0.003
	(0.015)	(0.006)	(0.029)	(0.006)
Partial-day citywide strike				
Rush and strike hour	-0.102 *	0.058 ***	-0.120 **	0.051 ***
	(0.059)	(0.013)	(0.047)	(0.011)
Non-rush and strike hour	-0.002	0.042 ***	-0.070	0.022 *
	(0.050)	(0.011)	(0.045)	(0.013)
Rush and non-strike hour	-0.051 *	-0.000	-0.033	0.007
	(0.050)	(0.008)	(0.040)	(0.009)
Non-rush and non-strike hour	-0.114	0.016 **	-0.069	0.013 *
	(0.045)	(0.008)	(0.048)	(0.007)
Time and weather controls	Included	Included	Included	Included
Number of observations	57,344	57,344	107,324	107,324
R^2	0.1095	0.9499	0.0919	0.9380

Note: See Table 4 for control variables. ***, **, * indicate 1%, 5% and 10% significance levels. Standard errors in parentheses are robust and clustered by day.

5 Road congestion and incident duration

5.1 Introduction[174]

Traffic congestion is an omnipresent phenomenon during rush hour in densely-populated regions (see, for example, Arnott and Small, 1994; Downs, 2004). We focus on non-recurrent congestion on highways, which is mostly caused by road accidents, and other types of incidents (e.g., object on road, car breakdown).[175] This type of congestion constitutes roughly one-quarter of highway congestion (Snelder et. al, 2013). In the current paper, we aim to estimate to what extent the level of non-recurrent congestion may be changed by public incident management policies and in particular by reducing the incident duration, i.e. the time it takes that all incident-associated traffic measures are lifted. Such measures include, for example, traffic warnings, speed reductions and lane closures. Lanes are seldom completely closed. For example, in the Netherlands, for 86% of incidents at least one lane is closed, but for only 8% of incidents all lanes are closed (Snelder and Drolenga, 2011). Given an incomplete closure of lanes, the time loss for a driver due to an incident is much shorter than the incident duration.[176] We assess the marginal costs of incident duration, distinguishing between the duration effects of accidents and other incidents.

Not only incident duration, but also traffic demand, and therefore recurrent congestion, determines non-recurrent congestion costs (for the literature on traffic demand and congestion, see, e.g., Beckmann et al., 1956; Goodwin, 2004; Small and Verhoef, 2007). The costs of non-recurrent congestion can be reduced through policies that shorten incident duration and re-establish traffic free flow.[177] The incident duration reduction effectiveness has been discussed widely, see for example, Carson et al. (1999). This connection between duration and non-recurrent congestion is also discussed

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[174] This chapter is based on Adler, M. W., van Ommeren, J., & Rietveld, P. (2013). Road congestion and incident duration. *Economics of transportation*, *2*(4), 109-118. This paper is funded by Kennis voor Klimaat. We thank Damir Vukovic and Maaike Snelder, from TNO, for support in data acquisition and constructive remarks and Paul Fortuin from Rijkswaterstaat for funding. Furthermore, we thank the audience at Tinbergen Institute seminar, Amsterdam, the 2013 NECTAR conference, Ponta Delgada, the 2013 NÁRSC conference, Atlanta, as well as two anonymous reviewers and the editor Mogens Fosgerau for constructive remarks.

[175] We define an incident as an 'irregular' occurrence on a highway, including objects on the road, car break downs, one-sided or two-sided accidents.

[176] Our data, discussed later on, suggest that the time loss is only 18 to 25 % of incident duration.

[177] Incident duration studies often focus on the effects of incident characteristics on incident duration for specific highways, see, for example, Guiliano (1989) and Jones et al. (1991). These studies point out that incident duration depends on incident type and severity. We will see that the effect of incident duration almost fully captures the effects of incident characteristics on non-recurrent congestion.

in Garrison and Mannering (1990), who use a traffic simulation model for highways in the Seattle urban area. They find that it an extremely congested location where three out of four lanes are closed, $2,000 is lost in travel time for each additional minute of accident duration. Nam and Mannering (2000) show that the public agency that leads the response to the incident (e.g., fire department or police) affects the length of the incident duration.[178]

We contribute to the literature by estimating the effect of incident duration on non-recurrent congestion using microdata on incidents for the entire Dutch highway network. Importantly, in our estimation methodology, we take into account time-invariant, i.e. location, on a 100m precision level, as well as time-varying road characteristics, such as the level of recurrent congestion. Furthermore, we deal with selection effects and endogeneity issues. Our results show that there is a strong positive, but concave, effect of incident duration on non-recurrent congestion for accidents and other incidents.

5.2 Data and descriptive statistics

Our data set comprises information on highway incidents from five types of road service providers (i.e., incident management organizations, towing companies, medical response teams, police and fire departments) for the years 2007 to 2009 for the entire Netherlands.[179] We also use traffic flow data from the Ministry of Infrastructure and the Environment (RWS), weather information of the Royal Netherlands Meteorological Institute (KNMI) and precipitation radar information (Buienradar).

In our analysis, the dependent variable is the level of non-recurrent congestion *as a result of an incident*. We focus on 100 meter locations where each incident at a location is an observation.[180] Most of the time, locations are incident free. However, at many locations traffic intensity may still regularly exceed road capacity and cause congestion. Hence, non-recurrent congestion is the *additional* increase of congestion due to an incident in comparison to the 'normal' situation - i.e. recurrent congestion level - at a certain location and time of the day. For each incident, we have accurate estimates for the levels of non-recurrent and recurrent congestion, based on traffic intensity and speed data obtained from

[178] Lee and Fazio (2005) findings suggest that response time, i.e. the time it takes the incident manager to arrive at the location of an incident and clearance time, i.e. the crash-removing duration, are also a function of time and incident characteristics (e.g. severity, type of cars).

[179] Figure A1 in the Appendix shows a map of the national Dutch highway network. For a minor number of highways with low traffic intensity (north of Amsterdam and west of Breda), data is not available.

[180] Our observations are representative of incidents on the highway network, but not representative of locations on the network.

induction loops.[181] Congestion levels are calculated at the time and location of the incident for the entire highway network. Therefore, our congestion measure includes both primary congestion, i.e. on the lane(s) of the incident, and secondary congestion, i.e. on the opposite lane and spillback on the connections to other highways. Primary non-recurrent congestion accounts for about 70% of overall non-recurrent congestion.

Table 5.1 – Descriptives of incident features

	Selected data set				Full data set
	(1) Positive recurrent congestion	(2) Positive recurrent congestion	(3) Positive recurrent congestion	(4) Zero recurrent congestion	(5)
	Accidents	Non-accidents			
Non-recurrent congestion (VLH)	449.6	367.1	424.9	61.1	62.1
Recurrent congestion (VLH)	103.9	94.2	101.0	0	22.6
Incident duration (minutes)	48.7	46.1	47.9	70.2	
Accident	1	0	0.70	0.61	0.39
Type of vehicle involved					
Passenger car	0.60	0.38	0.53	0.47	0.41
Truck	0.14	0.24	0.17	0.22	0.11
Motorcycle	0.019	0.0050	0.015	0.010	0.0053
Type of damage					
Injury and Fatality	0.10	0	0.073	0.079	0.014
Severe material damage	0.26	0	0.18	0.16	0.059
Number of observations	6,506	2,788	9,294	2,352	263,185

Note*:* Values refer to averages (and shares).

Recurrent congestion is measured by the median weighted road congestion for each incident location and time of day, using an eight week window around the incident.[182] To calculate the median, only observations within this window that are 'similar' to the time of the incident are included. [183] To be precise, it includes the other six days of the week of the incident and the same day of the week for four weeks before and after the incident (congestion on the day one week before and after the incident

[181] Congestion has been calculated through traffic flow data analysis for the entire highway network. Note that stationary cars are not a major concern. For details, see Snelder and Drolenga (2011) and Snelder et al. (2013). Also, see Figure A2 in the Appendix for an example of the traffic flow data.
[182] The probability to measure an outlier value is smaller with the median than with the mean.
[183] Our measurement of recurrent congestion is independent of the level of non-recurrent congestion, because the day of the incident is not included in the calculation.

receives twice the weight).[184] Non-recurrent congestion is calculated as the difference between total congestion and recurrent congestion.[185] Congestion is measured in vehicle-loss-hours (VLH).[186] Incident duration is measured in minutes from the time when the incident is registered by RWS (the road service provider) until the time all traffic measures associated with the incident are lifted.

The full data set contains 263,185 incident observations of which about 40% are accidents, defined here as incidents that involve a vehicle damage.[187] Registration of incident duration by the agencies involved (e.g., incident management crew, police) was not obligatory during the period of observation. For only 11,646 observations, the incident duration is known. We select these observations. Among these, recurrent congestion is zero for 2,352 observations (about 20% of the sample), but positive for 9,294 observations, see columns (3) and (4) in Table 5.1. We will focus on the latter group, because non-recurrent congestion levels are generally small when recurrent congestion is zero (see Table 5.1, (4)). So, a positive level of recurrent congestion is generally a condition that non-recurrent congestion occurs. The selected data set is clearly not random, which may bias our estimates, most likely upwards. For example, the shares of accidents and of incidents with injuries and fatalities are larger in the selected data set (see Table 5.1).[188] Plausibly, incident managers devote more attention to these incidents, increasing the likelihood of recording incident duration. Later on, we use a Heckman selection approach to deal with non-random data selection. The instrument for this approach is defined by the source that reported the incident to RWS. In addition, the average levels of non-recurrent and recurrent congestion are five to six times larger in the selected data set, likely because locations and times with high traffic intensity are prioritized by road service providers.[189]

[184] For an example of how this median is calculated, see Table 5.A1 in the Appendix.
[185] Non-recurrent congestion must be non-negative. However, due to limitations in the way recurrent congestion is approximated, non-recurrent congestion is negative in 0.02% of observations. We exclude these few observations.
[186] Hence, one car waiting in a traffic jam for one hour results in the same VLH as 60 cars delayed by one minute.
[187] We exclude observations when no information on type of incident (i.e., accident or no accident) is provided.
[188] For example, in the selected data set 68% of incidents are accidents whereas in the full data set it is 39%.
[189] For example, an incident (e.g., car break down) during the night on an empty highway will receive less attention from road service agencies than a fatal accident during rush hour on a congested highway.

Figure 5.1 – Density of non-recurrent congestion

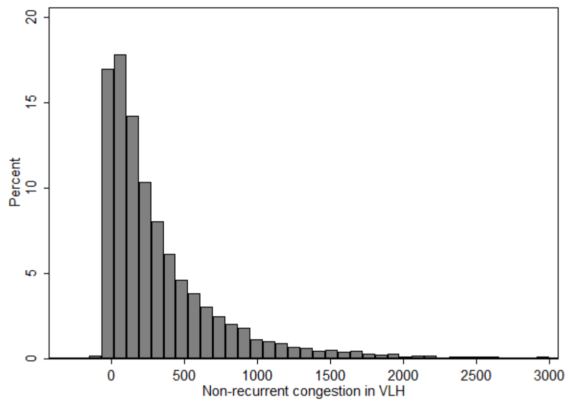


Figure 5.2 – Density of incident duration

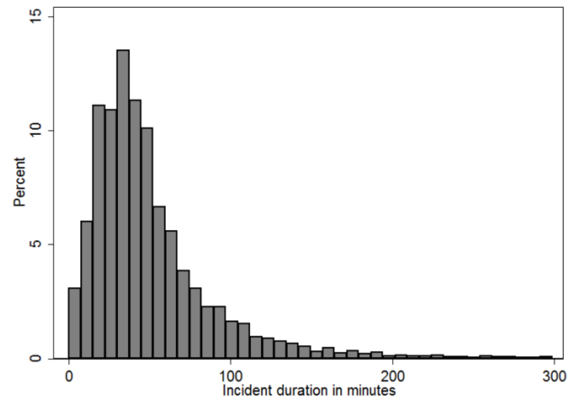
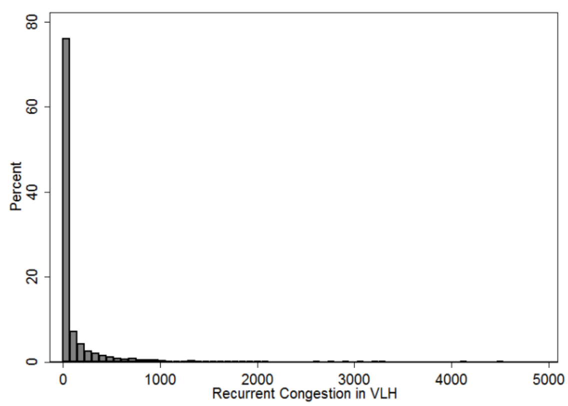
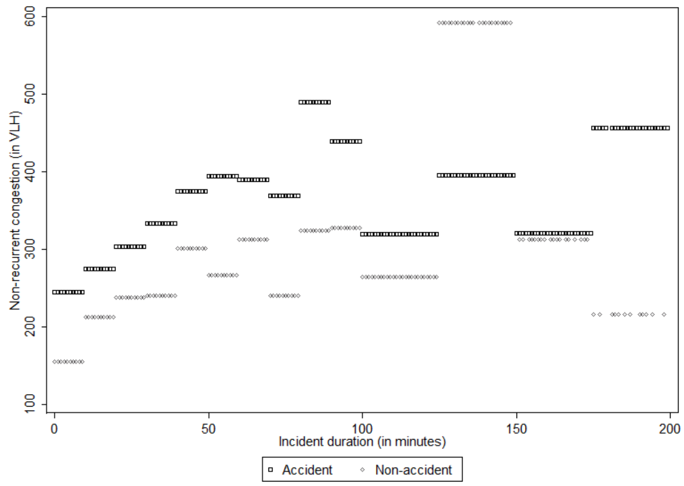


Figure 5.3 − Density of recurrent congestion



In the selected data set, accidents are similar to non-accidents in terms of average incident duration (46 and 49 minutes respectively) and recurrent congestion (94 and 104 VLH, respectively), but average levels of non-recurrent congestion are about 25% higher for accidents (450 and 361 VLH, respectively), see Table 5.1, (1) and (2). This table also shows that, by definition, incidents do not involve any damage or injuries, whereas about 36% of accidents involve fatalities, injuries or severe material damage.

Figure 5.4 − Non-recurrent congestion to incident duration



Recurrent and non-recurrent congestion follow approximately an exponential distribution, so low values are more common than high values, see Figures 5.1 and 5.3. For example, the maximum of recurrent congestion in our data is 4,271 VLH which is 40 times larger than the average value of 101 VLH. In our data the variation in recurrent congestion between locations is much larger than the within variation over time. Hence, it is useful to label locations with larger levels of congestion as 'congested locations'. Accordingly, in the analysis of the incident duration effect later, we will distinguish between locations with average recurrent congestion and congested locations. Incident duration is approximately log-normal distributed (see Figure 5.2), and durations up to 100 minutes are particularly common.

Figure 5.4 shows a positive, concave relationship between incident duration and non-recurrent congestion.[190] This positive effect is particularly clear for incident durations of less than 100 minutes (about 90% of observations).

5.3 Method

To estimate the effect of incident duration on non-recurrent highway congestion, we estimate a log-log specification for the 6,506 observations where recurrent congestion is positive.[191] This specification

[190] In this figure, incident duration is provided in intervals of 10 minutes for values below 100 minutes and in intervals of 25 minutes for values above 100 minutes. A few observations with durations that exceed 200 are excluded here.
[191] Later on, we also estimate a linear specification where we include locations with zero recurrent congestion (see, column 4 in Table 5.1).

is in line with the data.[192] Hence, we assume that the logarithm of non-recurrent congestion, $NRC_{i,t}$, at location *i* and time *t*, depends on the logarithm of recurrent congestion, $RC_{i,t}$, the logarithm of incident duration, $ID_{i,t}$, controls, $X_{i,t}$, location fixed effects, a_i, and an error term, $u_{i,t}$:

$$\log NRC_{i,t} = \beta \log RC_{i,t} + \gamma \log ID_{i,t} + \delta X_{i,t} + a_i + u_{i,t} \ . \tag{5.1}$$

We are particularly interested in the marginal effect of incident duration on non-recurrent congestion. Given the log-log specification, the marginal effect of incident duration is:

$$\frac{\partial \mathrm{NRC_{i,t}}}{\partial \mathrm{ID_{i,t}}} = \gamma \, \frac{NRC_{i,t}}{ID_{i,t}} = \gamma \, \frac{{RC_{i,t}}^{\beta} z_{i,t}}{ID_{i,t}^{1-\gamma}} \tag{5.2}$$

where $z_{i,t} = \exp(\delta X_{i,t} + a_i + u_{i,t})$. Because we will demonstrate that $\beta > 0$, this implies that the marginal effect increases with the level of recurrent congestion, so there is a multiplicative effect of incident duration and recurrent congestion.

We estimate equation (5.1) separately for accidents and non-accidents to allow for the possibility of a difference in their determinants. We control for accident severity (e.g. fatality), car type involved (e.g. truck) and weather.[193] In addition, we include hour of the day, week(-end), month and year dummies and also include location fixed effects. For the main results, we use 100m location fixed effects for accidents and 1km location fixed effects for non-accidents (we use fewer location fixed effects for non-accidents because of fewer non-accidents observations, which allows for sufficient degrees of freedom to estimate the effects we are interested in).

One may argue that incident duration is endogenous because congestion may block road service providers and therefore increase incident duration. However, this argument does not apply in the Netherlands, because incident management crew and first-response vehicles have access to emergency lanes (and may approach incident location in opposite direction of the traffic), which allows them to travel unhindered.[194] Therefore, reverse causality is not a major concern.

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[192] We address this specification issue in more detail when discussing the main results (section 5.4.1) and in the sensitivity analyses (section 5.4.2).

[193] Temperature and maximum wind gust in the past hour are recorded hourly at the national level (in a central location of the Netherlands). Precipitation is measured within 1km² of the incident location for intervals of 90 minutes (30 minutes before and 60 minutes after the incident registration). Furthermore, we construct a dummy for falling snow (the interaction of precipitation and temperature below zero degrees Celsius).

[194] They may also travel through the middle of two lanes as cars have opened up space as required by law.

We account for two other possible endogeneity problems: omitted variable bias and selection bias. First, heterogeneity in location, in terms of number of lanes, and proximity to on- and off-ramps may determine non-recurrent congestion. As stated above, we control for this unobserved heterogeneity in locations by using location fixed effects. Second, we account for data set selection bias with a Heckman correction two-step estimation approach (Heckman, 1979). In the selection equation, we use an instrument that directly affects the probability of incident duration being reported, but is unlikely to affect non-recurrent congestion directly.[195] So, the source that reported the incident is used as an instrument that distinguishes between police, incident management personnel and other source. One technical difficulty is the large number of location fixed effects because this approach is non-linear and cannot be estimated with 4,553 fixed effects. For this reason, when using the Heckman correction approach we use 5km location dummies. The Heckman model results are very similar to the location fixed effects model that does not correct for selection effects. Hence, we focus on the latter.

Another issue is measurement error in non-recurrent congestion, causing the incident duration effect to be biased. Our measure of non-recurrent congestion is based on the measurement of recurrent congestion. It is plausible that recurrent congestion has some measurement error (i.e. the median value is not representative for the true value of recurrent congestion). For example, the presence of spillbacks and dynamic effects (Fosgerau and Small, 2012), may introduce a bias in the measurement of recurrent congestion, and subsequently in non-recurrent congestion. We investigate this issue in the sensitivity analysis (5.4.2), by estimating the model without controlling for recurrent congestion. For this specification, we arrive at an almost identical incident duration effect. Hence, the bias due to measurement error in non-recurrent congestion is likely negligible.

5.4 Main results

Table 5.2 shows the main results. For accidents, the incident duration elasticity of non-recurrent congestion is 0.43, see column (1). In other words, a 1% increase in incident duration increases non-recurrent congestion by 0.43%. This estimate implies that an incident duration increase of one minute (about two percent of the mean duration) results on average in an increase in non-recurrent congestion

[195] Hence, the source that reported the incident is assumed to be independent of non-recurrent congestion (conditional on controls), but the source affects the probability that the incident duration is reported in our data.

of 3.95 VLH (0.88 percent of the mean non-recurrent congestion).[196] Assuming a VLH monetary value of €20, which is in line with the literature, this implies that one minute of incident duration costs about €79.[197]

Table 5.2 – Regression results for non-recurrent congestion of accidents and non-accidents

	(1) Accidents			(2) Non-accidents		
	Coefficient		Standard error	Coefficient		Standard error
Incident duration (log)	0.429	***	0.039	0.317	***	0.045
Recurrent congestion (log)	0.252	***	0.016	0.303	***	0.021
Injury and Fatality	0.055		0.095			
Material Damage (severe)	0.039		0.056			
Passenger car	0.101		0.063	-0.028		0.068
Truck	-0.033		0.063	-0.052		0.088
Motorcycle	0.216		0.183	0.270		0.343
Snow	-0.379		0.669	1.279	***	0.469
Max. wind gust (in m/sec)	0.005		0.008	-0.009		0.010
Rain (in mm/hour) 0 to 2.5	0.098		0.070	0.262	***	0.075
Above 2.5	-0.407		0.245	0.631	**	0.274
Temperature (in degree Celsius) 0 to 10	-0.161		0.147	-0.007		0.157
10 to 20	-0.115		0.167	0.169		0.189
Above 20	-0.265		0.190	0.177		0.219
Location-fixed-effects	100m			1km		
Year, month, hour and weekday of observation	Included			Included		
R^2 within	0.3327			0.2953		
R^2 overall	0.2808			0.2290		
Number of fixed-effects	4,553			1,139		
Number of observations	6,506			2,788		

Note: The logarithm of non-recurrent congestion is the dependent variable. ***, **,* imply 1, 5, 10% significance levels. Standard errors are robust.

[196] To be more precise, when incident duration increases by one minute (2.0467% of 48.7 minutes average incident duration) non-recurrent congestion increases by 0.8780% = (2.0467*0.429) of average 449.6 VLH which is 3.9475VLH.

[197] There is a range of monetary values of travel time in the literature, see, for example, Calfee and Winston (1998) and Lam and Small (2001). Given an average occupancy of 1.6 persons per car, we implicitly use a value of time of €12.5 per person.

For non-accidents, this elasticity is 0.32, see column (2), so about one-third lower than for accidents. Hence, one minute increase in non-accident duration leads to an increase of 2.49VLH, equivalent to €50.[198] Despite this difference, it appears that the elasticities of the accident and non-accident specification are not different at the 5% significance level (t=1.88). So, for our welfare calculations, we will not distinguish between the durations effects of accidents and non-accidents.[199] Similarly, the estimated recurrent congestion elasticities for accidents and non-accidents are almost identical (0.25 and 0.30 respectively, $t = 1.93$).

Because the incident duration elasticities of non-recurrent congestion for accidents and non-accidents are not statistically different, we use the weighted average of 0.343, i.e. €57 for a one minute reduction.[200] Our results imply that there are substantial benefits of reducing incident duration. For example, the (unit value) benefit of a one minute reduction in incident duration applied to all 135,000 annual incidents implies a decrease in non-recurrent congestion cost of almost €8 million.[201]

The results in Table 5.2, and the results in the sensitivity analyses, imply that the effect of incident duration on non-recurrent congestion is concave (consistent with Figure 5.4).[202] In other words, we find a decreasing marginal effect of incident duration on non-recurrent congestion, i.e. an elasticity below one. Hence, the marginal effect is the highest just after the incident occurs and becomes less for longer durations. [203] One possible reason for this concave effect is the effect of traffic information, rerouting and other incident management activities. For example, dissipation of traffic information about the incident-induced non-recurrent congestion to road participants may result in a decrease of inflow of

[198] One minute of 46.1 minutes is 2.17%. Multiplying 2.17*0.317%*367.1VLH = 2.49VLH. A 2.49 VLH increase in non-recurrent congestion per minute is worth €50.

[199] Accidents are a small part of overall incidents but the main cause of non-recurrent congestion, according to Jones et al. (1991). In our case, because of the larger share of non-accidents and the similar elasticities, we arrive at the opposite conclusion.

[200] There are roughly 100,000 non-accidents and 35,000 accidents in the Netherlands annually (Snelder et al., 2013). We use the accident/non-accident ratio to construct a weighted incident duration elasticity, 0.343, weighted averages for non-recurrent congestion, 388.5VLH, and incident duration, 46.7 minutes, from (1) and (2) in Table 5.1. Hence, the value of one minute duration is (100/46.7*0.343%*388.5VLH*€20) = €57. Results would be identical for the full data set when we assume 7.3 minutes average incident duration.

[201] We obtain the congestion reduction value of one minute duration for all 135.000 incidents by multiplying with the weighted average value of a one minute reduction, €57 arriving at €7.7 million. Results might differ when incident duration for all incidents would be available for calculation and also, when we would consider a minute reduction not around the average, but reducing the minute from each individual incident overall time.

[202] For a discussion of the results of polynomial and semi parametric estimation see the sensitivity analyses in section 5.4.2 We have also estimated models with a flexible dummy specification of incident duration. These models also show that the effect is concave.

[203] For example, the marginal effect of incident duration of accidents at 30 minutes is 6.4. At 48.7 minutes it is 3.96, and at 70 minutes it is 2.75.

cars. Other examples include, incident management personnel clearing the road, thereby restoring road capacity, better assessment of incident situation translating in better road management (i.e. speed reduction).[204] It might be that without (or with different) incident management policy and/or traffic information systems (i.e., in other countries), this effect is linear or even convex. For example, economic theory suggests that in a stylized case without rerouting and inelastic demand for travel, there is a quadratic effect of incident duration of non-recurrent congestion (Hall, 1993; Koster and Rietveld, 2011) suggesting that the elasticity would be 2 rather than values around 0.40 as reported by us. Theory might be improved by, for example, allowing incomplete closure of lanes, restoration of traffic capacity over incident duration (e.g., through incident management) and incident responsive traffic demand.

We emphasize that (above) we report the average benefit value of an incident duration reduction and the value strongly depends on the level of recurrent congestion, because of the multplicative effect with incident duration (see equation (5.2)). Therefore, the benefit of a reduction at a location with a larger recurrent congestion is much larger. For example, in our data, the average level is 100 VLH. At locations with 2000 VLH of recurrent congestion, our estimates imply that non-recurrent congestion is, on average, 2.1 times higher than the given average levels of non-recurrent congestion, implying that the marginal benefit of reducing incident duration is 2.1 times higher (€134) than the average.[205] Therefore, Incident Management policies should prioritize locations according to recurrent congestion to minimize non-recurrent congestion costs.[206]

We have noticed above that at more congested locations the benefit of a reduction in the incident duration is larger (as implied by the specification in logarithms). However, it is also plausible that the effects of logarithm recurrent congestion and logarithm incident duration interact. We address this issue for accidents. The results are reported in (1) of Table 5.3. We find a slight positive interaction effect but it is only significant at a 10% significance level.

Another way to address this issue is by excluding the large number of locations where recurrent congestion levels are low. Therefore, we re-estimate the model for accidents at locations with

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[204] One can imagine that heavier incidents with longer durations trigger a stronger response from incident management crews reducing non-recurrent congestion. This interpretation is however conflicting with our result that incident characteristics and severity do not play a significant role in explaining non-recurrent congestion.
[205] Note that $(2000/100)^{0.252} = 2.1$.
[206] After 2009 this has been acknowledged by RWS (Immers and Landman, 2008), where incident management crews response times are required to be less for locations with high levels of recurrent congestion.

recurrent congestion above 5VLH (62% of our observations). The accident duration and recurrent congestion elasticities both increase by roughly 20%, as shown in column (2). This is consistent with the small positive interaction effect reported in column (1).

Table 5.3 – Regression results for non-recurrent congestion of accidents

	(1)			(2)			(3)		
	Interaction incident duration and recurrent congestion			Recurrent congestion > 5 VLH			Recurrent congestion > 100 VLH		
	Coefficient		Standard error	Coefficient		Standard error	Coefficient		Standard Error
Incident duration (log)	0.363	***	0.059	0.491	***	0.048	0.378	***	0.090
Incident duration (log)*recurrent congestion(log)	0.025	*	0.014						
Recurrent congestion (log)	0.160	***	0.053	0.325	***	0.030	0.575	***	0.092
Injury and Fatality	0.062		0.094	0.064		0.114	0.153		0.165
Material Damage (severe)	0.037		0.056	0.034		0.066	0.236	*	0.132
Passenger car	0.106	*	0.063	0.052		0.070	0.023		0.135
Truck	-0.033		0.092	-0.050		0.101	0.065		0.188
Motorcycle	0.209		0.183	-0.084		0.192	-0.465		0.269
Snow	-0.366		0.675	0.275		0.361	0.375		0.592
Max. wind gust (in m/sec)	0.005		0.008	-0.002		0.009	-0.002		0.017
Rain (in mm/hour) 0 to 2.5	0.101		0.070	0.123		0.077	0.010		0.132
Above 2.5	-0.408	*	0.244	0.253		0.221	0.048		0.250
Temperature (in degree Celsius) 0 to 10	-0.157		0.150	-0.188		0.181	0.008		0.223
10 to 20	-0.128		0.166	-0.169		0.203	-0.111		0.278
Above 20	-0.278		0.189	-0.369		0.234	-0.374		0.324
Location-fixed-effects	100m			100m			100m		
Year, month, hour and weekday of observation	Included			Included			Included		
R^2 within	0.3342			0.2686			0.3636		
R^2 overall	0.2836			0.1818			0.1339		
Number of fixed-effects	4,553			2,842			1,200		
Number of observations	6,506			3,992			1,499		

Note: In all three models, the logarithm of non-recurrent congestion is the dependent variable. ***, **,* imply 1, 5, 10% significance levels. All standard errors are robust.

Further evidence of this is provided in (3) of Table 5.3 where we restrict the data to congested locations with recurrent congestion above the average value of 100 VLH. The recurrent congestion elasticity doubles to 0.575, but the incident duration elasticity remains similar to the original estimate (see (1) of Table 5.2). Therefore, the incident duration elasticity is robust over different data set selections and over different model specifications, whereas the recurrent congestion elasticity is larger for congested locations. According to (3) in Table 5.3 at very congested locations (with 4000 VLH of recurrent congestion), the marginal effect of incident duration is 8.3 times larger than the marginal effect where the recurrent congestion is equal to the average, so a one minute duration costs about €1200.[207] This reinforces our conclusion that Incident Management policies should prioritize those congested locations. Note that our estimate is low in comparison to the $2000 of Garrison and Mannering (1990) who also focus on congested locations but who consider a major urban highway with a severe incident that reduces capacity by 75% during rush hour. Our €1200 refers to the *average* effect of incident duration for congested locations, irrespective of the numbers of lanes closed and irrespective of the hour of the day.

Non-recurrent congestion is not the only component of incident welfare losses. Another component is time loss due to rerouting. In case the incident duration is long and congestion levels are high, so expected time loss in the queue is long, it may be beneficial for drivers to make a detour that increases their travel time costs but reduces their time in the queue. [208] In our data, drivers' average delay in the queue is 18% to 25% of incident duration (because most of the time not all lanes are closed).[209] Hence, it is plausible that drivers make only a detour for very long incident durations (i.e. longer than an hour).

The additional costs of an incident vary with the number of road users who make a detour, which depends on the availability of route alternatives (e.g., a link to another highway) and information to the road user about the occurrence of the incident. According to the Wardrop (1952) principle, when drivers are well-informed, a certain proportion of drivers decide to make a detour so that in the end the travel time for those who stay in the queue and those who make a detour is the same.[210] In the Netherlands, around 20% of road users choose to detour if they have been informed on a delay of one

[207] For congested locations (recurrent congestion above 100VLH), incident duration is 44.15 minutes and non-recurrent congestion 830.93VLH on average. Using the duration elasticity 0.378 for 1 minute (2.26%) we arrive at 7.114VLH, with the multiplicative effect of recurrent congestion of $8.3 = (4000/100)^{0.575}$ is €1180.96.

[208] The average distance between two highways is 13.2km for the most frequented urban area (i.e. Randstad). In the Netherlands, highways have predominantly replaced the pre-existing provincial road network, so usually taking a detour on another highway is the only reasonable alternative. If road users choose the route alternative that minimizes (expected) travel time, the detour time has to be equal to or less than, the congestion delay. So only for very long incident duration drivers consider detours.

[209] This is calculated as follows. For incidents longer than one hour the non-recurrent congestion average is 880VLH. The drivers delay is then between 880/4800=18% (for a four-lane highway with 4,800 vehicles per hour) and 880/3600=25% (for a three-lane highway with 3,600 vehicles per hour) at congested locations.

[210] Note that by making the detour, the latter reduce the waiting time of those who continue to wait in the queue.

hour (Peer, 2013). The results by Emmerink et al. (1996) suggest a similar percentage. Assuming this percentage to be true, we may underestimate the total welfare loss (i.e. the sum of non-recurrent congestion and detour time costs) by up to 25% at very congested locations with long incident durations. So, on average, detour time cost adds much less than 25% to the overall welfare costs.[211] Note that in addition to rerouting there are other behavioural responses such as rescheduling of activities that imply welfare losses that are not included here.

Incident characteristics (e.g. injury, truck involved) are an explanatory factor of incident duration, as shown, for example by Guiliano (1989) and Nam and Mannering (2000).[212] When controlling for 100m location fixed effects and incident duration the effect of accident characteristics is insignificant. Therefore, incident duration is the important factor in explaining non-recurrent congestion and captures the effects of the other accident characteristics - vehicle type and severity. However, when using less location fixed effects or not controlling for fixed effects some of the accident characteristics become significant. Weather conditions do not seem to affect accident non-recurrent congestion, but precipitation increases non-recurrent congestion of non-accidents.[213]

5.5 Sensitivity Analyses

We conduct several sensitivity analyses of the results. We focus here on the accidents for which we have more observations. First, we increase the location-fixed-effects group variable to 1km (see Table 5.4, (1)) as well as to 5km (Table 5.A2, (2) in the Appendix), and estimate models without controlling for location fixed effects (see Table 5.4, (2)).[214] The effects of incident duration and recurrent congestion are very similar in size with those discussed before. So, our main results are not sensitive to the inclusion and specification of fixed effects.

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[211] Of the 100% of drivers affected by an incident, 80% do not change route and 20% make a detour. Using the Wardrop principle, the travel time loss of the group that changes route is 20/80=25% of the group that does not change route. This would imply an extra welfare loss of 25%.

[212] We also estimated the effect of incident characteristics on non-recurrent congestion without including incident duration. The effects of many characteristics become then significant (results are not shown here). We also estimated models on incident duration as a function of incident characteristics, time of day, week, month, year and weather. These results are similar to those found in Vukovic et al. (2013).

[213] For example, the presence of snow strongly increases non-recurrent congestion. The effect of snow and heavy rain between recurrent and non-recurrent congestion cannot be disentangled here because we do not observe the weather for recurrent congestion.

[214] The location precision level decrease may result in introducing unobserved heterogeneity bias. For example, a 1km road segment with an on- and off-ramp in front of the accident could change the resulting non-recurrent congestion because of the possibility of re-routing. Also, incident clearance, number of lanes, and other factors could be non-homogenous in space.

Table 5.4 – Sensitivity Analysis- Non-recurrent congestion of accidents

	(1)			(2)			(3)		
	1km location			No location control			Recurrent congestion not included		
	Coefficient		Standard error	Coefficient		Standard error	Coefficient		Standard error
Incident duration (log)	0.406	***	0.028	0.370	***	0.027	0.447	***	0.043
Recurrent congestion (log)	0.236	***	0.113	0.204	***	0.007			
Injury and Fatality	0.161	***	0.059	0.150	***	0.058	0.011		0.102
Material Damage (severe)	0.109	***	0.037	0.115	***	0.037	0.067		0.060
Passenger car	0.090	**	0.043	0.239	***	0.042	0.115		0.071
Truck	0.065		0.061	0.102	*	0.057	-0.049		0.102
Motorcycle	0.255	**	0.111	0.202	*	0.118	0.360	*	0.199
Snow	-0.043		0.474	0.433		0.462	-0.512		0.707
Max. wind gust (in m/sec)	0.007		0.006	0.005		0.005	0.001		0.008
Rain (in mm/hour) 0 to 2.5	0.096	**	0.042	0.082	**	0.041	0.135	*	0.076
Above 2.5	-0.436	**	0.022	-0.399	*	0.217	-0.435		0.300
Temperature (in degree Celsius) 0 to 10	-0.434		0.104	0.018		0.104	-0.246		0.168
10 to 20	0.020		0.113	0.083		0.115	-0.189		0.190
Above 20	-0.119		0.126	0.014		0.129	-0.226		0.214
Location-fixed-effects	1km			Not included			100 meters		
Year, month, hour and weekday of observation	Included			Included			Included		
R^2 (within)	0.3217			0.3167			0.1915		
R^2 overall	0.3066						0.1397		
Number of fixed-effects	1,680						4,553		
Number of Observation	6,506			6,506			6,506		

Note: In all three models, the logarithm of non-recurrent congestion is the dependent variable. ***, **,* imply 1, 5, 10% significance levels. Standard errors are robust.

Second, for the Heckman correction model (see (1) of Table 5.A2, in the Appendix), the elasticities of incident duration and recurrent congestion are almost identical to the results dicsussed above. It also appears that our instrument is highly statistically significant and has the expected effect on the probablitiy of reporting incident duration.[215] We find that when the police is the source of reporting the duration is more likely to be reported. One possible explanation is that when the police reports the incident to the traffic control regional office, traffic measures (e.g., speed reduction) are more likely to be applied, which increases the probability that incident duration is observed and

[215] A F-test indicates that the instrument is jointly significant at the 1% level. Our results are robust to different instrument specifications with other incident reporting sources, such as: fire department, traffic participants and towing companies.

recorded. In contrast, when incident management crews are the first to report the incident, the duration might not be recorded because the crew is busy dealing with the incident and does not request traffic measures.

Third, we re-estimate the model not controlling for recurrent congestion. The results ((3) in Table 5.4) show that the incident duration elasticity estimate is then biased upwards. Therefore, controlling for recurrent congestion is important to obtain consistent estimates of the incident duration effect on non-recurrent congestion.

Fourth, we re-estimate the model for a quadratic specification of incident duration (no logarithms). We do this for the data set that excludes and for the data set that includes recurrent congestion observations that are zero (the descriptives are reported in (1) and (3) of Table 5.1). For the former, the point estimate of incident duration of accidents equals 4.630 and the point estimate of its square is -0.004. For the latter, the point estimate equals 3.677 and the point estimate of its square is -0.003 (these coefficients are all significant at the 1% significance level). The marginal effects of accident duration are then 4.238 and 3.389 respectively (evaluated at the mean values). This translates to an accident duration elasticity of non-recurrent congestion of 0.47 and 0.38 respectively, which is similar to the results reported in Table 5.2. Moreover, we re-estimate a semi-parametric specification of the model where the incident duration function is captured by means of three linear splines. The estimated decreasing marginal effect substantiates our choice of a log specification of incident duration.[216] Therefore, our result that incident duration has a concave effect on non-recurrent congestion is robust over different specifications and data selections.

5.6 Conclusion

Our estimates show that incident duration substantially increases the level of non-recurrent congestion on highways. The incident duration elasticity of non-recurrent congestion is about 0.35 and similar for accidents and non-accidents. This implies that one marginal minute incident duration costs about €57 per incident. The annual economic value of one marginal minute incident duration reduction is then about €8 million for the Netherlands. In addition, we show that the marginal effect of incident duration

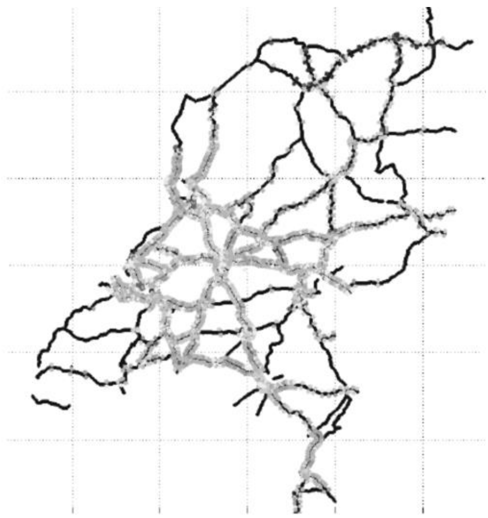
[216] The 0 to 45 minutes incident duration spline coefficient is 0.019, the 45 to 90 minutes coefficient is 0.0050 and the coefficient above 90 minutes is equal to 0.00037.

on non-recurring congestion is diminishing. Therefore, incident management policies should focus on reducing all durations, not in particular the longer ones.

Furthermore, recurrent congestion has a strong positive effect on non-recurrent congestion. Recurrent congestion and incident duration have a multiplicative effect on non-recurrent congestion. This implies that incident management policy should focus on locations with larger recurrent congestion levels, because there the reduction in incident duration has a larger impact. For very congested locations the marginal cost of one minute duration is about €1200 per incident. Including other aspects of incident management policies in the future research, such as the type of road measures applied, may increase our understanding of the effect of incident management on welfare.

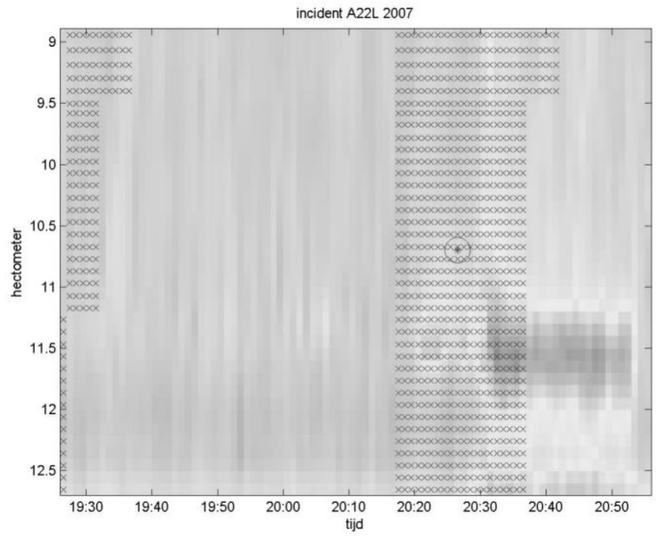
Appendix 5.A

Figure 5.A1 – National Dutch highway network



National Dutch highway network where the areas with high levels of recurrent congestion between urban centers is grey.

Figure 5.A2 – Traffic flow data



Highway specific traffic flow data with precipitation (crosses) and incident (dotted circle). Time of day on horizontal axis (10-minute intervals) and distance on vertical axis (500 meter intervals). Speed reduction increase in shades of grey.

Source: Vukovic et. al., 2013

Table 5.A1 – Recurrent congestion matrix

<table>
<tr><td rowspan="2"></td><td colspan="9">Time in Weeks</td></tr>
<tr><td>-4</td><td>-3</td><td>-2</td><td>-1</td><td></td><td>+1</td><td>+2</td><td>+3</td><td>+4</td></tr>
<tr><td rowspan="3">Weekdays</td><td colspan="4"></td><td>Monday
Tuesday
Wednesday
Thursday</td><td colspan="4"></td></tr>
<tr><td>Friday</td><td>Friday</td><td>Friday</td><td>Friday
weighted</td><td>Friday (F)</td><td>Friday
weighted</td><td>Friday</td><td>Friday</td><td>Friday</td></tr>
<tr><td colspan="4"></td><td>Saturday
Sunday</td><td colspan="4"></td></tr>
</table>

Note: Here, the incident is on a Friday (in grey). Recurrent congestion values of the Friday one week before and after the incident receive a weight of two. The non-recurrent congestion on the incident Friday is excluded in the calculation of recurrent congestion.

Table 5.A2 – Heckman selection model for logarithm of accident non-recurrent congestion

		(1) Heckman			(2) Standard		
		Coefficient		Standard error	Coefficient		Standard error
Logarithm non-recurrent congestion	Incident duration (log)	0.388	***	0.023	0.388	***	0.024
	Recurrent congestion (log)	0.228	***	0.011	0.221	***	0.006
	Injury and Fatality	0.281		0.200	0.157	**	0.055
	Material Damage (severe)	0.200		0.124	0.124	**	0.037
	Passenger car	0.230	**	0.071	0.191	***	0.039
	Truck	0.192	**	0.097	0.139	**	0.055
	Motorcycle	0.265	*	0.148	0.206	**	0.120
	Snow	0.155		0.295	0.086	**	0.041
	Max. wind gust (in m/sec)	0.005		0.005	0.005		0.001
	Rain (in mm/hour)						
	0 to 2.5	0.101	**	0.041	0.086	**	0.041
	Above 2.5	-0.492		0.171	0.005		0.005
	Temperature (in degree Celsius)						
	0 to 10	0.029		0.095	0.030		0.096
	10 to 20	0.118		0.105	0.108		0.107
	Above 20	0.038		0.120	0.041		0.121
	Location-fixed-effects	5km			5km		
	Year, month, hour and weekday of observation	Included			Included		
Selection - incident duration reported	Recurrent congestion (log)	0.047	***	0.003			
	Injury and Fatality	0.930	***	0.035			
	Material Damage (severe)	0.546	***	0.021			
	Passenger car	0.254	***	0.029			
	Truck	0.378	***	0.029			
	Motorcycle	0.436	***	0.074			
	Snow	-0.381		0.135			
	Max. wind gust (in m/sec)	0.002		0.003			
	Rain (in mm/hour)						
	0 to 2.5	-0.059	***	0.021			
	Above 2.5	-0.210	**	0.083			
	Temperature (in degree Celsius)						
	0 to 10	0.052		0.050			
	10 to 20	0.081	**	0.056			
	Above 20	0.120	**	0.064			
	Report police (instrument)	**0.084**	*******	**0.024**			
	Report Incident Management (instrument)	**-0.206**	*******	**0.037**			
	Location-fixed-effects	5km					
	Year, month, hour and weekday of observation	Included					
	Sigma	1.200					
	Rho	0.156					
	Lambda	0.188		0.293			
	Number of observations	34,524			6,506		

Note: In both models the logarithm of non-recurrent congestion is the dependent variable. Standard errors are robust. ***, **, * imply 1, 5, 10% significance levels. Rho is the correlation between the error terms of the two models. Sigma is the natural log of the standard error of the residual of the non-recurrent congestion equation. Note, Lambda equals Rho*Sigma.

6 Conclusion

6.1 Estimation results

The economics of road transport is at the core of this thesis. Throughout the chapters we demonstrated that road congestion is an economic problem with large cost to society and henceforth worthy of scientific research. We focus on measuring the cost of congestion to car users (Chapter 2 and 3) and to bus users (Chapter 3). Then we measure the benefits of public transit provision (Chapter 2 and 4) and incident management (Chapter 5).

We are interested in the social (i.e. marginal external) cost of congestion which requires us to estimate the effect of vehicle flow on travel time in Chapters 2 and 3. Since this effect is not trivial to estimate for hours when car travel exceeds road capacity – during hypercongestion, i.e. when the road supply curve is backward bending – we estimate travel time as a function of vehicle density. Vehicle flow and density are not necessarily exogenous because of reverse causality and measurement error. Therefore, we demonstrate that the use of exogenous and correlated instruments such as public transit share, bicycle flow and hour-of-weekday dummies are suitable to account for endogeneity. We obtain consistent and unbiased estimates of the road supply curve. The estimated function closely mimics the data and provides a functional form in line with the fundamental diagram of traffic and stationary-state congestion theory. The method is well suited for data in inner cities and on highways in Rome (Chapter 2) and Rotterdam (Chapter 3) as well as for a broad range of temporal and spatial aggregation.

We demonstrate how these estimates of the road supply curve can be used to obtain the marginal external time cost of vehicle travel. We demonstrate that, for the city of Rome, the marginal external cost of congestion is substantial: it is, on average, at least as large as half of private travel time cost, while reaching considerably higher levels during peak hours. Further, we found that an increase in road congestion from cars induces a travel time loss for bus travelers sharing the same road. About one third of the marginal external cost of road congestion in Rome is borne by bus travelers.

Public transit can help reduce road congestion. We measure the benefits of public transit by estimating the effect of multiple public transit strikes on car travel time losses for inner city roads and highways of Rome (chapter 2) and Rotterdam (chapter 4). These quasi-natural experiments – strikes – allow us to determine the congestion relief benefit, i.e. the monetary value of a reduction in car congestion due to public transit provision. We find substantial benefits of public transit on travel time of cars users for both cities. The benefits are larger for hypercongested roads and during peak hour traffic. Further study of long-run effects is recommended as our estimates of the congestion relief benefit of public transit are not necessarily representative of the long-run since car ownership and location decisions of households and firms are not fully accounted for.

Traffic incidents can be a cause of congestion. We demonstrate that incident duration contributes to non-recurrent congestion on highways. The incident duration elasticity of non-recurrent congestion is about 0.35 and similar for accidents and non-accidents. This implies that one marginal minute incident duration costs about €57 per incident. The annual economic value of one marginal minute incident duration reduction is then about €8 million for the Netherlands. In addition, we show that the marginal effect of incident duration on non-recurring congestion is diminishing. Furthermore, recurrent congestion has a strong positive effect on non-recurrent congestion. Recurrent congestion and incident duration have a multiplicative effect on non-recurrent congestion.

6.2 Policy recommendations

Our findings support a range of policies aimed at congestion reduction. For example, the high relevance of hypercongestion suggests that road pricing or the use of quantitative measures to curb traffic on heavily congested roads (e.g., through adaptive traffic lights, parking fees) may be warranted (Fosgerau and Small, 2013; Van Ommeren et al., 2014). Our findings suggest that separate lanes for buses might be a priority in Rome, as road congestion has a strong effect on travel time delays of buses (Basso and Silva, 2014; Börjesson et. al, 2016).

Public transit provision is a widely-accepted policy measure to reduce road congestion. The level of public transit provision and therefore the level of subsidies to public transit are subject of debate in many countries (e.g. Parry and Small, 2009; Anderson, 2014). Our main finding is that the congestion relief benefit is substantial and about half of the public transit operating cost, equivalent to about 80% of public transit subsidies. Consequently, this indicates that for Rotterdam, and likewise for other cities that are mildly congested, substantial subsidies to public transit are economically justified. This is even more true for highly congested cities such as Rome.

Our results for Rome 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 on average by 15 percent in the morning peak. 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 75 percent of the operational costs in Rome, is justified and should possibly be even increased.

An alternative second-best policy to reduce congestion is to subsidize the use of bicycles. We show for Rotterdam that the increase in bicycle users is about equal to the increase in car travelers, on a strike day. This may be a typical result for a city in a country that is well known to have above-average bicycle use, nevertheless, this finding supports the claim that bicycle-promoting policies (such as bicycle lanes) may be a cost-effective way of reducing car travel time losses from recurrent congestion.

Incident duration substantially increases the level of non-recurrent congestion on highways. We show that the marginal effect of incident duration on non-recurring congestion is diminishing. Therefore, incident management policies should focus on reducing all durations, not in particular the longer ones. Furthermore, recurrent congestion has a strong positive effect on non-recurrent congestion. Recurrent congestion and incident duration have a multiplicative effect on non-recurrent congestion. This implies that incident management policy should focus on locations with larger recurrent congestion levels, because there the reduction in incident duration has a larger impact. For very congested locations the marginal cost of one minute duration is about €1200 per incident.

6.3 Future research and outlook

This thesis provides ample basis for policy and future research. The methodology we introduce to estimate road supply curves is suitable to inform decision makers on the national and local level about congestion costs and to update road supply curves currently in use in traffic simulations. The marginal external congestion cost from the methodology proposed here can be compared to the marginal external congestion cost from other methodologies and using data for an entire road network. Since the marginal external costs are an essential input to transport policy decisions making, it is possible to (re-)evaluate policy decision about public transit provision, bicycle and bus lanes as well as parking fees.

We provide evidence that public transit subsidies are welfare improving for a medium and a large city and that further subsidies can increase welfare even further. Policy makers might benefit from research that helps to prioritize between; e.g. increasing transit supply and quality or reducing transit prices. We focus predominantly on benefits of public transit on the intra-city level, whereas the benefits for inter-city level are also highly relevant for decisions such as investments into the rail network. An empirical study about the interaction between congestion reduction policies might also be of interest.

In the next decades, the road transport sector is likely to undergo fundamental transformations. The advent of autonomous vehicles and the better use of information for mobility services will provide gains in travel time, reliability and travel comfort. The associated reductions in travel costs will most likely result in more frequent and longer travel. Some of the results of the thesis, such as methodology to measure road supply curves and the marginal external congestion cost will continue to apply. Other results, such as the road supply curve themselves might change, for example, due to reductions in safety distance from car connectivity. The discussion about the costs and benefits of public transportation are likely to further intensify (Adler et al., 2018b) and our contributions hopefully manage to aid this discourse.

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Summary

Road transport is important to the modern economy. An increase in trade and personal mobility has intensified road use in the last decades and thereby exacerbated congestion and the associated losses in travel time, public health and environment. This thesis contributes to the on-going discussion on how to measure road congestion and examines the cost and benefits of some of the main policy remedies.

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. We also show that road congestion has a strong effect on travel time delays of bus travelers.

One of the unanswered questions in the field of urban economics is to which extent subsidies to public transit are justified. We examine one of the main benefits of public transit, a reduction in car congestion externalities, the so-called congestion relief benefit, using quasi-natural experimental data on citywide public transit strikes for Rotterdam, a city with mild congestion levels. On weekdays, a strike induces travel times to increase only marginally on the highway ring road but substantially on inner city roads. During rush hour, the strike effect is much more pronounced. The congestion relief benefit of public transit is substantial, equivalent to about 80% of the public transit subsidy. We demonstrate that during weekends, travel time does not change noticeable due to strikes. Further, we show that public transit strikes induce similar increases in number of cyclists as number of car travelers suggesting that bicycling-promoting policies to reduce car congestion externalities might be attractive.

We estimate the marginal external losses from vehicle traffic for inner city roads and a highway in Rotterdam based on the external effect of traffic density on travel time. We account for endogeneity issues from reverse causality and measurement error through a two-stage instrumental variable approach using bicycle use and hour-of-the-weekday as instruments. Our approach captures the

backward-bending function of the relationship between travel time and flow. We use this road supply cost curve for economic evaluation of marginal external cost. Larger travel demand during peak hours has much higher external cost due to hyper-congestion. With tolls between €0.40 and €0.50 per kilometer during these hours, hyper-congestion could be prevented.

Non-recurrent congestion is frequently caused by accidents and other incidents. We estimate the causal effect of incident duration on drivers' time losses through changes in non-recurrent road congestion on Dutch highways. We demonstrate that incident duration has a strong positive, but concave, effect on non-recurrent congestion. The duration elasticity of non-recurrent congestion is about 0.35 implying that a one minute duration reduction generates a €57 gain per incident. We also show that at locations with high levels of recurrent congestion, non-recurrent congestion levels are considerably higher. At very congested locations, the benefit of reducing the incident duration by one minute is about €1200 per incident. Public policies that prioritize duration reductions at congested locations are therefore more beneficial.

The Tinbergen Institute is the Institute for Economic Research, which was founded in 1987 by the Faculties of Economics and Econometrics of the Erasmus University Rotterdam, University of Amsterdam and VU University Amsterdam. The Institute is named after the late Professor Jan Tinbergen, Dutch Nobel Prize laureate in economics in 1969. The Tinbergen Institute is located in Amsterdam and Rotterdam. The following books recently appeared in the Tinbergen Institute Research Series:

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