[Preliminary draft]

Road supply curve estimation and marginal external congestion cost

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Abstract ─ Road congestion is a global problem with hundreds of billions of Euros in travel time lost each year. 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.

JEL code: R41, D62, R48

Keywords: marginal external road congestion cost, cost function, control function, road toll

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1. Introduction

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. For example, 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).[1] 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 economist 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 cannot be interpreted as a causal effect of flow on time.[2] 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 fall in capacity due to something such as an accident. Whereas ‘congestion’ is more frequent than ‘hyper-congestion’, we demonstrate that the latter is substantially costlier.

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[1] 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).

[2] 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).

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).[3]

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 which 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.[4] Indeed, we find somewhat larger optimal road tolls for the town of Rotterdam.

[3] 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.

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

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.[5] 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 2, we explain the empirical framework. Then we introduce the dataset according to descriptive statistics in Section 3. Afterwards, in Section 4, we present the empirical results that are used for a brief welfare analysis in Section 5. The last Section concludes.

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. The inverse of vehicle speed is travel time T, in minutes per kilometer, which itself is an identity of vehicle density D, the number of vehicles on a kilometer length of road, divided by vehicle flow 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:

$$\log T_{i,t} = \beta_i + \alpha D_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}, \qquad (1)$$

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.[6]

[5] 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.

[6] 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.

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

$$\log T_{i,t} = \beta_i + f(D_{i,t}) + \theta X_{i,t} + \varepsilon_{i,t}. \quad (2)$$

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 (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 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 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 (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).[7] 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.[8] 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

[7] 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).

[8] 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.

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.

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 $X_{i,t}$:

$$D_{i,t} = \Phi\left(z_{i,t}\right) + \vartheta X_{i,t} + \mu_{\ i,t} \tag{3}$$

Then we insert the residual $\iota_{i,t}$ as a control function into equation (2), so that:

$$\log T_{i,t} = \beta_i + \alpha D_{i,t} + \gamma D^2{}_{i,t} + \theta X_{i,t} + \iota_{i,t} + \varepsilon_{i,t} \tag{4}$$

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.[9] 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:

$$MEC \ = \frac{d[FT(D)]}{dF} - T \ = \frac{dT}{dF}F + \ T - T \ = \frac{dT}{dF}F \ = \frac{\frac{\partial T}{\partial D}D}{1-\frac{\partial T}{\partial D}F}. \tag{5}$$

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

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 flow constitutes a welfare improvement, see also Adler et al. (2017). From the estimation of a linear equation (1), where we assume that $T=\beta e^{\alpha D}$ then $MEC = \alpha\mathrm{D}\,T\,/(1-\alpha\mathrm{D})$.[10] 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 (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. 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.[11] We focus on (motorized) vehicles at one measurement location in the inner city, see Figure 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.[12]

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)

[10] For equation (4), the marginal external congestion is $(\alpha\mathrm{D}\,T+2\gamma D^2\mathrm{T})/(1-\alpha\mathrm{D}-2\gamma D^2)$.

[11] 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: $F \times T = D$.

[12] 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.

shows that for most hours of the day, car users travel at speeds close to the speed limit of 50 km/h. See Table 1 for descriptive statistics. The maximum travel time for a kilometer in the inner city is 3.83 minutes which is rather short.[13]

Table 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

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.[14] On the highway, travel time is 0.62 min/km, only slightly more than the time it takes to travel at the speed 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.[15]

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

[13] 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.

[14] 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.

[15] For the inner city we show the histograms of flow, density and travel time in the Appendix, Figures A2-A4. The histograms of the highways are similar and hence not depicted.

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.

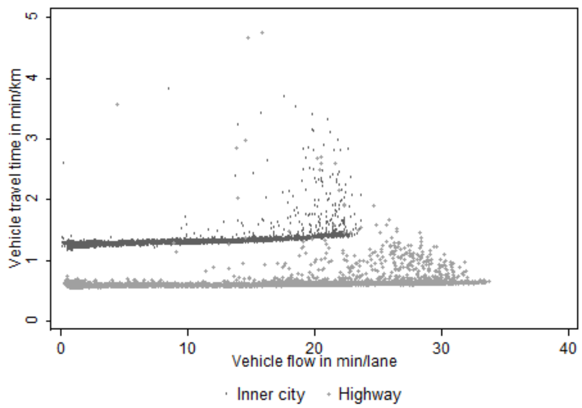
Bicycles use separate infrastructure from motorized vehicles in Rotterdam.[16] So, vehicle flow and density are independent of bicycle flow. The two modes usually do not share road space and are also measured separately. We have data for 32 one-directional bicycle paths across the city and focus on three of these, all crossing the river Maas in proximity to the car measurement points.[17] 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.

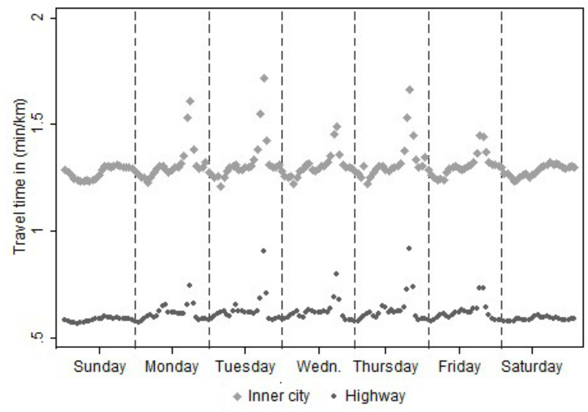
Bicycle flows are less than one-fifth of vehicle flows in Table 1. This reflects trip modal split of 14% for bicycle use and 57% car use in Rotterdam. The coefficient of variation is larger for bicycle use than for car use, suggesting a larger variation of bicycle use over the day. However, correlation between hourly car density and bicycle flow is large, above 0.5 (and above 0.8 for flow).[18] 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.

Figure 1 – Travel time and flow

Figure 2 – Travel time over the day

[16] Intersections and traffic lights are shared in Rotterdam by bicycles and cars. However, both are at least 500 meters from our observation locations.
[17] 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.
[18] 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 A5.





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.

Figure 3 – Inner city: Car flow and bicycle flow

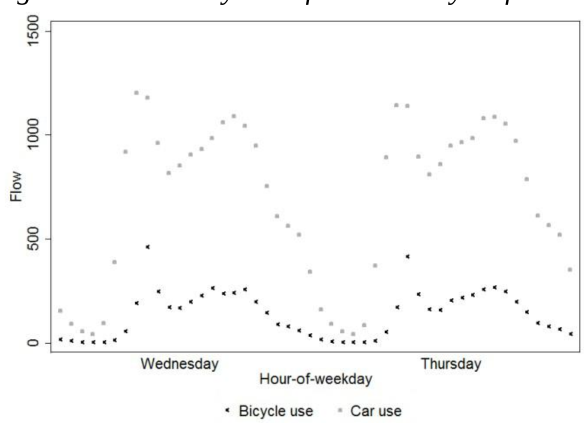
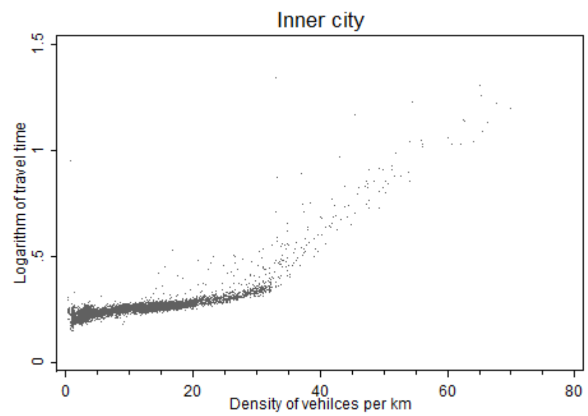


Figure 4 – Vehicle density and travel time



We show the travel time-flow relationships in Figure 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 1 with the flow histogram (Figures 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.

Travel time has a clear pattern over the hour and day of the week in Figure 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 for a more detailed view for Wednesday and Thursday. Not surprisingly, especially morning and evening peak flows are pronounced.[19] 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 4. Travel time is increasing in density and in particularly so after about 35 vehicles per kilometer.[20]

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 2 and 3.[21]

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.[22] This downward bias is a result of the measurement error in the 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 2 – Travel time (log) inner city

	(1)	(2)	(3)	(4)	(5)	(6)

[19] 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 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).

[20] There is a positive, concave correlation between vehicle density and the instrument bicycle use, see Figure A6.

[21] For the estimations using flow as an explanatory variable in which we find comparable results in magnitude, see the Tables 1 and 2 in the Appendix. This similarity in results is expected because hyper-congestion is infrequent.

[22] 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-value.

	OLS	IV	IV	OLS	Control function	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 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. 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).

The specification of the estimation matters for the road supply curve. In Figures 5 and 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 2 and 3). For comparison, we also plot the OLS estimate using flow instead of density as the independent variable in equation (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.

Table 3 – Travel time (log) highway

	(1)	(2)	(3)	(4)	(5)	(6)

	OLS	IV	IV	OLS	Control function	Control function
Density	0.0232^{***} (0.000856)	0.00789^{***} (0.000586)	0.00864^{***} (0.000436)	-0.00526^{***} (0.00138)	-0.00952^{***} (0.0024896)	-0.00876^{***} (0.000580)
Density^2				0.000771^{***} (0.0000486)	0.000635^{***} (0.0000751)	0.000731^{***} (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 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 5 – Road supply curves inner city

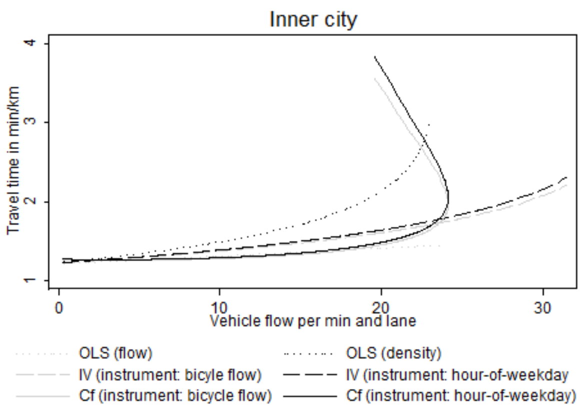
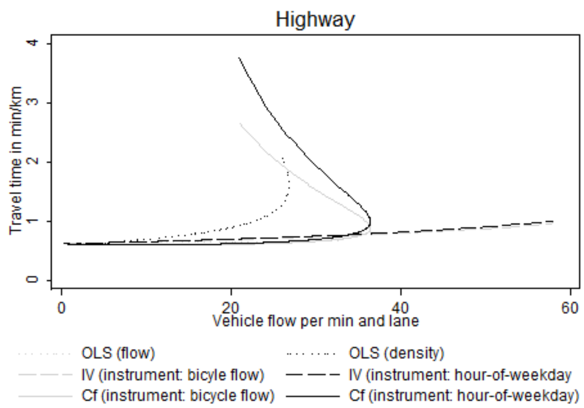


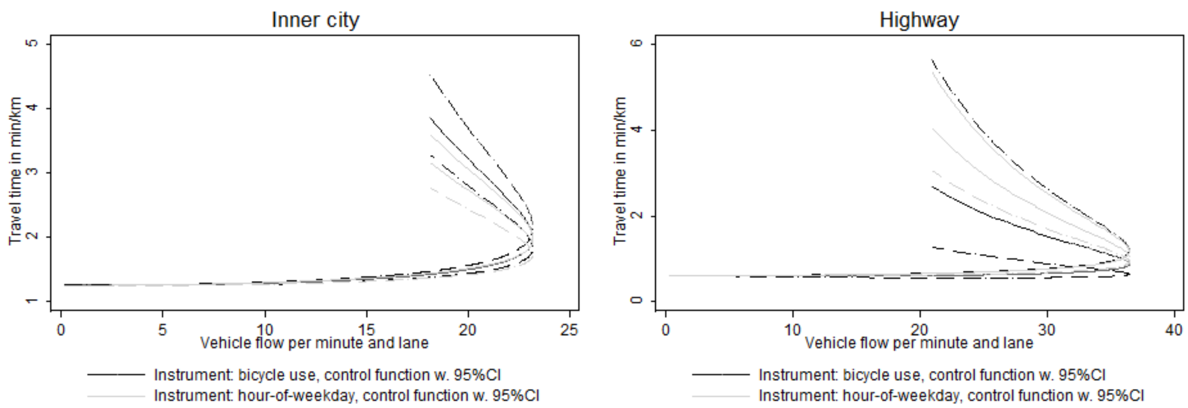
Figure 6 – Road supply curves highway



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.

Figure 7 – Control functions inner city

Figure 8 – Control functions highway



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.[23] 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.

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 7 and 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.

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 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

[23] 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)\.

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%).

Figure 9 – Road supply curves inner city

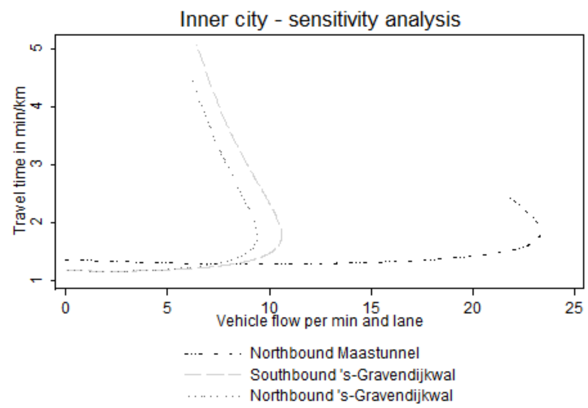
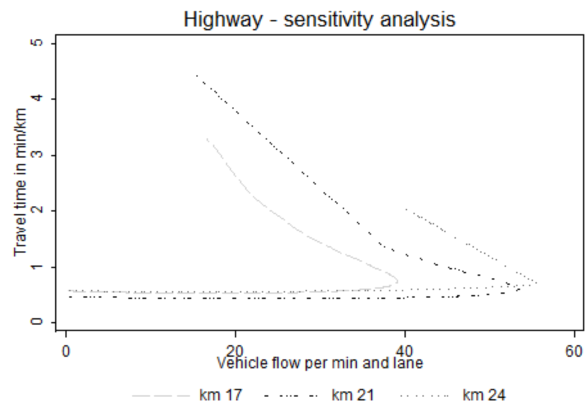


Figure 10 – Road supply curves highway



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 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.

The methodology we propose is also suitable to less aggregated data. For example, we can estimate equation (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 A10 in the Appendix). We prefer the main result in Table 3 of section 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.

6. Welfare implications

When we focus on the positive MEC, we can estimate the MEC using the instrumental variable approach and tabulate the results in Table 3. In the inner city, the marginal external costs are 0.20 min/km per additional vehicle for all hours of the day. 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 - 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.[24] The road toll needs to take into account the varying 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.[25] Our road tolls are based on the quadratic control function approach of equation 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 10 and 11. 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.

We are interested in the optimal equilibrium given a linear, elastic demand function and the quadratic supply function estimated in equation (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 $T = \tau_r - \varphi F$ to the marginal cost curve so that:

$$\tau_r - \varphi F = T + MEC \tag{6}$$

This can be rewritten using equation 5 as:

[24] 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.

[25] 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.

$$0= \tau_r - \varphi \left(\frac{D}{T}\right) - T - (\alpha DT + \delta D^2 T)/(1 - \alpha D - \delta D^2) \quad (7)$$

We optimize for values $\varphi = [0.2; 1]$. The implied corresponding average demand elasticities for the inner city are [-1.4;-7.1] since $\partial T/\partial F = -\varphi\ F/T$, and for the highway respectively [-4.3;-21.7] corresponding to values in the literature.[26]

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 4. Above the critical density, large welfare gains of 17.12 min/km are possible from eliminating hyper-congestion. We find a similar potential welfare gain from removing hyper-congestion for a less elastic demand function. However, only smaller gains are possible during congested hours for the case of $\varphi = 1$. The highway confirms the general picture that optimal densities are similar to average density as most observations are on the congested part of the supply function. Welfare gains from reducing hyper-congestion are 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 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
Hypercongested: D>Dc	17.12	17.77	15.47	7.34

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.

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

[26] 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).

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.[27] This amount to €158,000 per working day and €40 million annually.[28]

Figure 11 – Toll inner city weekday

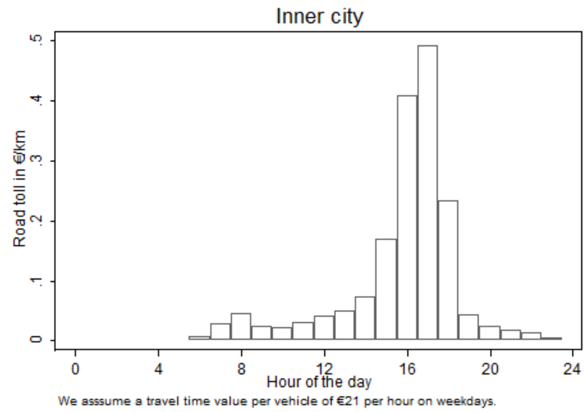
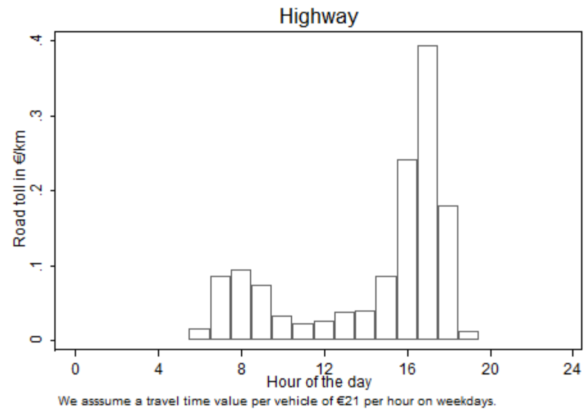


Figure 12 – Toll highway weekday



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.[29] Since we 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.[30]

[27] 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.

[28] 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.

[29] 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).

[30] 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).

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 inner cities and on highways and is suitable for various level 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. Hence, optimal tolls are between 40 to 50 cents during rush hours and 10 to 20 cents over the course of the day.

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Appendix

Figure A1 – Measurement points Rotterdam

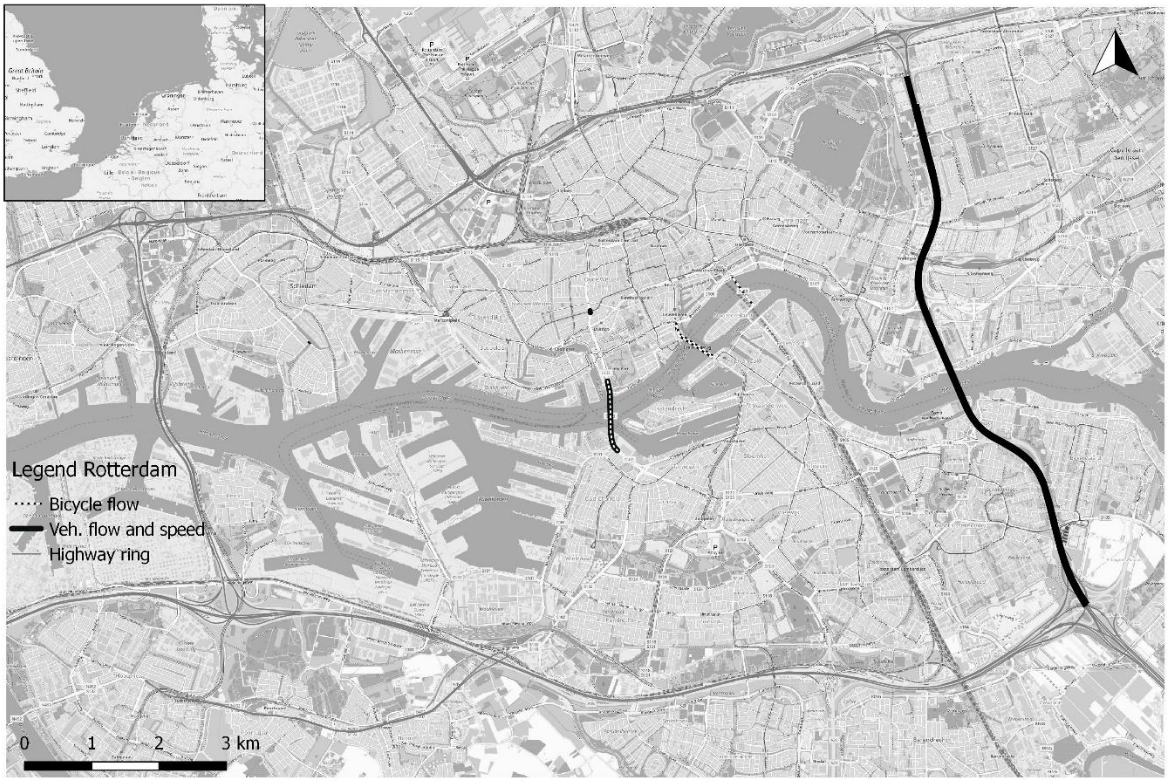

Figure A2 – Vehicle flow

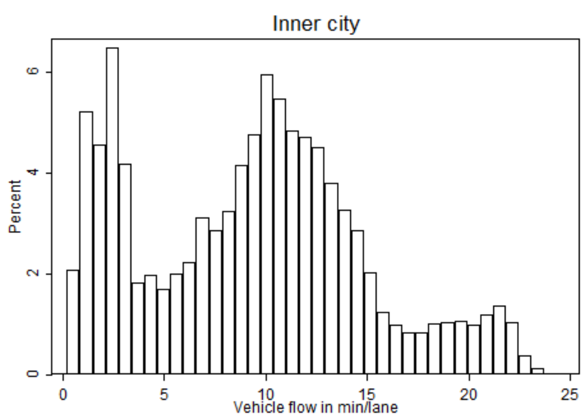

Figure A3 – Vehicle density

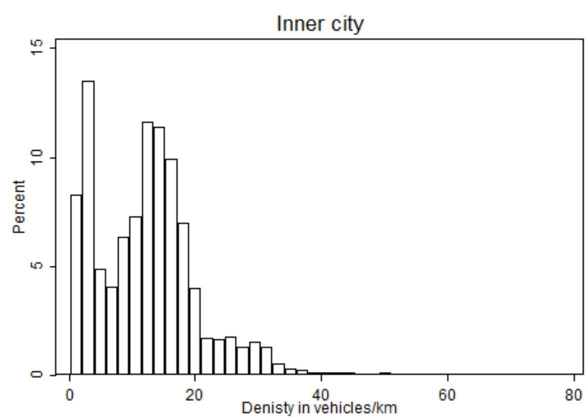

Figure A4 – Travel time

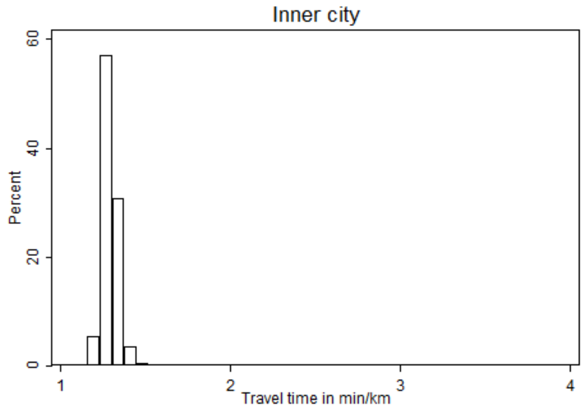

Figure A5 – Bicycle flow

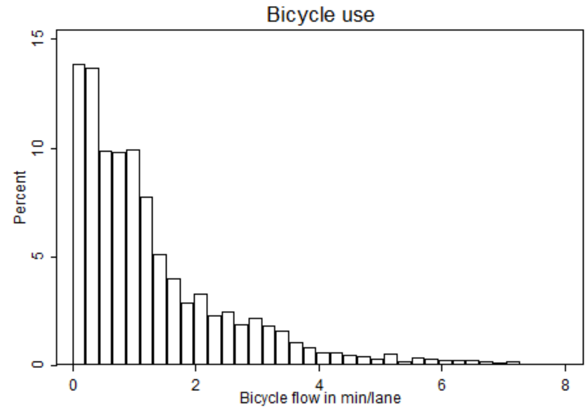

Figure A6 – Bicycle flow and vehicle density

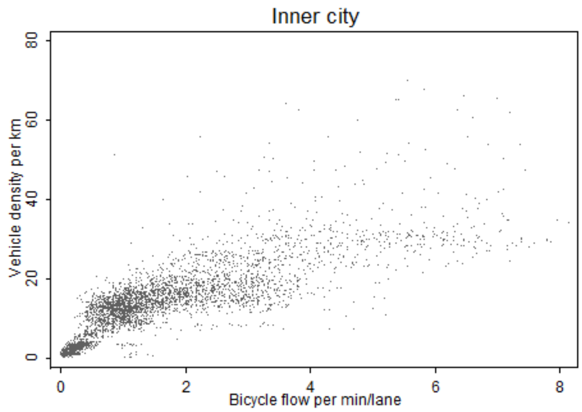

Figure A7 – Road supply and confidence interval

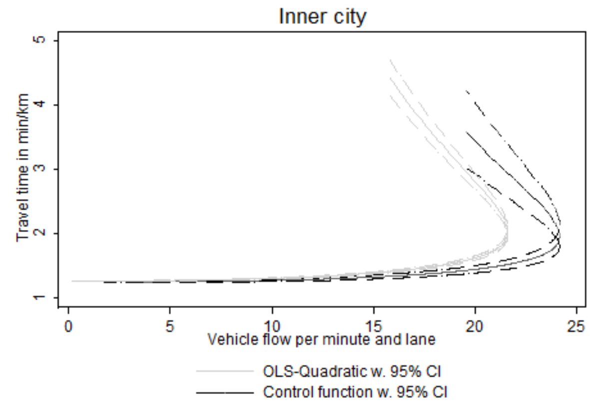

Figure A8 –Road supply and confidence interval

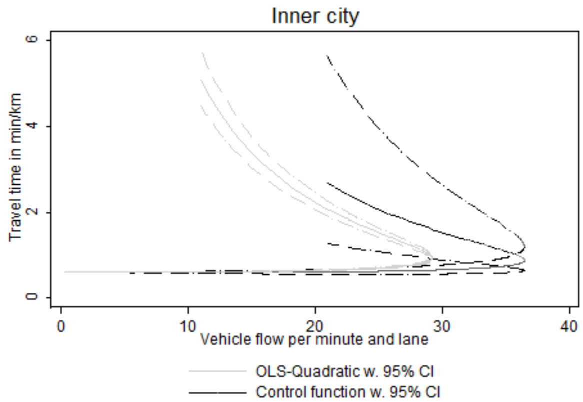

Figure A9 – Road supply curve

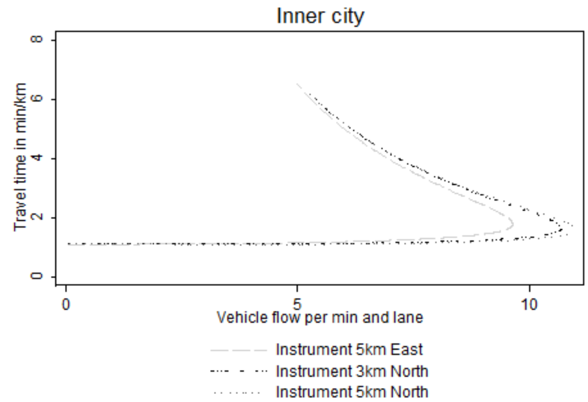

Figure A10 –Data aggregation sensitivity

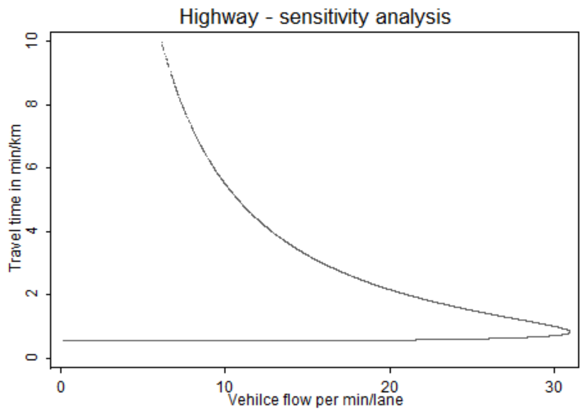

Table A1 – Travel time (log) inner city

	(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 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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$