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Citywide parking policy and traffic: Evidence from Amsterdam

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Citywide parking policy and traffic: Evidence from Amsterdam[*]

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We examine the effect of citywide parking policy on parking and traffic demand. Using a large increase in on-street parking prices for the city of Amsterdam, we show that the policy caused a substantial drop in on-street parking demand, which is not offset by an increase in off-street demand. The overall reduction in parking demand implies a 2% – 3% reduction in traffic, which is confirmed with traffic flow data. The reductions in traffic are larger during the evening peak, which indicates that parking prices are effective at reducing congestion in the evening peak, but lesser in the morning peak.

Keywords: parking, prices, traffic flow, congestion
JEL Codes: R41, R48, R51, R52

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1. Introduction

Parking prices are a widely accepted policy tool to manage parking and traffic demand in cities. The theoretical economic literature has extensively studied parking policy as a second-best alternative to tackle traffic externalities by reducing the number of car trips in urban areas.[1] In light of the technical and political challenges of implementing road pricing, parking policies have come under renewed interest because they already exist in many cities and therefore extending these policies may be more feasible (Small and Verhoef, 2007). Nevertheless, the empirical literature has yet to confirm or refute the effectiveness of parking prices in reducing traffic demand.

In this paper, we aim to fill this gap by examining to what extent hourly on-street parking prices are an effective second-best policy tool to mitigate urban traffic externalities by reducing citywide road traffic. We focus on the city of Amsterdam, where on-street prices are high and comparable to off-street prices. We use information on on-street parking, off-street parking, and traffic flow for a period during which on-street parking prices were suddenly and strongly increased throughout the city.

To estimate the causal effect of the price increase on parking demand and traffic flow, we apply an event study approach, where we examine changes in parking demand before and after the policy change, controlling for seasonality, location fixed effects, and time trends. Our key identification assumption is that the timing of the policy is random and that in the absence of the policy, parking as well as traffic flow should follow similar trends in the pre and post period, for which we provide convincing graphical evidence. Alternatively, we exploit spatio-temporal variation in parking prices, which identifies local parking demand elasticities to support our citywide estimates.

We first show that the price effect on on-street parking demand is large and robust. The increase in parking prices due to the policy caused overall hourly on-street parking demand to decline by around 17% and the number of arrivals to decline by 9%, corre-

[1] See e.g. Anderson and de Palma (2004), Albert and Mahalel (2006), Arnott and Inci (2006), Arnott and Rowse (2009), Calthrop and Proost (2006), Fosgerau and De Palma (2013), and Arnott et al. (2015).

sponding to a citywide price elasticity of demand of -0.37 and -0.19, respectively. We also find negative, but much smaller, effects in the (commercial) off-street parking market, as off-street providers increased prices as a reaction to the policy, but to a lesser extent. Taking into account that about one quarter of car trips in Amsterdam use hourly on-street parking, this implies that the policy decreased *citywide* traffic flow by around 2.5%. Furthermore, we find that the total effect on parking arrivals and exits is over twice as large during afternoon peak hour traffic as compared to the morning peak. These results are confirmed using traffic counts from road loop data, where we find a subsequent average reduction in traffic flows of around 2% – 3%, and larger effects in the afternoon.

These findings are important to understand the extent to which prices reduce parking demand and traffic at the city level. One straightforward implication is that parking prices reduce overall traffic flow and thereby serve as a second-best congestion and environmental policy. Interestingly, we show that even though parking prices were not differentiated within the day, the policy had larger effects on traffic during the evening peak hours because of heterogeneity in parking demand within the day. Our estimates are also relevant for cities aiming to convert on-street parking into alternative uses, such as parks, cycling lanes, and restaurants, without causing additional externalities from cruising or additional costs from building new off-street capacity.

Our paper relates to three strands of literature. First, our paper relates to the empirical literature studying the effects of prices on demand. Lehner and Peer (2019) present a meta-analysis on the price elasticity of parking.[2] Second, our paper relates to a large theoretical literature, which emphasises the importance of using parking prices to reduce congestion (Albert and Mahalel, 2006; Arnott and Inci, 2006; Shoup, 2006; Arnott and Rowse, 2009; Arnott and Inci, 2010; Fosgerau and De Palma, 2013; Arnott et al., 2015). Third, our paper links to the literature on second-best congestion policies. This includes public transport subsidies (Anderson, 2014), licence plate restrictions (Davis,

[2] Notable contributions include Kelly and Clinch (2009) (on-street parking demand), Pierce and Shoup (2013), Ottosson et al. (2013), Chatman and Manville (2014) (on-street parking occupancy), and De Groote et al. (2019) (off-street parking demand).

2008; Kreindler, 2016), and HOV lanes (Bento et al., 2014; Hanna et al., 2017). Most closely related to our paper, Krishnamurthy and Ngo (2020) study the effects of a local parking policy on traffic flow and find that the introduction of a dynamic pricing scheme in San Francisco resulted in 6% lower vehicle counts in treated areas. However, the latter study is silent on the effect at the city level.

Our study contributes to the existing literature in three ways. First, we estimate on-street as well as off-street parking demand functions for the whole city of Amsterdam, where we exploit a substantial increase in the hourly price for on-street parking for essentially the whole city. In the parking demand literature, typically a local price change is investigated, either for a specific parking garage or parking zone (Kelly and Clinch, 2009; Van Ommeren and Wentink, 2012; Krishnamurthy and Ngo, 2020). Effects on local parking demand are then a combination of a reduction in car use and substitution to other locations.[3] Using *all* on-street parking data *and* a representative sample of commercial off-street garages for essentially the whole city offers the key advantage that we are able to address substitution over space to other locations within the city.[4] The policy we examine increased average prices by 66%, from €2.55 to €4.22 per hour, so the price increase was not only large in relative terms, but also in absolute terms.

Second, our study presents a significant improvement in data quality compared to the previous literature (Lehner and Peer, 2019). We use administrative micro-data from over 70 million parking transactions at more than 3,000 parking meters and 60 visitor permit zones throughout the city, which represents the complete hourly on-street parking market. These data allow us to estimate citywide parking elasticities and distinguish between the extensive (parking arrivals) and intensive margin (parking duration). This is crucial, as information on parking arrivals allows us to gauge the effects on traffic flow. Furthermore, we also have a representative sample on off-street garages which indicates

[3]For example, it is unclear whether the effects on traffic flows found in Krishnamurthy and Ngo (2020) were redirected to other locations in the city that were not part of the pilot programme.

[4]For larger cities it is unlikely that many motorists decrease parking demand within the city by increasing parking demand just outside the city. Even if this would be the case the reduction in citywide traffic flow is still captured by the reduction in parking demand in the city as drivers do not enter the city.

that off-street prices in Amsterdam also increased in response to the policy and rules out substitution to off-street parking.

Third, using traffic flow data from road loops, we explicitly estimate the effect of the citywide increase in parking prices on traffic flow, largely confirming the parking results.

The rest of this paper is structured as follows. Section 2 describes the policy context and data, Section 3 explains the methods employed, and Section 4 discusses our results, robustness checks, and implications. Finally, Section 5 concludes.

2. Data and context

2.1. *Context*

Amsterdam is a historic European city, characterized by narrow one-way streets and by a transportation system that offers many modal alternatives to travellers. In 2017, auto travel represented 27% of trips, while cycling, walking, public transport, and scooters, each accounted for 26%, 19%, 26%, and 2%, respectively (Gemeente Amsterdam, 2019). About half of all car trips, excluding those made by residential parking permit holders, are made by non-residents.[5]

Figure 1 illustrates a map of the Amsterdam municipal area and shows the major transport and parking infrastructure. Travelling from one side of the city to the other by car is fastest and most convenient via the A10 ring road, so most cars do not travel through the city unless they are going to a destination within the ring road. The river IJ cuts the city in two parts. Access from the South to the North of Amsterdam by car is only possible via three tunnels, one to the West and two to the East of the central train station.[6] The dark gray area indicates the paid parking area which represents 63% of the total on-street parking supply in Amsterdam. Peripheral areas without paid parking are predominantly residential suburban or industrial, are generally not well connected

[5]Trips to and from home by Amsterdam residents account for around 30% of all car trips, however these do not end in (hourly) paid parking.

[6]For non-motorized transport, the only way to get to the North side is by ferry from Amsterdam Central Station, or by taking the North-South metro line that was opened in July 2018.

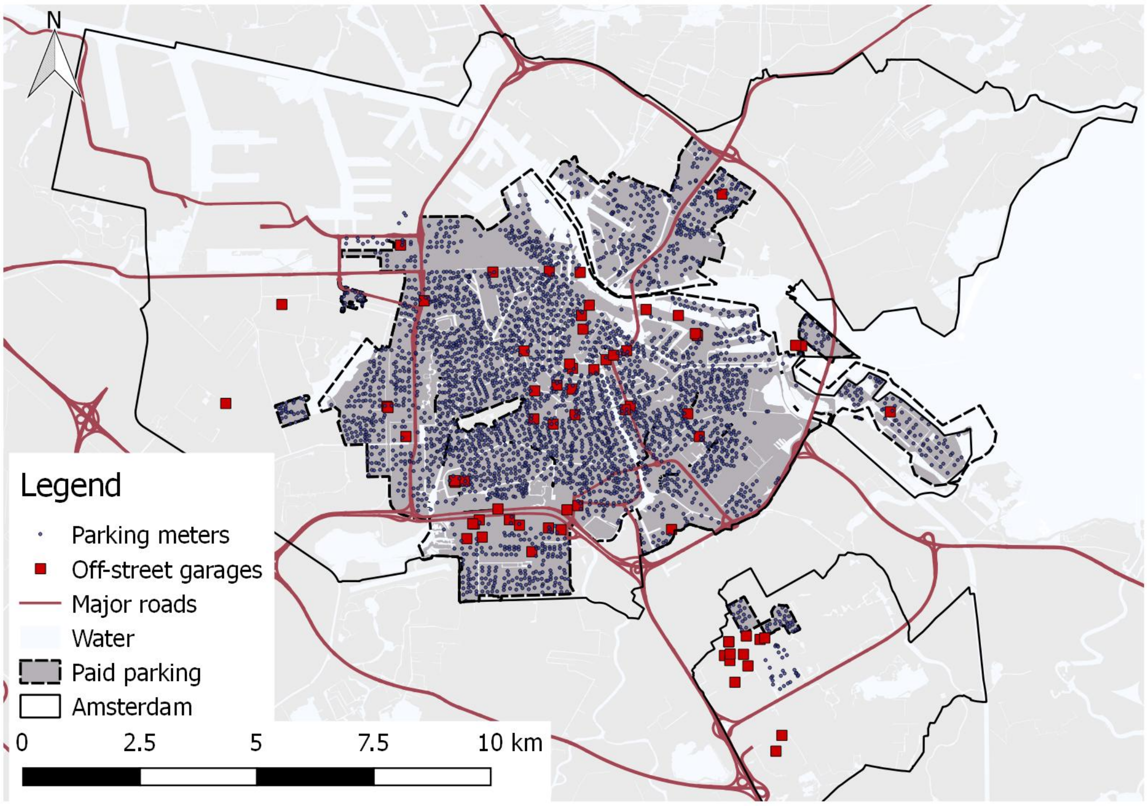


Figure 1: Major transport and parking infrastructure in Amsterdam.

to tram, metro or bus lines, and are generally not considered as a viable substitute for motorists with a destination in the paid parking area. There are three clusters of off-street parking garages. The first cluster, which contains the majority of garages, are located around the city centre and are small in terms of capacity. The other two clusters are around the South Axis business park and the Bijlmer ArenA towards the South East, which tend to have larger capacities.

2.2. *Parking policy in Amsterdam*

In this section we briefly describe the policy context and main impacts of the policy we analyse (for a more detailed overview, please see Appendix A.1). In Amsterdam on-street parking is accessible to drivers who pay hourly rates as well as residents using residential permits, close to their home.[7] Around one third of motorists (excluding residents parking with a permit) use off-street commercial parking garages. These garages are mainly provided by private operators and charge slightly higher prices as compared to nearby on-street parking.

In May of 2018, the city of Amsterdam committed to a mobility agenda to prioritise cycling and pedestrian transport, while reducing car use in the city (Gemeente Amsterdam, 2018, pg.47). Following a decade of constant on-street parking prices, the new coalition government, headed by the Green party, mandated a parking price increase for (hourly) on-street parking and the conversion of freed on-street parking supply to other uses. By late October 2018, it was announced that (hourly) prices were to be raised throughout the city effective Sunday April 14, 2019 (week 16).

A map of Amsterdam municipality illustrating the spatial extent of the paid parking area and parking prices per zone before and after the policy can be seen in Figure 2. There are eight price zones that differ in their hourly prices. Prices are the highest in the historical city centre and fall with distance to the centre. Price increases were large in both relative and absolute terms (see Figure A4 in Appendix A). Average hourly on-street prices (weighted by the number of arrivals per area) increased by €1.67, or 66%, from €2.55 to €4.22. In the historic city centre, hourly prices went up from €5.00 to €7.50, making Amsterdam the most expensive city for on-street parking in the world (Parkopedia, 2019).

Price increases were implemented in every parking zone except for three non-central industrial zones with a time limit of three hours and a few streets with a time limit of one hour, priced at €0.10 and intended to be used for shopping (see Figure A1 in Appendix A).[8] The largest relative price increase occurred just outside the city centre where prices doubled from €3.00 to €6.00. The smallest relative price increase occurred in northern areas and a few peripheral areas of the city where price increases were negligible.

[7] This is in contrast to countries such as the UK, where most cities have 'residential parking only' areas. Residential permits are only valid in a residential permit zone.

[8] Reducing parking demand through time limits is common in North American and Australian cities, but is relatively rare in Europe.

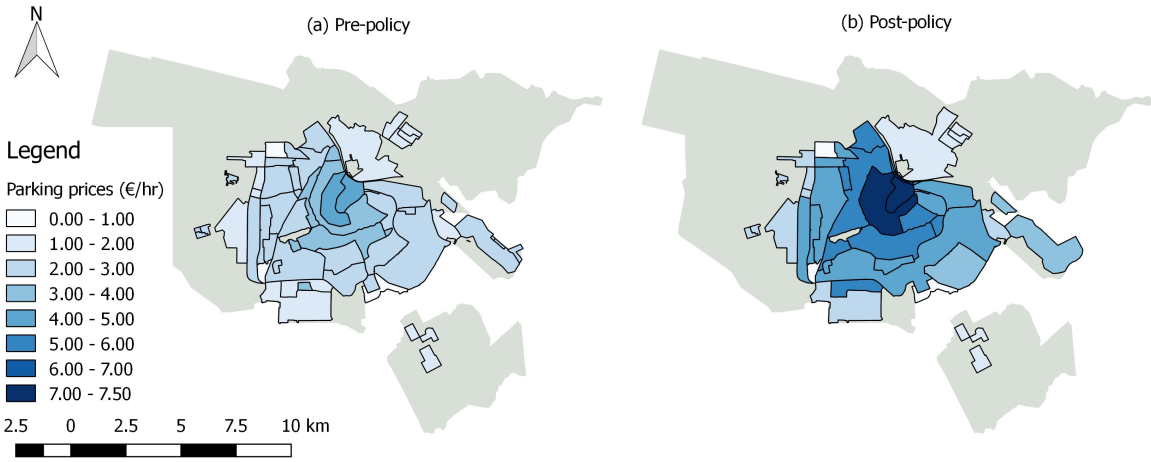


Figure 2: Hourly parking prices pre and post policy.

The new policy did not alter paid parking hours. Paid parking hours, which vary by zone, start at 9:00 and end between 19:00–23:59. For the majority of parking areas within the ring road, parking hours end after 21:00. Furthermore, as shown in Figure 2, the policy did not affect the total paid parking area, but it slightly changed the delineation of certain parking zones within this area.[9]

Alongside the price increase, the municipality aims to gradually reduce the supply of on-street parking in areas where parking pressure was relieved due to the price increase. In 2019, 1,141 parking places were redeveloped into public spaces such as park benches, playgrounds, and bicycle parking (Gemeente Amsterdam, 2020). The reduction was gradual, relatively uniform over space, and represents less than one percent of the total paid on-street parking supply. Hence, this is unlikely to be a confounding factor in evaluating the effect of the price increases, because the reduction in supply was a *response* to lower demand, and the reduction is only a fraction of the decrease in demand implied by our results. Hence, the reduction in supply is unlikely to have contributed to increased cruising and therefore to reduced parking demand.

Hourly prices at commercial off-street garages (weighted by garage capacity) were, on average, almost 30% higher than nearby on-street prices before the policy (€3.33 and

[9]The policy also expanded a visitor permit scheme which accounts for a small share of on-street parking demand (1.57%). In our analysis, visitor permits are included.

€2.57, respectively), but after the policy the difference was less than 10% (€4.37 and €4.01, respectively).[10] So prices for off-street parking garages increased substantially (by 19% – 31%), but less than the on-street prices close to these garages (which went up by 56%).[11] While cruising for parking is limited compared to other major cities, the reduction in the difference between on-street and off-street parking prices suggests a (small) reduction in the level of cruising costs (Arnott et al., 2015).

2.3. *Parking data*

2.3.1. *On-street parking*

The on-street parking analysis is based on administrative data of 87.51 million unique on-street parking transactions from 2017 to 2019, provided by the municipality of Amsterdam.[12] This micro dataset contains information about the start and end time of each transaction, as well as other transaction attributes such as the total price charged, the parking meter, as well as the type of use and method of payment.[13] We exclude 3.51% transactions which are used for special purposes, such as handicapped parking and long term construction work.

Motorists are required to pay at the closest available parking meter, but the majority use mobile phone apps (76%). The latter allows for flexibility in terms of duration as compared to physically paying at the machine, where duration must be chosen beforehand. On-street parking is also possible via visitor permits, which are available through residents. These permits offer a discount of between 50% – 75% on the hourly rates for up to 40 hours per residential household per month, and must be activated via an online web application.[14] Each transaction is tied to a vehicle number plate and enforcement

[10] We define 'nearby' as parking meters within a 500 m buffer around each off-street garage and calculate the average price of these parking meters. Note that off-street *day* prices are generally lower than for on-street parking (before and after the policy) so the overall price difference is less than indicated in the main text.

[11] In our full sample it is 31%. For some garages we do not observe prices pre-policy. Excluding these garages results in an increase of 19%.

[12] For 2017, observations for 9 weeks are missing.

[13] Parking meters are close together. The median distance between a parking meter and the next closest parking meter is 69 meters.

[14] Transactions have a visitor parking zone as a spatial identifier which contains about 42 parking

is performed using a car equipped with cameras, therefore infraction is difficult, however illegal parking still accounts for over 2% of arrivals (Egis Group, 2019).[15]

We exclude 3.85% of transactions shorter than five minutes and 0.01% of transactions longer than one week as they are likely to be the result of human and machine errors. Furthermore, we exclude transactions on Sunday (3.3%) as parking hours and rates differ compared with the rest of the week and on-street parking tends to be free. Finally, there was a large expansion of the parking area in the North of Amsterdam on July 1, 2018, corresponding to the introduction of a new metro line. Because the North is geographically separated from the main area of Amsterdam by the IJ river and faces different trends, we exclude this area (7.5% transactions) and perform a sensitivity check where we include these parking areas, while controlling for area specific time trends.

After these selections we are left with 67.13 million parking transactions, of which 98.7% pay the full price and park for an average duration (weighted by the number of arrivals) of 2.4 hours, while 1.3% use visitor permits with a slightly higher average (weighted) duration of 3 hours. Using these micro data we calculate daily parking demand per area resulting in a panel of 2.71 million daily observations.[16] For motorists that pay the full price we know the parking meter and for those that use visitor permits, we know the visitor parking zone. In total we have 3,238 parking meters and 67 visitor parking zones.[17]

Daily parking demand per area is measured in three ways: volume (total hours parked), the number of arrivals, and the mean duration of arrivals. Most transactions (96.2%) start and end on the same day, therefore volume is (approximately) equal to the

meters per zone.

[15]In 2017, the municipality issued 780,000 fines, which corresponds to around 2% of arrivals (Parool, 2019). This is a lower bound of the prevalence of illegal parking as it is inevitable that some infractions go undetected. Nevertheless, the effect on arrivals is likely to be smaller because many infractions occur due to underpayment. If no infraction is detected, the number plate data is removed on privacy grounds.

[16]We trim outliers with volume $\geq$ 1000 hours, duration $\geq$ 24 hours, and arrivals and exits $\geq$ 500 cars (0.2% of observations). See Section A.3.1 in Appendix A for a detailed description of the aggregation process.

[17]Most parking meters are active throughout the entire period. However, 73 parking areas were either defective for a period of at least one month or were added/removed during the study period. These areas correspond to 0.56% total arrivals, are evenly spread throughout the city, and are included in the analysis.

product of arrivals and duration at the daily level. Based on hourly data from the nearest weather station, obtained from KNMI,[18] average daily temperature (°C), windspeed (kmph), and a dummy for rain and temperatures below 0 °C between 08:00 – 20:00 are added. We also add public holidays and school holidays as additional controls as vacation times change by region from year to year.

2.3.2. *Off-street parking*

We observe the location and hourly prices for all 70 off-street garages. Garages have an average capacity of 455 spaces. The municipality of Amsterdam owns 40% of garage capacity and charges market prices, so these garages are defined as commercial.

For a (representative) sample of 27 garages (out of 70), we have occupancy data based on API requests to dynamic parking information systems which allow us to calculate hourly parking volume.[19] There are two limitations of these data. First, we do not observe the number of off-street garage arrivals (or exits) in which we are interested to gauge the policy effect on traffic flow. As will be explained in detail later on, the estimate of the policy effect on volume can be used to bound the effect on the number of arrivals. Second, we only observe garage data after July in 2018. This means that we have less information on longer term (pre)trends, however given a sudden change in on-street prices, we still expect to be able to detect changes around the policy window.

Our aggregated daily dataset consists of 10,395 daily parking volume observations for 16 commercial garages, covering 31% of total commercial off-street capacity, and 7 P&R facilities, covering 63% of P&R capacity, between July 4, 2018 and February 29, 2020.[20] Average hourly prices at commercial garages increased by 23%, while prices at P&R facilities, which charge cheap daily rates of €1, conditional on drivers parking after 10:00 and demonstrating a valid public transport ticket to and from the city centre, did

[18]Data from the Schipol weather station is used, located 12 km away from the city center. The KNMI is the Dutch National Weather Institute.

[19]See Figure A1 in Appendix A for spatial distribution of garages in the sample. Garage occupancy is observed every 2 minutes.

[20]We exclude 0.75% of observations for unrealistic outliers and 5.18% of observations with incomplete hourly data. We drop 4 garages because of missing data and select the period until March 1, 2020 due to COVID-19 lock-down measures.

not change.[21]

2.4. *Traffic data*

We further obtain hourly flow data from primary (non-highway) roads measured using induction loops at various points within the city for the years 2018 and 2019 from the municipality of Amsterdam. Our aggregated data consists of 12,696 daily observations for a total of 31 loops where traffic flow are collected, where each loop represents one flow direction.[22]

2.5. *Trends*

Figure 3 shows that on-street parking volume and the number of arrivals both exhibit a slight positive linear growth rate, as indicated by the black linear fit, over the period before the introduction of the policy, while duration is constant. There is a sharp decline in parking demand at the beginning of the policy, followed by a continuation of the linear trend until the end of 2019. It can also be seen that there is a dip in the volume and number of arrivals around the school summer holidays and there is variation in the number of arrivals around April and May, which is the result of a large number of public and school holidays falling in this period (7 out of of 11 mandatory public holidays fall in April or May).

Figure B5 in Appendix B illustrates trends in traffic flow over time.[23] Traffic flow appears to follow similar patterns over time as parking demand with dips in the summer period and more fluctuation around holidays.

Figure 4 shows that commercial off-street parking volume is constant pre-policy, while P&R volume is falling. At the beginning of the policy, there appears to be a slight drop

[21] Other drivers pay hourly rates that are similar to on-street prices. Based on other monthly data from the municipality, we can calculate that there are almost 2,000 daily P&R arrivals (80% of these exit the same day).

[22] Several loops have defective measurements and experienced nearby road works over the period of study. We pre-select locations for which we have consistent observations over the period of analysis.

[23] As we do not have a balanced panel, the data is demeaned per loop-direction to ensure comparability over time.

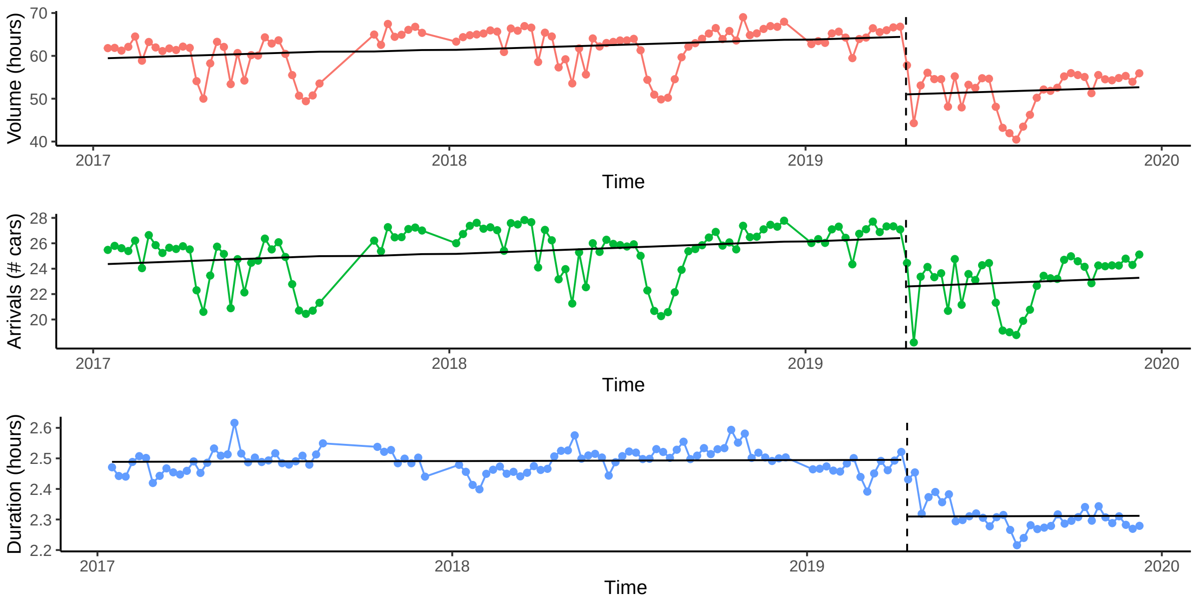
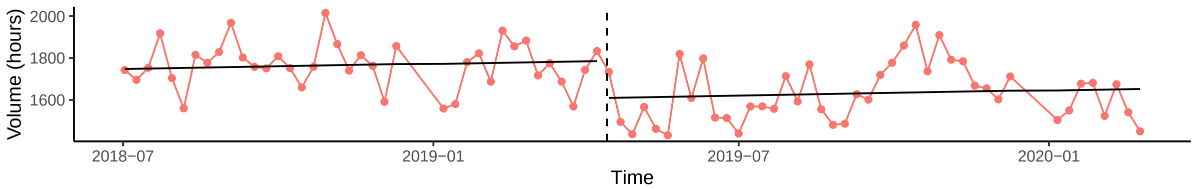
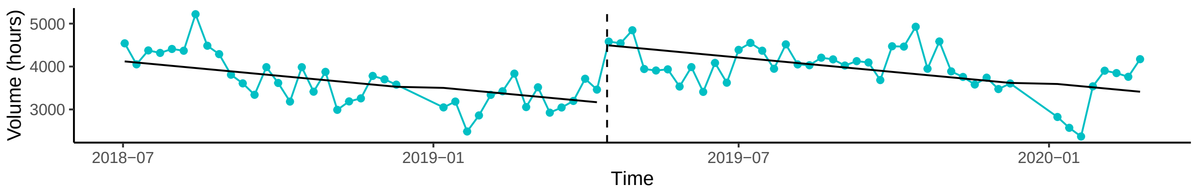


Figure 3: Mean daily on-street parking demand per area.



(a) Commercial



(b) P&R

Figure 4: Mean daily off-street parking demand per garage.

in commercial off-street parking and an increase in P&R demand.

2.6. *Descriptive statistics*

Table 1 presents the descriptive statistics. Panel A shows that there are around 25 daily arrivals per parking area and the mean duration is 2.5 hours, the product of which approximately equals the daily parking volume per area, which is 61 hours parked.[24]

[24]There are slightly fewer observations for duration as a small proportion (2.02%) of parking areas face no arrivals on a given day.

Table 1: Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Max
Panel A: On-street parking					
Volume (hours)	2,710,535	59.37	73.99	0.00	999.97
Arrivals (# cars)	2,710,535	24.76	27.66	0.00	439.00
Duration (mean hours)	2,655,737	2.52	1.43	0.08	23.99
Panel B: Off-street parking					
Volume commercial (hours)	6,514	1,704.61	1,242.71	0.00	6,181.83
Volume P&R (hours)	2,797	3,863.66	1,564.74	0.00	11,288.00
Panel C: Traffic flow					
Flow (# cars)	12,696	8,863.69	3,786.36	1,994	26,060

Panel B shows that the average daily volume at off-street commercial garages is about 1,700 hours while P&R facilities have slightly over double the daily volume. Panel C indicates that average daily traffic flow is about 9,000 cars per loop-direction.

In Appendix A.5 we present histograms of the key variables and the distribution within the day. Figure A5 shows that on-street parking volume peaks between 10:00 and 15:00 and gradually falls until midnight. Average duration is constant during the day and becomes slightly longer in the evening. Arrivals peak at 09:00 when paid parking starts and is relatively constant until 18:00, after which arrivals begin to fall. There are few exits before 10:00 and peak around 15:00. Figure A8 indicates that off-street parking volume follows a similar hourly distribution and accounts for around one third of total paid (hourly) parking demand. Finally, Figure A9 illustrates that traffic flow peaks at 08:00 and 17:00, but does not fluctuate a great deal over the day.

3. Empirical methods

Our aim is to estimate the causal effect of parking policy on parking demand and traffic flow at the city level. The policy implied higher on-street and off-street prices as the policy induced commercial off-street providers to increase garage prices. The causal effect of the policy on parking demand is estimated using an event study approach, controlling for seasonality, area fixed effects, and time trends. Our key identification assumption is that the timing of the policy is random and that in the absence of the policy, parking demand would have followed a similar trend in the pre and post period, for which we provide convincing graphical evidence (see Section 4.1.1). We first introduce the econometric model, and subsequently discuss how we deal with various endogeneity issues that arise in our setting.

3.1. *On-street parking*

We first aim to examine to what extent the policy impacted on-street parking demand using only temporal variation from the introduction of the parking policy. Hence, our dependent variable of interest is parking demand, which we define as D_{it}, for each parking area i at day t. Parking demand is measured in three ways: volume (i.e. 'total demand'), arrivals (i.e. the 'extensive margin'), and average duration (i.e. the 'intensive margin'). Parking areas $i = 1, ..., n, n+1, ..., N$ refer to n parking meters and $N - n$ visitor permit areas. We consider the following exponential mean function:

$$E[D_{it}] = \exp(\beta T_t + \phi_i + \kappa \mathbf{S}_t + \tau \mathbf{W}_t + L(t)), \tag{1}$$

where $E[D_{it}]$ denotes the expected demand and the policy effect is denoted by $T_t = \{P_t, \log(\bar{p}_t)\}$.[25] P_t is a dummy equal to one after the policy was introduced and $\log(\bar{p}_t)$ equals the natural logarithm of the average price level over the city at time t. Therefore β represents the semi-elasticity of *citywide* parking demand with respect to the policy and citywide average prices, respectively. Standard errors are clustered at the time-invariant level of a parking area.

We have a slightly unbalanced panel as new parking meters have been added over time. Therefore we include parking area fixed effects, ϕ_i, which capture time-invariant

[25]This is estimated using a Poisson Quasi-Maximum likelihood estimator. The exponential mean model has an advantage over log transformations because it allows for zero counts and is insensitive to the level of spatial aggregation. In Table B5 of Appendix B we show that our estimates are conservative compared to the log transformation.

characteristics related to demand, such as the availability of substitutes (i.e. public transport) and the attractiveness of the area (i.e. availability of shops and firms), and parking supply (i.e. parking demand by residents with a permit). Parking demand fluctuates over the year due to time varying demand factors, such as holidays, weekends, and weather conditions. While this is unlikely to affect the consistency of our estimates, we control for temporal fluctuations in demand to improve efficiency by including fixed effects, represented by $\mathbf{S}_t$, for day-of-week, week-of-year, public holidays, school holidays, and a vector of weather controls $\mathbf{W}_t$.[26] Finally, time trends are an important confounding factor as our key identifying assumption relies on the correct specification of the time trend. Trends in parking demand appear to indicate a small, positive, linear time trend (see Figure 3), therefore in our main specification we include a linear time trend, $L(t)$, and perform various sensitivity checks where we include parking area specific trends and include higher order polynomials. Lastly, in spirit of a Regression Discontinuity Design, we also perform the analysis over a shorter time window of one, two and three-months pre-post, to abstract from longer term trends.

3.2. *Off-street parking and overall parking demand*

One issue with equation (1) is that the policy may induce motorists to substitute to off-street garages (including P&R), which would result in an overestimate of the policy effect on traffic. As mentioned in Section 2.2, prices at off-street garages also increased and parking off-street remained more expensive than on-street, however off-street parking became relatively cheaper. Furthermore, the price for P&R garages did not change, so it became more attractive for drivers to park in the *outskirts* of the city and to take public transport *into* the city.

To get an understanding of the overall effect on (hourly) paid parking demand, we first estimate the effect of the policy on commercial off-street and P&R parking demand

[26] Weather controls include average daily temperature, windspeed, and a dummy for whether there was rain or temperatures below 0 °C between 08:00 – 20:00. These controls potentially increase the efficiency of the estimates. They will also improve the consistency as the price increase was not on the first of January, so it is partially correlated to seasonal factors.

separately. This provides an indication of how increasing hourly on-street parking prices affects off-street parking demand. To estimate the overall effect of the parking policy on the entire market for hourly parking in Amsterdam, we include all hourly parking (including on-street parking) into one combined estimate. We only have parking volume data for a sample of garages over a shorter period, so we weight each off-street and P&R garage by the sum of total capacity divided by the sum of capacity for garages we observe.[27] Under the assumption that the policy effect on garages in our sample is representative, the combined regression estimates the overall effect of the parking policy on the entire market for hourly parking in Amsterdam.[28]

Another potential issue with equation (1) is that the policy may induce drivers to park (for free) outside the paid parking areas and commute into the city using public transport. Although we cannot measure this effect, it is likely to be small for three reasons. First, the majority of motorists park for a short period of time (64% park for less than two hours), so the additional time cost of parking outside the paid area frequently exceeds the duration of the activity. Second, it costs around €4.00 for a return trip by public transport from outside the paid parking area to the city centre, so the monetary opportunity costs are substantial. Third, motorists are unlikely to significantly contribute to traffic *within* the paid parking area, which we are mainly interested in.

Finally, if the policy induces more illegal parking our estimates of parking demand may be downwards biased (Yang and Qian, 2017). This can take the form of drivers that leave after the end time stated in the transaction data, or that simply park illegally (without paying). In Amsterdam, this is unlikely to be a large issue as enforcement is strong and technologically advanced.[29]

[27]In effect, commercial garages get a weight of 3.2 and P&R facilities get a weight of 1.6 each.

[28]In Amsterdam, in contrast to many other cities around the world, (free) parking offered by retail companies (e.g. supermarkets and malls) is negligible, so traffic related to shopping is included in hourly parking demand measures.

[29]Illegal parking accounts for about 2% of arrivals (see Section 2).

3.3. *Temporal and spatial variation in on-street prices*

On-street parking price increases varied throughout the city (see Figure A4 in Appendix A), so we expect drivers to react to spatial differences in prices within the city to varying degrees. Therefore our second identification strategy exploits both temporal and spatial variation from changes in parking prices as an internal consistency check to verify that parking price changes are driving our results, rather than other confounding factors. We estimate a similar equation as above:

$$E[D_{it}] = \exp(\beta \log(p_{it}) + \phi_i + \kappa \mathbf{S}_t + \tau \mathbf{W}_t + L(t)), \tag{2}$$

where the policy effect is now captured by $\log(p_{it})$, which represents the natural log of on-street parking prices for parking area i at time t. Here, β represents the elasticity of parking outcomes with respect to parking prices *at a specific parking location*, but does not provide an unbiased estimate of the *citywide* parking price effect, estimated in equation (1), as it captures spatial substitution within the city. For instance, if prices in one area increase, while in a neighbouring area prices stay the same, we might expect drivers to substitute to these areas, in which case demand shifts to another location *within* the city, but overall *citywide* parking and traffic demand remains unchanged. So, prices in neighbouring areas may affect parking demand at location i.

Therefore, we estimate two variants of equation (2). First, parking areas far from boundaries are likely to have less substitution due to long walking distances, so we examine whether excluding parking areas close to the border of parking rate zones affects our estimates. Second, we calculate the difference in parking prices between parking area i and neighbouring areas, $j \neq i$, by calculating the average price of parking meters within a 500 meter buffer. We then include this variable non-linearly into equation (2) to check whether differences in neighbouring prices influence the local estimates.[30]

[30]According to Van der Waerden et al. (2017), the maximum distance car drivers are willing to walk is about 50 m for work, 100 m for weekly shopping, and above 500 m for non-weekly shopping. As we focus on weekdays and Amsterdam has considerably larger spatial differences in parking fees we apply a

We also apply a different empirical strategy where we estimate a variant of equation (2) that exploits spatio-temporal variation from changes in price differences between locations using a two-way fixed effects model. Therefore, we include parking area fixed effects, ϕ_i, *and* day fixed effects, γ_t, leading to the following regression equation:

$$E[D_{it}] = \exp(\beta \log(p_{it}) + \phi_i + \gamma_t), \tag{3}$$

where all time-varying covariates are absorbed by the day fixed effect and β represents a difference-in-differences estimator, where treatment is continuous and is determined by the intensity of relative price changes.[31] Therefore, our alternative identifying assumption is that in the absence of the policy, areas with larger relative price increases should face similar changes in parking demand as compared to areas with smaller changes.

3.4. *Traffic effects*

We focus on paid parking arrivals, which capture a substantial share of total traffic, but far from all. Total traffic also relates to trips by residents using residential parking permits or private parking, by commuters who predominantly use (free) employer parking, by public and shared transport vehicles, such as buses and taxi's, and by delivery vehicles. Therefore, we also examine to what extent the policy impacted traffic outcomes in the city using traffic flow data in order to validate our estimates of parking demand. We define $\log(F_{it})$ as the natural logarithm of total traffic flows (measured by cars per day) for each measurement area i at day t and estimate a model with the same set of controls as in equation (1):

$$\log(F_{it}) = \beta P_t + \phi_i + \kappa \mathbf{S}_t + \tau \mathbf{W}_t + L(t) + \epsilon_{it}, \tag{4}$$

slightly conservative approach with 500 m.

[31] In effect, we compare changes in parking demand for areas that experience, for example, a 50% increase in prices with areas that experience an 80% increase in prices and identify β based on the difference in changes (i.e. 80% − 50% = 30%).

where β represents the semi-elasticity of citywide traffic flow with respect to the policy. The (loop-direction) area fixed effect, ϕ_i, captures time-invariant characteristics of the traffic measurement location, such as the road type, route direction, and proximity to the highway. As in (1), our identification strategy exploits temporal variation in the introduction of the parking policy. Standard errors are clustered at the week-year level.

4. Results

In this section we first demonstrate that the policy had a large, robust, impact on both on-street and off-street parking demand, including the number of arrivals. We then investigate the impact on overall traffic flow and examine the heterogeneity within the day.

4.1. *Parking*

4.1.1. *Identical trends*

In Section 2 we have shown that on-street parking demand has a slight positive trend and a sharp decline after the policy is introduced. In Figure 5 we plot estimates of a weekly policy effect, while including all controls and fixed effects as in our preferred specification in (1).[32] Here, the coefficients are estimated by including year-week dummies and excluding the week prior to the introduction of the policy.[33] There appears to be no significant pre-trends, and the overall impact of the price increase in April 2019 is clear from the immediate and sustained drop in overall parking demand of around 20%. We find effects of around 10% for arrivals and duration (see Figures B1 and B2 in Appendix

[32] For the raw weekly aggregates see Figure B1 in Appendix B.

[33] Specifically, the figure plots the β_τ coefficients from estimating:

$$E[D_{it}] = \exp\left(\sum_{\tau=51}^{156} \beta_\tau P_{t-\tau} + \phi_i + \kappa \mathbf{S}_t + \tau \mathbf{W}_t + L(t)\right), \tag{5}$$

where $P_{t-\tau}$ is a year-week dummy and β_τ is the effect of the policy for each year-week t. Given week fixed effects in this setting, we omit the year-week dummies for 2017 and the missing weeks from 2018; otherwise perfect multicollinearity emerges. The error bars represent the 95% confidence interval for each weekly point estimate, clustered at the parking area level.

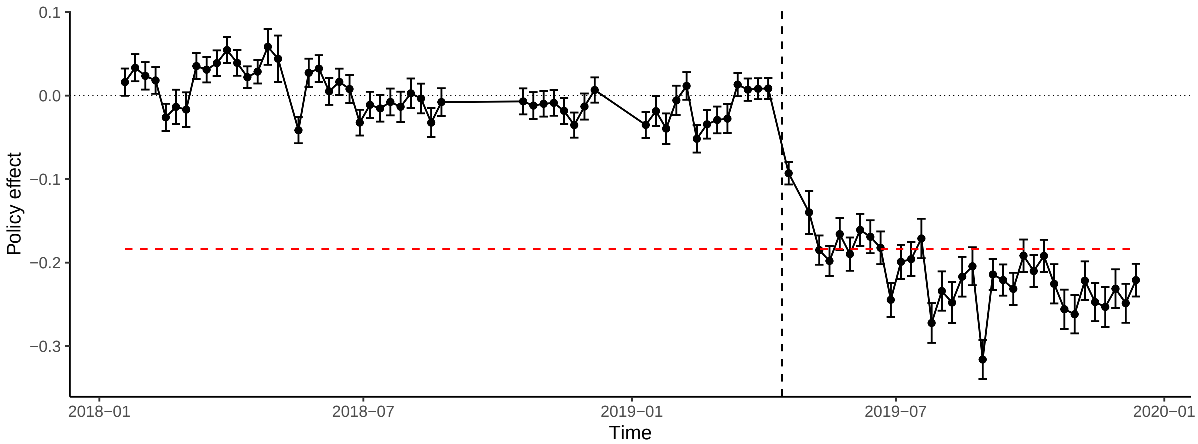


Figure 5: On-street parking volume policy effect after including all controls.

Table 2: Citywide results: On-street parking volume

	Volume				
	(1)	(2)	(3)	(4)	(5)
Policy effect	-0.178***	-0.182***	-0.187***	-0.184***	
	(0.007)	(0.007)	(0.007)	(0.007)	
Price citywide (log)					-0.366***
					(0.014)
Year 2019	0.019***	0.029***	0.026***	-0.032***	-0.032***
	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)
Post week 15	-0.041***	-0.039***			
	(0.004)	(0.003)			
Time trend				0.040***	0.040***
				(0.005)	(0.005)
Area FE		Yes	Yes	Yes	Yes
Weekday FE			Yes	Yes	Yes
Week FE			Yes	Yes	Yes
Public holiday FE			Yes	Yes	Yes
School holiday FE			Yes	Yes	Yes
Observations	2,710,535	2,710,535	2,710,535	2,710,535	2,710,535
Pseudo R^2	0.0057	0.69107	0.71469	0.71491	0.71491

Notes: Estimated using Quasi-ML Poisson regression. Standard errors in parentheses are clustered at the parking area level. Weather controls include the average daily temperature, windspeed, and a dummy for whether there was rain or temperatures below 0 °C between 8-20hr.***, **, * indicate significance at 1%, 5%, and 10%.

A).

4.1.2. *On-street parking*

Table 2 shows the estimation results for parking volume with incremental levels of controls and fixed effects. Column (1) shows that with only a year dummy and a post week 15 dummy, we find a statistically significant effect of 16.3%.[34] Columns (2) and (3) show that controlling for parking area fixed effects and time varying controls (day-of-week, week-of-year, public and school holiday fixed effects, and weather controls) has essentially no effect on the coefficient of interest. In column (4) we replace the year dummy with an annualised daily linear time trend. The coefficient on the time trend indicates that there is a positive, and statistically significant, increase in parking demand by around 4% annually.[35]

Our preferred specification in column (4), which controls for parking area fixed effects, seasonality, and trends, implies that the citywide effect of the parking policy resulted in 16.8% fewer on-street parking hours. In column (5) we replace the post indicator with mean citywide on-street parking prices pre and post policy. The result indicates that the citywide parking demand elasticity with respect to parking prices is equal to -0.37.

In Table 3 we estimate the policy and price effect on arrivals and duration. Both effects remain highly stable to the introduction of controls. In our preferred specification (column (2)), the number of arrivals declines by 9.2%, which corresponds to a citywide price elasticity of -0.19, while average duration declines by 8.7% with a citywide price elasticity of -0.18.[36] It appears that the citywide price elasticity of arrivals is approximately equal to the price elasticity of duration (by construction, the sum is approximately equal to the volume elasticity).[37]

[34] The year dummy captures annual growth in parking demand over time and the post week 15 dummy captures seasonal differences in demand over the year which are correlated to the introduction of the policy, such as summer school holidays. Note, the coefficients from a Poisson model can be interpreted as a percentage change using $(e^{\beta} - 1) \cdot 100\%$.

[35] We divide the daily time trend by 365 so the coefficient can be interpreted as an annual effect.

[36] Note the effect on duration captures that drivers park for a shorter duration and driver sorting, i.e. that drivers with long durations stopped parking.

[37] Arrivals increase by about 4% annually, while duration remained constant, consistent with trends in Figure 3.

Table 3: Citywide results: On-street arrivals and duration

	Arrivals			Duration		
	(1)	(2)	(3)	(4)	(5)	(6)
Policy effect	-0.091***	-0.096***		-0.090***	-0.091***	
	(0.005)	(0.005)		(0.004)	(0.003)	
Price citywide (log)			-0.191***			-0.181***
			(0.010)			(0.007)
Year 2019	0.016***	-0.036***	-0.036***	-0.0007	0.0002	0.0002
	(0.006)	(0.006)	(0.006)	(0.003)	(0.004)	(0.004)
Post week 15	-0.061***			0.025***		
	(0.003)			(0.002)		
Time trend		0.038***	0.038***		0.0010	0.0010
		(0.005)	(0.005)		(0.003)	(0.003)
Area FE		Yes	Yes		Yes	Yes
Weekday FE		Yes	Yes		Yes	Yes
Week FE		Yes	Yes		Yes	Yes
Public holiday FE		Yes	Yes		Yes	Yes
School holiday FE		Yes	Yes		Yes	Yes
Observations	2,710,535	2,710,535	2,710,535	2,655,737	2,655,737	2,655,737
Pseudo R^2	0.00258	0.68113	0.68113	-23.52087	-21.08404	-21.08404

Notes: Estimated using Quasi-ML Poisson regression. Duration is weighted by the average number of arrivals per parking area. Standard errors in parentheses are clustered at the parking area level. Weather controls include the average daily temperature, windspeed, and a dummy for whether there was rain or temperatures below 0 °C between 8-20hr.***, **, * indicate significance at 1%, 5%, and 10%.

4.1.3. *Off-street parking and overall parking demand*

Our estimates for the impact of the parking policy on on-street parking ignores the effect on the off-street parking market. The policy may have increased off-street demand as drivers substitute away to off-street parking or it may have decreased off-street demand because garage prices increased. In Table 4 we estimate the policy impact on parking volume at commercial off-street garages.

One issue is that we have a much shorter period of observation for off-street parking demand (only from July 2018). To examine the importance of having a shorter observed period, in column (1) of Table 4 we first re-estimate the main results in the on-street market for parking volume over the same time period for which we have off-street data. Due to the shorter time period and detailed set of temporal controls, the year dummy and time trend (included in Table 2) cannot be identified, however the effect of interest is

Table 4: Results: offstreet parking.

	Volume				
	On-street (1)	Off-street (2)	Combined (on & off) (3)	P&R (4)	Combined (all) (5)
Policy effect	-0.190***	-0.058***	-0.173***	0.049**	-0.148***
	(0.003)	(0.014)	(0.003)	(0.019)	(0.003)
Area FE	Yes	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes
Public holiday FE	Yes	Yes	Yes	Yes	Yes
School holiday FE	Yes	Yes	Yes	Yes	Yes
Observations	1,434,729	6,514	1,441,243	2,797	1,444,040
Pseudo R^2	0.73038	0.72621	0.82366	0.47118	0.87003

Notes: Subsample of on-street parking data starting on 2018-07-04. Garages in column (3) and (5) are weighted by the inverse proportion of garage capacity in the sample as compared to the entire off-street parking market. In effect, commercial garages get a weight of 3.2 and P&R facilities get a weight of 1.6 each. Standard errors in parentheses are clustered at the year-week level. Weather controls include the average daily temperature, windspeed, and a dummy for whether there was rain or temperatures below 0 °C between 8-20hr.***, **, * indicate significance at 1%, 5%, and 10%.

essentially identical to our main result. This implies that controlling for this variable is not essential and this specification can be used to estimate the effect on off-street parking.

In column (2) we estimate the impact on commercial off-street garage demand and find a negative and statistically significant effect of around 5%. In column (3) we estimate the effect on on-street and off-street demand combined. The estimate indicates that the combined parking demand declined by 15.9% due to the policy. In column (4) we find a positive and statistically significant effect of around 5% on P&R facilities. This makes sense as P&R prices did not change and therefore these garages became more attractive. As P&R arrivals are small compared to on-street parking arrivals (2.35% arrivals), these findings have little impact on overall traffic flow within the city.[38] In column (5) we estimate the policy effect on the demand for on-street, off-street, and P&R combined. The estimated effect, which represents the overall citywide impact of the parking policy

[38] Applying the estimate from column (4) suggests that overall arrivals increased by around 48 cars due to P&R, or 0.61% of the reduction in total daily on-street parking. In addition, P&R garages are all outside the main city limits, so for traffic flow *within* the city, it is plausible that this effect is negligible.

on the entire hourly parking market is 14%.[39] This implies that the policy did not result in a net increase in demand for off-street parking, but even a decrease because off-street garages responded by raising prices, albeit to a lesser degree than on-street.

We do not have information on off-street parking arrivals, but our estimates for volume suggest that the policy effect on on-street arrivals is likely an underestimate of the total policy effect on traffic flow. Under the assumption that the reduction in off-street arrivals accounts for half of the reduction in off-street parking volume, as is the case with on-street parking (see Table 3), these results indicate that off-street arrivals declined by about 2.5%, or about a quarter of the percentage decline in on-street parking (and about one eighth in absolute value). As this estimate is based on an assumption which seems plausible, but we cannot test, later on we will also make the more conservative assumption that the reduction in on-street volume is entirely due to a reduction in duration, so there was no net effect on the on-street arrivals.

4.1.4. *Temporal and spatial variation*

On-street parking price increases varied throughout the city between 0% and 100% (see Figure A4 in Appendix A). We therefore expect drivers to react to spatial differences in prices within the city to varying degrees, and areas where price increases are higher should face larger reductions in demand as compared to areas where price increases are lower.

In columns (1), (3), and (5) of Table 5, we estimate equation (2).[40] The results indicate that the average *local* price elasticities are somewhat higher than the citywide effects in Table 3, and are equal to -0.43, -0.21, and -0.21, for on-street volume, arrivals, and duration, respectively. In columns (2), (4), and (6) we estimate equation (3), therefore time-varying controls are essentially absorbed by the day fixed effects and the regression

[39] In Table B7 of Appendix B, we further examine the sensitivity of off-street parking demand to other specifications. We show that the effects are similar when we focus only on parking garages located in the city centre, control for changes in short-term capacity throughout the week, and include an extended period until February 2020.

[40] In these regressions, we exploit both temporal *and* spatial variation in on-street parking prices, so we can interpret the price coefficients as on-street parking elasticities at the local level.

Table 5: Local on-street parking demand elasticities

	Volume		Arrivals		Duration	
	(1)	(2)	(3)	(4)	(5)	(6)
Price (log)	-0.429***	-0.431***	-0.208***	-0.195***	-0.208***	-0.205***
	(0.019)	(0.035)	(0.015)	(0.028)	(0.008)	(0.014)
Area FE	Yes	Yes	Yes	Yes	Yes	Yes
Weekday FE	Yes		Yes		Yes	
Week FE	Yes		Yes		Yes	
Public holiday FE	Yes		Yes		Yes	
School holiday FE	Yes		Yes		Yes	
Date FE		Yes		Yes		Yes
Observations	2,710,535	2,710,535	2,710,535	2,710,535	2,655,737	2,655,737
Pseudo R^2	0.71649	0.7175	0.68148	0.68242	-21.07682	-21.06902

Notes: Estimated using Quasi-ML Poisson regression. Duration is weighted by the average number of arrivals in a parking area. Standard errors in parentheses are clustered at the parking area level. Weather controls include the average daily temperature, windspeed, and a dummy for whether there was rain or temperatures below 0 °C between 8-20hr.***, **, * indicate significance at 1%, 5%, and 10%.

exploits spatio-temporal variation in the difference in changes in parking prices between areas. The elasticities are of a similar magnitude and still statistically significant at the 1% level, despite larger standard errors.

These local estimates may be biased downwards (overestimate) if prices in neighbouring districts are cheaper as this may cause drivers to substitute over space. Therefore, in Table B1 in Appendix B we show that controlling for differences in on-street parking prices within 500 m and excluding areas within 500 m of a price boundary has little effect on the results, suggesting that substitution over short distances is relatively minor. This is not surprising as prices decline gradually with distance to the city centre, also after the increase in prices. Therefore changes in price discontinuities over space are small.

4.1.5. *Robustness checks*

Our preferred specification of the citywide effect indicates that on-street parking arrivals decline by around 9% due to the policy. Furthermore, we find that it is unlikely that many drivers substitute to off-street parking and we find similar policy effects locally. In this section we perform a range of additional robustness checks. Tables and additional discussion of the results are available in Appendix B.

Our key identification assumption relies on the correct specification of the time trend. Therefore, in Table B2 we consider how the specification of the time trend impacts the estimated policy effect on arrivals. Some areas may have become more attractive for parking over time, so we interact the time trend with parking price regimes, but find essentially identical effects. It may also be the case that time trends are non-linear, so we allow for a flexible time trend by adding a third-order polynomial term and find that the policy effect becomes somewhat smaller.[41] To abstract from long-run trends we also estimate the policy effect using a shorter time window around the introduction in week 16, 2019. We gradually make the time interval larger from one month pre-post to two and then three months pre-post. The results suggest that the short-run effects are similar in magnitude to the estimated policy effect with the linear time trend, which may indicate that the non-linear time trend is absorbing part of the policy effect of interest. Therefore, in our main estimates and in further analysis, we apply a linear time trend.

In the main analysis we exclude the Northern part of Amsterdam because they experienced an expansion in the parking area in July, 2018. In Table B3, we include the Northern part of Amsterdam and a specific time trend for new areas and find essentially identical results. Furthermore, prices are the highest in the city centre and fall with distance to the periphery. Therefore, we also estimate the policy effect separately for central and non-central parking zones and find that the policy effect and price elasticity of arrivals in central zones is around 50% larger than the effect outside these areas.

Motorists may be substituting to other on-street options. This is relevant because other parking policies may have (un)intentional consequences. In Table B4 we examine to what extent drivers substituted to discounted €0.10 shopping areas (with time limits of either one or three hours) and visitor permits as a result of the policy. We show that there was a significant increase in arrivals of around 7% at inner city shopping areas (which

[41]The second-order term on the time trend is negative and significant, which is not intuitive, as there is no convincing explanation for why parking demand should fall in a time of strong economic growth. This suggests that there is 'overfitting', which makes this specification less convincing.

have one hour time restrictions) while there was no increase in demand in the peripheral industrial parking areas (which have three hour time limits). This result is interesting as shopping areas generate substantially more traffic per parking space as they have a higher turnover.[42] Finally, we show that visitor permit demand increased substantially as a result of the policy by around 65%, which indicates that residents make significantly more use of these discounts due to the policy, although it is still a small share of total arrivals (1.8% after the policy).

Finally, standard errors may be too small if parking demand is serially positively correlated (Bertrand et al., 2004). To address this issue, we cluster our standard errors at the time-invariant level of a parking area. In addition, we run a robustness check where we focus only on time-series variation around the policy introduction and aggregate our data into six periods, pre and post week 15 in each year (therefore, for each parking area, we have only six observations). Table B6 presents the results. The results are essentially identical to our main estimates and the standard errors only slightly increase.

4.2. *Traffic*

4.2.1. *Implied traffic effects using parking estimates*

Our main estimate indicates that on-street arrivals decline by around 9%, whereas off-street arrivals decrease by around 2.5%. Given 84,600 daily on-street arrivals pre-policy, the arrivals effect implies there are around 7,800 fewer cars travelling within the city due to the policy. Furthermore, given the off-street estimate of 2.5% and around 42,000 daily off-street arrivals, this implies an additional reduction of up to 1,200 arrivals, or an overall reduction in flow of around 9,000 cars. Travel surveys indicate that there are approximately 640,000 daily (one-way) car trips within the paid parking area of Amsterdam, excluding tourists. Under the assumption that trips that end in on-street parking travel a similar distance within the city, this implies around 2.4% – 2.8% less

[42] It follows that the policy effect would have been much larger in the absence of these discounted shopping areas, and would be much smaller in the hypothetical case that Amsterdam would have much more discounted shopping areas.

Table 6: Main results: Traffic flow.

	Flow (log)				
	(1)	(2)	(3)	(4)	(5)
Policy effect	-0.030***	-0.021***	-0.021***	-0.028***	
	(0.007)	(0.006)	(0.006)	(0.005)	
Price citywide (log)					-0.055***
					(0.011)
Post week 15	0.005				
	(0.006)				
Year 2019	0.036***	0.030***			
	(0.006)	(0.006)			
Time trend			0.031***		
			(0.006)		
Loop-direction FE	Yes	Yes	Yes	Yes	Yes
Weekday FE		Yes	Yes	Yes	Yes
Week FE		Yes	Yes	Yes	Yes
Public holiday FE		Yes	Yes	Yes	Yes
School holiday FE		Yes	Yes	Yes	Yes
Observations	12,696	12,696	12,696	12,696	12,696
R^2	0.93704	0.96235	0.96235	0.96937	0.96937

Notes: Standard errors in parentheses are clustered at the week-loop level. Weather controls include the average daily temperature, windspeed, and a dummy for whether there was rain or temperatures below 0 °C between 8-20hr.***, **, * indicate significance at 1%, 5%, and 10%.

traffic flow as a result of the policy.[43]

4.2.2. *Traffic effects based on loop data*

In Table 6 we directly examine the effect on traffic flow by estimating equation (4). In column (1) we include a year dummy, a post week 15 dummy, and loop-direction fixed effects, which are important because we have an unbalanced panel and traffic flow varies by location. We find that the policy results in around 3.0% less traffic flow. In columns (2) and (3), when we control for additional time-varying controls and a linear trend, the effect becomes smaller and equal to around 2.1%. Finally, in column (4) we interact the time trend with each loop-direction fixed effect to capture area specific trends and find that the policy reduces traffic by around 2.8%.

Consequently, this implies that the citywide effect of the parking policy results in

[43] For every return trip, we assume one parking action. Survey data on trips within Amsterdam support this assumption with few trips including more than one destination. Therefore, $\frac{9{,}000}{0.5 \times 640{,}000} = 2.8\%$, of which 2.4% corresponds to reductions in on-street parking.

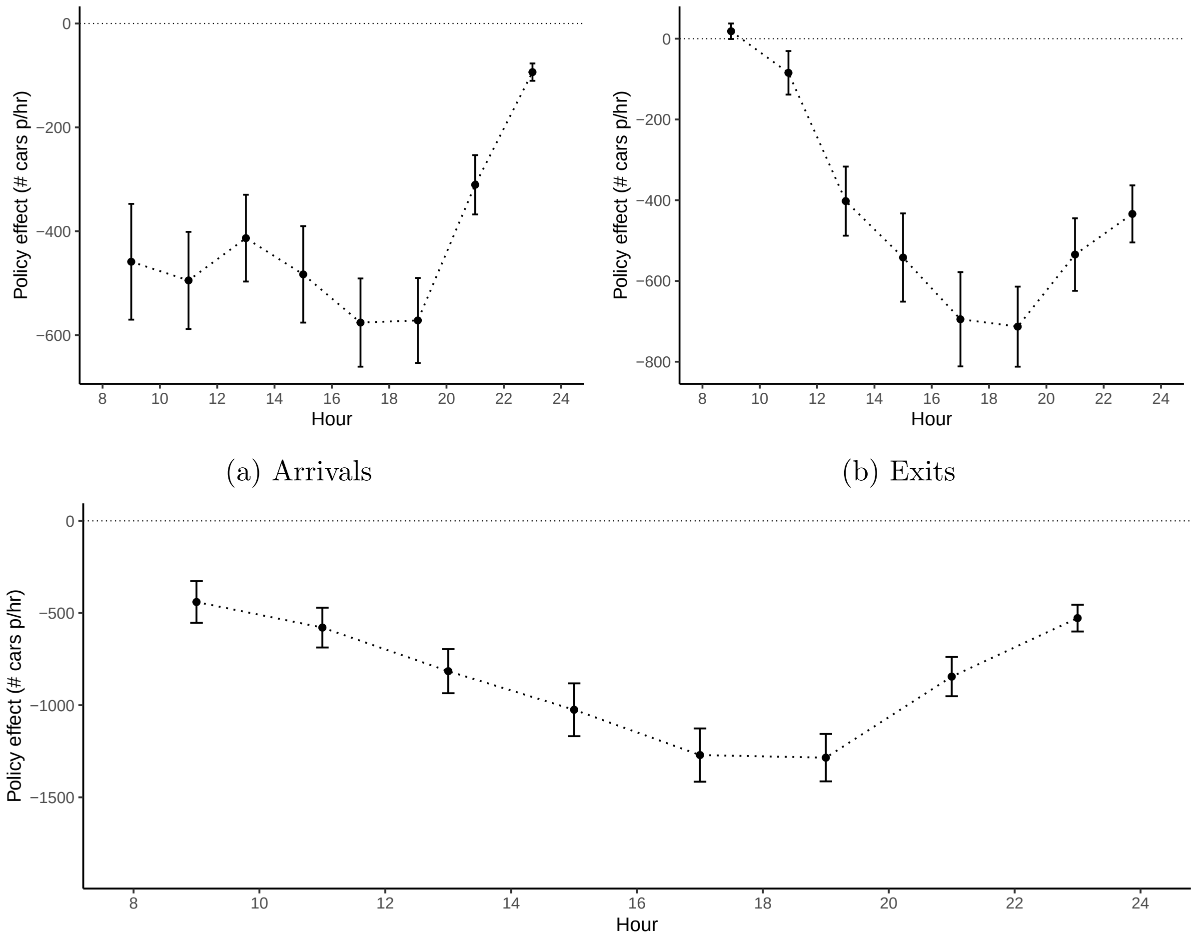
around 2% – 3% less traffic flow. The estimated effect is in line with the estimates implied by the impact of the parking policy on parking demand. In column (5) we replace the policy dummy with citywide on-street parking prices pre and post policy. This implies that the citywide traffic elasticity with respect to prices, is around -0.06, or a quarter of the size of the arrivals elasticity in Table 3, consistent with the share of (hourly) paid on-street parking in the total number of daily trips.

4.2.3. *Implied traffic effects within the day using parking estimates*

Up until now, we have focused on the effect of the policy on arrivals and traffic flow at the daily level. However, when used as a second-best congestion policy, it is more efficient when the policy reduces traffic during peak hours of the day. Generally, it is believed that hourly parking charges only reduce congestion by reducing the total number of trips, as fees do not differentiate by how much a given driver adds to congestion (Small and Verhoef, 2007). Therefore, in this section we examine how the policy effects vary *within the day*. We emphasise here that we also focus on exits, as within the day, the effects on arrivals and exits differ from each other.

Figure 6 plots the effect of the policy on the number of cars arriving or exiting within the day. Here we estimate the level effect because it is the absolute number of cars during peak hours that matters for congestion. Panel (a) indicates that the policy effect on arrivals is relatively uniform up to 20:00 and becomes becomes smaller late in the evening as there are few arrivals during this time. Panel (b) shows that the policy effect on exits is largest in the evening peak hours between 16:00 – 20:00. In panel (c), we provide an estimate of the citywide reduction in traffic flow generated by on-street parking within the day. We find that the largest reductions in traffic are in the afternoon peak hours between 16:00 – 20:00 (a reduction of around 1,300 cars), which is more than double the reduction between 08:00 – 12:00 (around 500 cars).

This traffic effect is driven by two key factors. First, the traffic generated by on-street parking varies within the day, with the sum of arrivals and exits peaking between 14:00 –



(a) Arrivals

(b) Exits

(c) Total effect on daily traffic

Figure 6: Policy effect based on parking data within the day.

16:00 (see Figure A7 in Appendix A). Second, the behavioural responses to prices differ within the day, with larger arrival and exit price elasticities in the evening (see Figure B6 in Appendix B). This is in line with trip purpose data from travel diaries which indicate that most activities involving parking are not work related (see Figure A10 in Appendix A).

4.2.4. *Traffic effects within the day using loop data*

In Figure 7 we show the policy effects and the implied total effect on citywide traffic within the day. This is calculated by multiplying the estimated hourly effects in percentages by the mean number of trips for each hourly interval (see Figure B7 in Appendix B).[44]

[44]The mean number of trips per hour are estimated based on the proportion of traffic over the day (from the loop data) and the total number of car trips (from travel survey data), where the number of

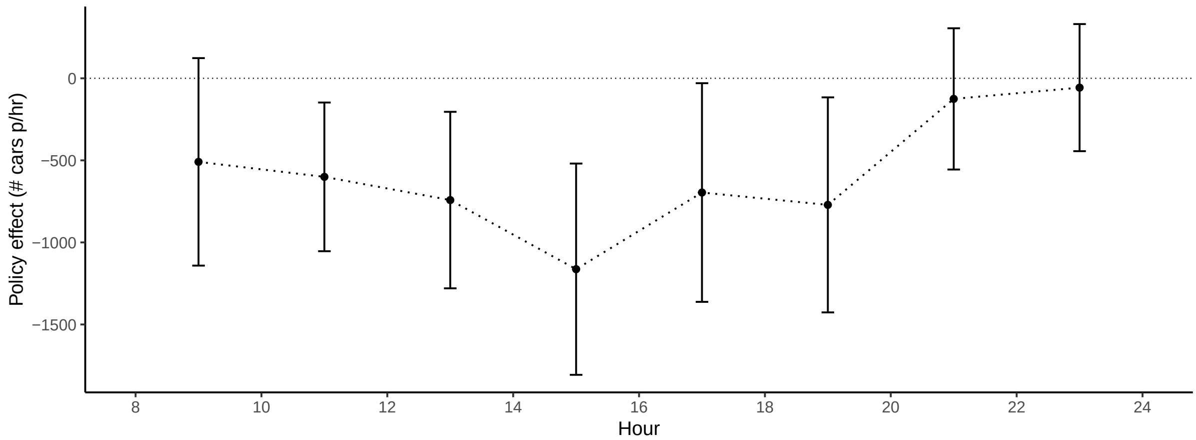


Figure 7: Policy effect based on traffic flow data within the day.

Although the standard errors are larger, we find a similar patten and similar order of magnitude to the on-street parking estimates from Figure 6.

4.3. *Counterfactuals*

4.3.1. *Welfare implications*

A higher on-street parking price may generate societal benefits, because it reduces cruising and travel externalities from congestion, pollution, and accidents, while also freeing up parking space for other uses. Furthermore, it generates revenues that can be used to finance public goods, such as parks and pedestrian walkways. It also increases the producer surplus of commercial parking operators. Meanwhile, it will also impose societal costs in the form of a lower consumer surplus due to higher on-street and off-street prices. In this section we aim to provide a back-of-the-envelope welfare calculation where we distinguish between the implications to residents, non-residents, and commercial operators (see Section B.7 in Appendix B for details).

In order to get a benchmark estimate we make several simplifying assumptions. First, we assume that, conditional on the supply of off-street parking and the provision of residential permits, on-street parking prices *after the policy* are at the socially optimal

trips T for each hour h equals: $T_h = \frac{MeanFlow_h}{\sum_{i=8}^{24} MeanFlow_i} \times T_{day}$.

level in the land market (i.e the price of parking is equal to the marginal benefit of land after the policy). This is potentially a restrictive assumption, which we relax in Appendix B Section B.7.6, where we assume that on street prices before the policy are at the socially optimal level in the land market. We believe that our benchmark assumption is plausible in the light that hourly on-street parking prices were lower than hourly off-street prices *and* on-street prices had remained constant for the last 10 years, despite strong increases in prices of substitutes (housing, commercial land, and off-street parking), as well as increases in national income and car ownership. Second, we assume that prices for commercial providers are above marginal costs. This makes sense because there is no free entry into the off-street market in Amsterdam and therefore off-street parking supply is essentially fixed.

We first calculate the daily welfare effects, excluding travel externalities. Daily parking demand is approximately equal to 213,000 hours on-street and 106,000 hours off-street before the policy. Considering that the policy caused parking demand to decline by 17% on-street (36,000 hours) and 5% off-street (5,000 hours), the net gain to society is approximately €27,000 per day.[45]

This benefit however excludes travel externalities in the form of congestion, pollution, and accidents. Our estimates suggest that the policy caused the number of car trips to decline by about 2.4% (15,600 trips). Taking into account that the average trip distance *within* Amsterdam is around 7 km, this implies that overall VKT in the city declined by about 109,000 km.[46] The passenger vehicle externality of petrol cars (the sum of congestion, pollution, and accident externality) is thought to be about €0.12 per km in the Netherlands (Schroten et al., 2014), slightly above the (implicit) marginal tax on fuel of €0.09 per km, therefore the societal benefits are approximately €3,000. This may be

[45]This is equivalent to the rule of half ($0.5 \times dP \times dQ$). In the on-street market, supply can be replaced by other uses, therefore the policy leads to welfare gains, whereas in the off-street market, parking becomes idle which is a welfare loss (maximum capacity off-street during the day is generally below 80%). Hence reductions in demand on-street lead to a welfare gain (of €30,000) but changes off-street results in a small welfare loss (of €3,000).

[46]This is potentially a gross underestimate of the total distance reduction as non-residents travel much longer distances, on average 36 km, outside of Amsterdam.

an underestimate because pollution externalities are larger in urban areas and we exclude VKT outside of Amsterdam. Nevertheless, pollution only accounts for a small share of marginal external costs and motorists may substitute trips to other locations, so these effects may be small.

The above benefit also excludes cruising for parking. Arnott et al. (2015) find that in a static parking market where on-street and off-street parking are perfect substitutes, the number of cars cruising for parking is proportional to on-street arrivals and the fee differential between on-street and off-street parking. This differential was reduced by €0.40 per hour. Given an average parking duration of 2.4 hours, this implies that the policy reduced the willingness to pay to avoid on-street parking search by up to €0.96. Taking the average VOT for car travel in the Netherlands of around €15.40, this roughly translates to travel time savings of around 4 minutes. Given 77,000 daily arrivals after the policy, the expected increase in welfare is maximally €74,000 per day. This may be a large overestimate because (a) cruising only occurs at peak hours, (b) we ignore price differences between discounted shopping areas, and (c) motorists may prefer to park off-street for reasons other than avoiding private cruising costs, and (d) some garages are cheaper for day parking. Therefore we assume that the private cruising gains are around one quarter of the size (€18,000 per day), but acknowledge that this estimate has extreme uncertainty.

Adding up the gains in the parking market (€27,000), the reduction in traffic externalities (€3,000), and the gains from less cruising (€18,000) implies an overall daily societal gain of around €48,000 due to the price increase. This gain however masks substantial heterogeneity between residents, non-residents, and commercial operators. The total daily gains to residents are approximately €195,000, commercial profits increase by around €52,000 (of which one third, €17,000, goes overseas), and non-residents lose around €196,000 (see Appendix B for calculations). Given that there are around 850,000 inhabitants in Amsterdam, this suggests that the *annual* gains are around €84 per inhabitant. These benefits are largely in the form of increased government revenues (35%)

and the hypothetical value of reclaimed land previously designated to on-street parking.

This conclusion is based on the assumption that on-street parking prices after the policy are at the socially optimal level in the land market. The alternative assumption is that these prices before the policy are at the socially optimal price in the land market (i.e. the price of parking is equal to the marginal benefit of land before the policy), which we believe provides a lower bound of the welfare effect, the overall welfare effects becomes slightly negative (see Section B.7.6 of Appendix B). Consequently, it is reasonable to believe that the welfare effect of the policy is positive.

4.3.2. *Automated vehicles*

In the near future, automated vehicles (AVs) will not require parking close to their destination. This has implications for parking demand in cities because AVs will either not park at all or will be able to park outside the city where parking is cheaper (Gelauff et al., 2019; Millard-Ball, 2019). We make several (heroic) assumptions on how AVs might operate and apply our estimates to gauge the order of magnitude impacts of AVs on traffic flow in the city centre and in the periphery of Amsterdam in a partial equilibrium setting (see Section B.8 in Appendix B for more details).

We first consider a (private ownership) AV scenario where all motorists, currently using (hourly) paid on-street parking, park outside the city and pay cheaper rates. Given that the proportion of traffic generated by on-street parking is around one quarter, our estimates for the price elasticity of arrivals and duration imply that traffic flow is expected to increase by about 27% − 33%, of which 2 and 8 percentage points are generated by new car trips due to the lower parking prices in the periphery and in the city centre, respectively, but the majority (25 percentage points) is generated by empty AVs travelling to and from parking facilities outside the city.

In the alternative (shared) AV scenario, AVs do not drive to the periphery but parking prices become essentially zero. Our estimates then imply that duration increases by 2.9 hours in the city centre and 2.6 hours in the periphery, while traffic increases by around

16% and 12%, respectively.

This counterfactual application assumes that there will be *no policy intervention.* This is unlikely as parking is heavily regulated in most cities and AVs are likely to have large effects on traffic and government revenues, so local governments may respond by implementing road pricing or other vehicle restrictions.

5. Conclusion

In this paper, we provide novel evidence on the effect of parking policy on citywide parking demand and traffic flow. We use temporal variation from a large citywide increase in average hourly on-street parking prices of 66%. Our findings show that overall on-street parking demand fell by around 17%, while the combined demand for the entire hourly parking market (on-street and off-street) declined by 14%. We do not find that the reduction in on-street parking is offset by an increase in demand off-street.

Our results also show that on-street parking arrivals declined by 9% which corresponds to a citywide parking price elasticity of -0.19. Taking into account that about one quarter of car trips in Amsterdam uses paid on-street parking, this implies an effect on citywide traffic flow of around 2.4%. This result is confirmed using traffic road loop data, where we find a subsequent reduction in traffic flows of around 2% – 3%, and larger effects in the evening. A back-of-the-envelope calculation suggests an increase in welfare, mainly enjoyed by local residents.

Our findings also have implications for policies that aim to reduce citywide traffic. Generally, it is believed that parking charges only reduce congestion by reducing the total number of trips, as fees do not differentiate by how much a given driver adds to congestion. Our results show that the parking policy had larger effects during evening peak hours because at these times, parking demand is more elastic and there is more traffic generated by on-street arrivals and exits. Theoretical models can better reflect reality by accounting for this heterogeneity.

Our study also has implications for policies aiming to replace on-street parking spaces with other uses. Even before COVID-19 forced many cafes, bars, and restaurants to spread out onto side-walks and parking spaces, cities around the world have been looking for new ways to improve the urban environment. Higher parking prices can be used as a policy tool to raise government revenues and convert on-street parking to other uses, such as parks, cycling lanes, and restaurants, without causing additional externalities from cruising or building new off-street capacity.

Further research should aim to study the long-term impacts of parking policy and examine the wider implications on modal choice and the decision to travel.

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Appendix

A. Additional descriptives

A.1. *Detailed policy context*

Parking policy in Amsterdam is also described in detail in a range of studies such as Van Ommeren et al. (2011) and De Vos and Van Ommeren (2018). The total on-street parking supply in Amsterdam is 260,000 (including residential areas in the periphery), 163,000 of these are located in paid parking areas. Almost all on-street parking is shared between residents using permits and all other paid (hourly) parking. Minor exceptions to shared use include disabled parking spots, reserved for residents, and discounted shopping streets which have time limits of one hour and can not be used with a residential permit.

During the day, the majority of on-street parking demand comes from residents using cheap residential permits, with the remaining share available for hourly parking, which is substantially more expensive. For example, in the city centre, permit fees cost around €1.50 per day (€535 per year), while an identical on-street spot currently costs non-residents €80 per day. According to the transport department at the municipality, approximately 80% of on-street parking is occupied by residential permit holders during the day however, this is likely to vary by location in the city.

Around one-third of visitors parking in Amsterdam use off-street commercial parking garages, which are mainly provided by private operators and charge approximately the same price as nearby on-street parking. Cruising for parking is limited compared to other large cities because of high on-street prices however, relatively higher (pre-policy) off-street prices in the inner city may indicate the presence of cruising. Furthermore, cruising is likely to occur in the evening as residents come home from work and in a limited number of discounted shopping streets and industrial zones (€0.10), where one and three-hour parking duration restrictions apply, respectively.

Visitor permits allow residents to obtain a 50% – 75% discount on the hourly on-street fares to their visitors. The permit is limited to a maximum number of hours per residential household and can only be used within the close vicinity of the residence (valid within the residential parking zone). After the policy change, this limit increased from 10 or 30 hours to 40 hours per month.

Parkers always have to provide their license plate number when a transaction is initiated, tying the car identifier to a specific parking location. Vehicles from an enforcement entity, fitted with cameras, sweep the number plates of all vehicles parking on-street and send the information to a centralised system. Licence plates are then cross-checked against a database of paid (hourly) transactions and residential permits. Local authorities are then automatically alerted when an infraction is detected and fines are sent to the address of the car owner (Egis Group, 2019). Parking fines increased by €15 in May 2019 from €47.60 to €62.60 in 2019. In 2017, there were 780,000 parking fines in the city, which represents about 2% of the annual number of parking arrivals and adds up to around €40 million in fines (Parool, 2019).

A.2. *Substitutes to paid on-street parking*

As discussed in the main text, the key issue is that motorists may switch to off-street parking. In Amsterdam, motorists parking without a residential permit may also switch to other on-street parking alternatives, namely discounted shopping zones (€0.10) designated for shopping and discounted visitor permits available to residents. In our analysis, we explicitly control for these factors by including these substitutes in our main regressions. Here we discuss these types of parking in more detail and the implications for our results.

Figure A1 illustrates the areas with time restrictions and a fixed rate of €0.10, designated as shopping and industrial activities. Although these areas are small, the proportion of arrivals is not negligible (13.5% of all arrivals). Parking in these areas is particularly attractive for drivers parking up to one hour (26.88% of arrivals pre policy). So, we include these areas when estimating equation (1) and in a sensitivity check, ex-

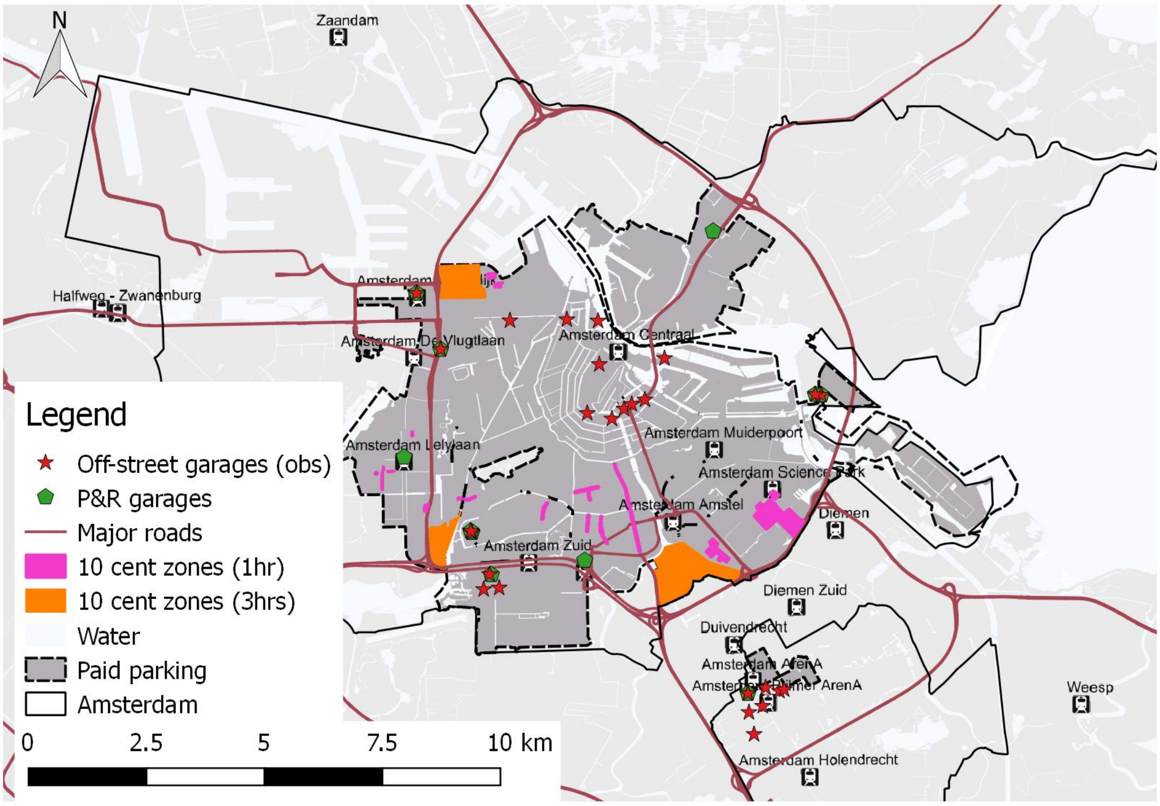


Figure A1: Parking infrastructure in Amsterdam (detailed).

amine to what extent separately estimating the effect on shopping areas affects our main results.

Residents have access to visitor permits that offer a 50% – 75% discount on the hourly paid on-street rates. This option becomes more attractive after the price increase and some car drivers that used to pay hourly rates may start using these visitor permits, so we also include parking demand at the residential parking zone level when estimating equation (1) and examine to what extent excluding these groups affects our main results.

A.3. *Detailed data description*

A.3.1. *Aggregating parking data*

In this section we describe in more detail how we aggregate the transaction data to create the parking demand variables in our analysis. We define:

- t_1 and t_2: as the interval start and end time,

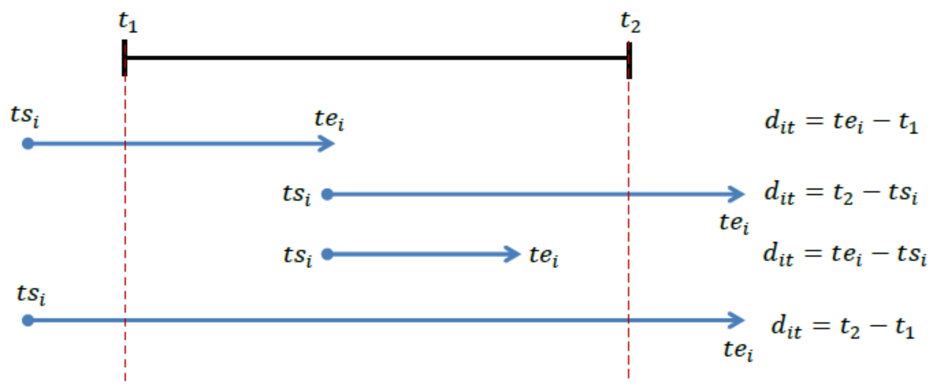


Figure A2: Aggregating transactions data to parking demand.

- ts_i and te_i: as the transaction i start and end time.

Figure A2 illustrates the four distinct cases that a transaction can fall into and the approach to aggregate the data into daily (or hourly) data. The time window is represented by t_1 and t_2, which is the start and end of the day in our main application, so $t_1 = 00{:}00$ and $t_2 = 11{:}59$. In the first case from the top, the transaction starts *before* and ends *within* the time interval. In this case, the car is parked for $d_{it} = te_i - t_1$ hours during the time interval and corresponds to one exit. In the second case from the top, the transaction starts *within* and ends *after* the time interval. In this case, the car is parked for $d_{it} = t_2 - ts_i$ hours and corresponds to one arrival. In the third case from the top, the transaction starts *within* and ends *within* the time interval. In this case, the car is parked for $d_{it} = te_i - ts_i$ hours and corresponds to one arrival and one exit. In the last case, the transaction starts *before* and ends *after* the time interval. In this case, the car is parked for $d_{it} = t_2 - t_1$ hours and does *not* correspond to an arrival or an exit.

Therefore, we can calculate the total number of hours parked (volume), arrivals, and the mean duration per day (or any other time interval) and area as:

- Volume (parking hours): $V_t = \sum_{i=1}^{N} d_{it}$,
- Arrivals (number of cars): $A_t = \sum_{i=1}^{N} [t_1 \leq ts_i < t_2]$,
- Mean duration (of arrivals): $D_t = (\sum_{i=1}^{N} [t_1 \leq ts_i < t_2] D_i)/A_t$.

A.3.2. *Holidays definition*

In the Netherlands, there are five school holiday periods, of which two (Christmas and May) are the same for the entire country and three (spring holiday in February-March, summer holiday in July-Aug, and autumn holiday in October) are staggered by region and therefore start and end at different times. There are three school regions (north, middle, and south), of which Amsterdam is part of the Northern region, so we include school holidays from this region. In our analysis, we include separate fixed effects for each type of public and school holiday, and distinguish between whether the holiday falls on a weekday or weekend (in essence, we interact a weekend dummy with each holiday). Therefore we add a total of eight dummies for school holidays (week or weekend) and seven dummies for public holidays.

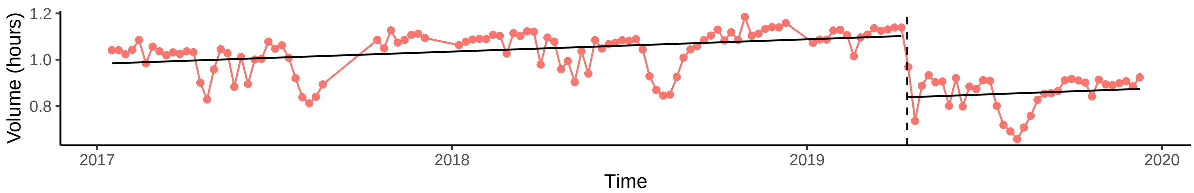
A.3.3. *Off-street parking data*

The majority of municipality-owned garages are located around the Bijlmer arena to the South-East of the central part of the city. Commercial and public garages located in the close vicinity charge similar prices.

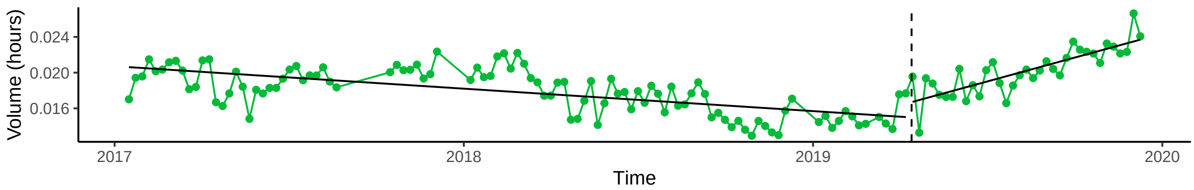
P&R tickets are valid for the entire day, under the condition that drivers can show a validated travel card indicating that they used public transport to travel to and from the city centre on the day. There are three tariff types for P&R facilities. Peak hours (8.89% arrivals) which cost €10 per day, off-peak hours (63.18% arrivals) and weekend (27.94% arrivals) which cost €1 per day.

A.4. *Trends*

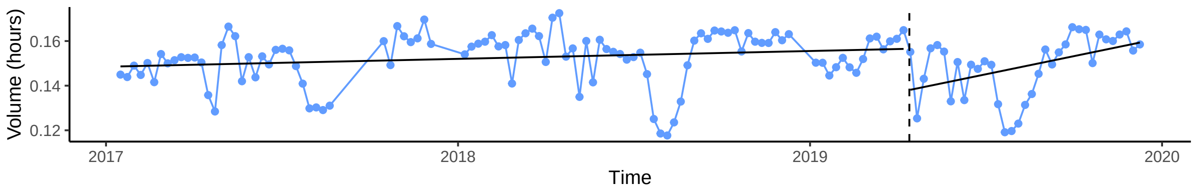
Figure A3 indicates that this relation holds for (hourly) paid parking and discounted shopping areas (which account for 98.51% of arrivals), while parking with a visitor permit essentially has no growth in demand up until the policy announcement at the end of October 2018, after which the trend appears to become positive. This is likely to be associated to the information relating to the upcoming policy adjustment and news



(a) Paid (regular) parking



(b) Visitor permit



(c) Shopping areas

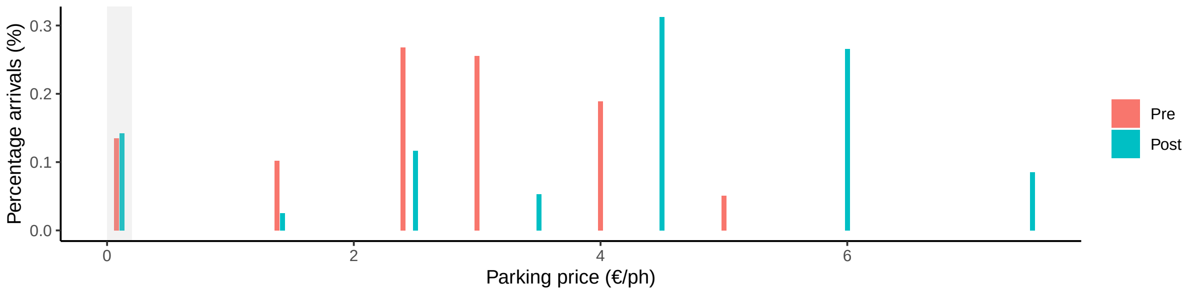
Figure A3: Sum of weekly on-street parking volume (millions of hours) by type.

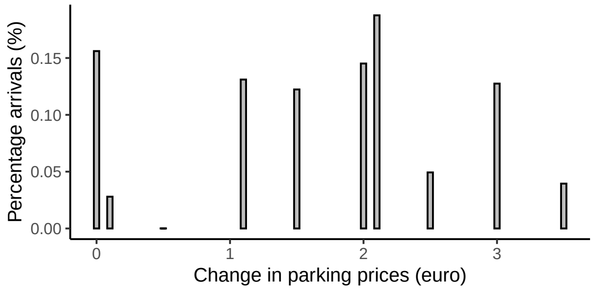
articles about the availability of permits. Data from the municipality also indicates a substantial growth in the request for these permits around this time.

A.5. *Distribution of key variables*

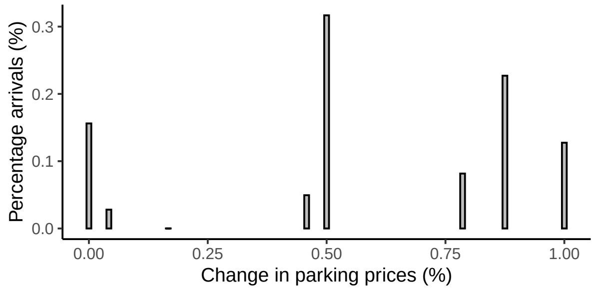
A.5.1. *On-street parking prices*

Figure A4 illustrates the effect of the parking policy on the distribution of parking prices, weighted by the number of arrivals. As can be seen, the policy results in a large shift in prices at all levels, except for discounted parking areas which remain unchanged. Panels (a) and (b) further illustrate the large absolute and relative change in parking prices. Panels (c) and (d) illustrate the absolute and relative change in prices throughout the city. It indicates that price changes varied substantially over space, but not uniformly with distance from the city centre. This is primarily because the delineation of some parking zones changed as a result of the policy.

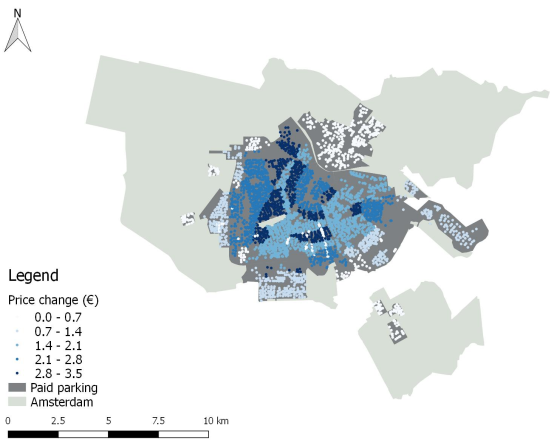




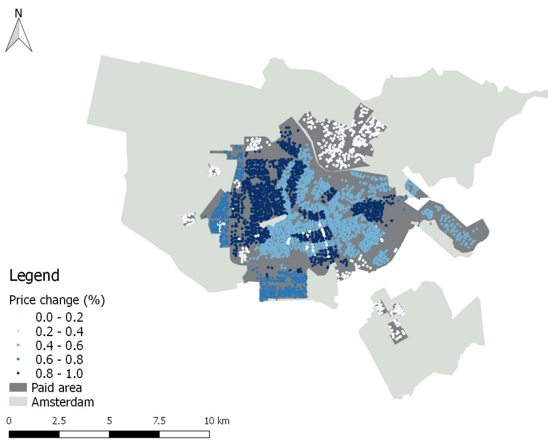
(a) Absolute change (€)



(b) Relative change (%)



(c) Absolute change (€)

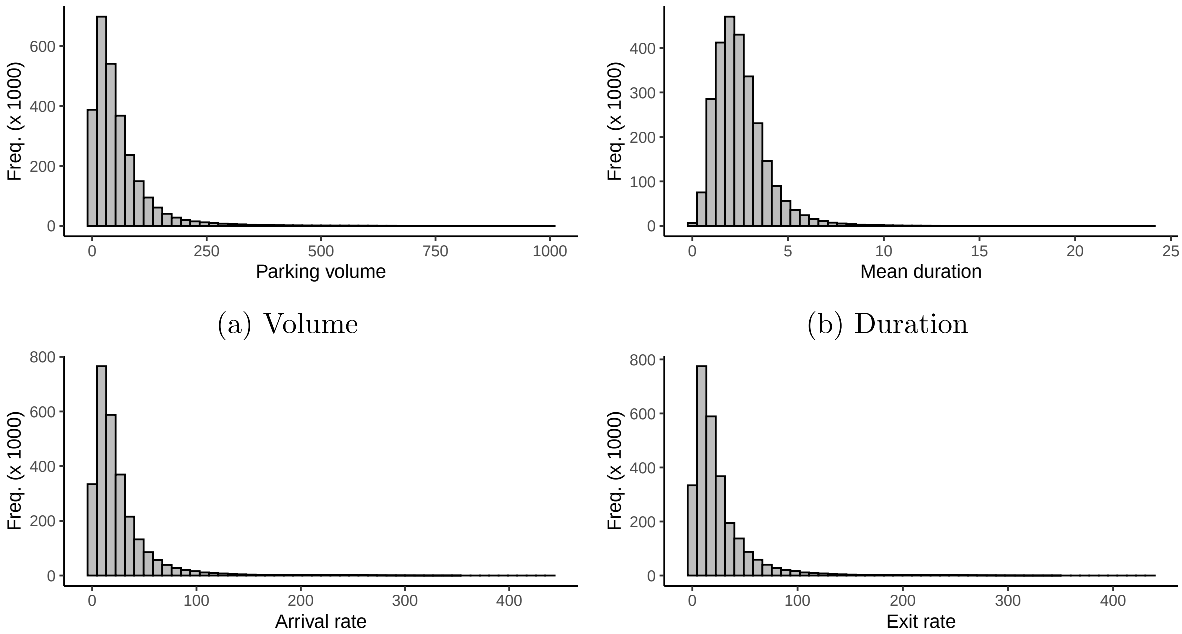


(d) Relative change (%)

Figure A4: On-street parking prices pre and post policy.

A.5.2. *On-street parking demand*

Figure A6 illustrates the distribution of the dependent variables over the day. Volume is low before 06:00 and steadily increases throughout the day with the highest occupancies around 14:00, after which volume begins to decline. Parking arrivals are relatively uniformly distributed over the day with a spike at 09:00 when paid parking becomes active. There are also some arrivals before 09:00 because people using their phone or arriving early can already arrange parking to avoid forgetting and receiving a fine. Arrivals start



(a) Volume

(b) Duration

(c) Arrivals

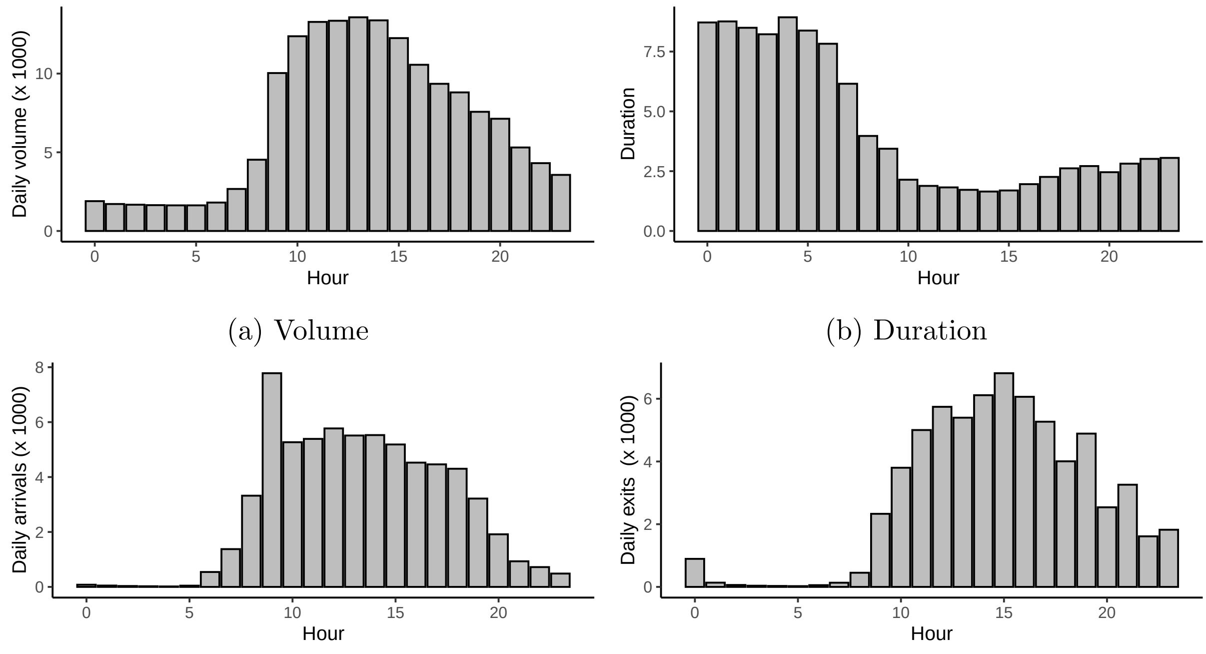
(d) Exits

Figure A5: Histograms of on-street parking demand variables.

to decline around 19:00. Exits rates are highest around 15:00, and also face a spike around 19:00 when many areas become free. Figure A7 illustrates the arrivals, exits, and the total per two hour interval. This essentially shows the distribution of traffic over the day generated by (hourly) on-street parking. The key take away is that traffic generated by on-street parking is relatively uniform between 10:00 – 18:00, with the peak between 14:00 – 16:00.

A.5.3. *Off-street parking demand*

Figure A8 compares daily on-street and off-street parking volume (excluding P&R) per hour. We assume that the occupancy rate in our sample is representative for all garages and approximate off-street parking volume for all garages by multiplying the mean daily parking volume in our sample of garages by the proportion of total capacity (1/0.31). The figure illustrates that the proportion of off-street to on-street parking demand is approximately one third (0.36).



(a) Volume

(b) Duration

(c) Arrivals

(d) Exits

Figure A6: Histograms of hourly on-street parking demand.

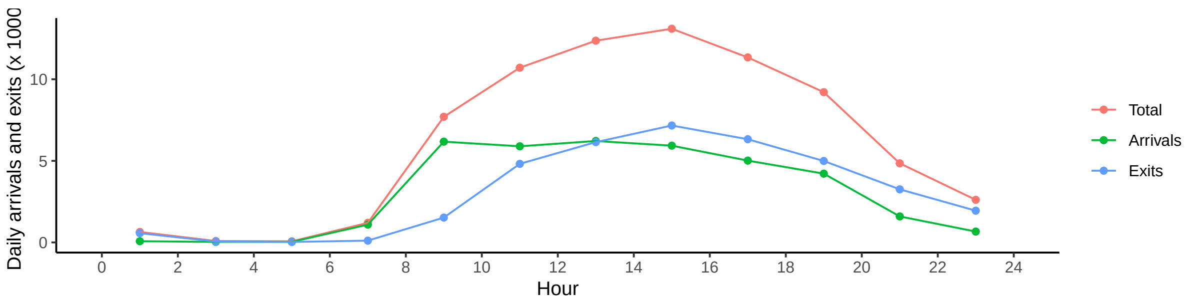


Figure A7: Traffic from on-street parking within the day.

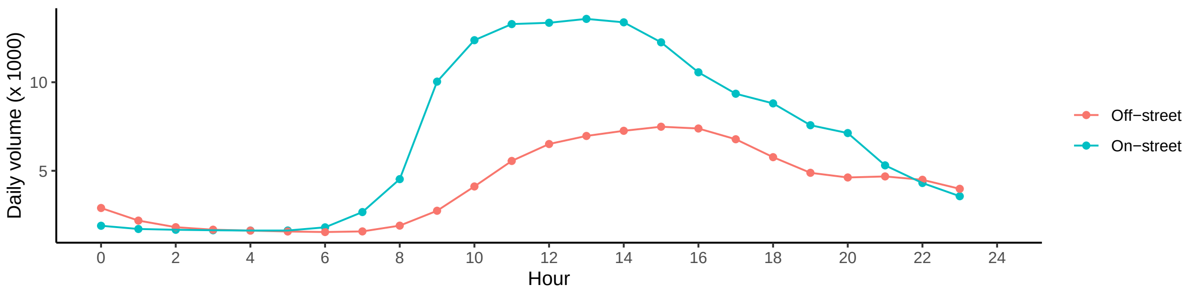
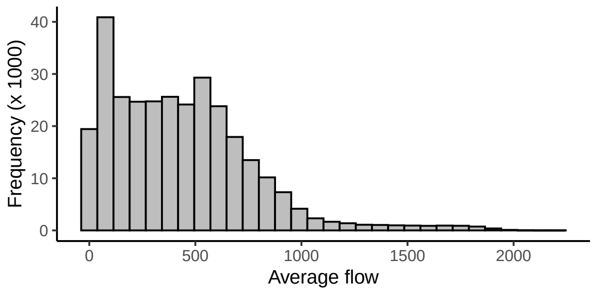


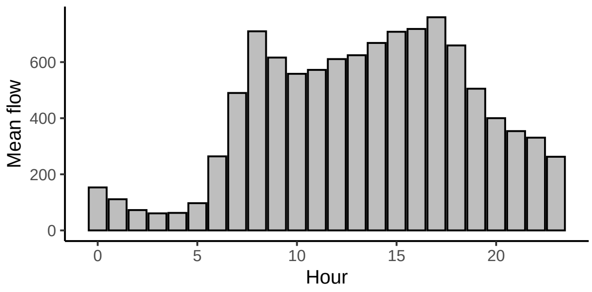
Figure A8: Parking volume on-street and off-street (estimated).

A.5.4. *Traffic flow*

Figure A9 illustrates the traffic flow and speed data. As can be seen, traffic flow is low in the evening hours and relatively uniform over the day, with a peak at 08:00 and 17:00.



(a) Flow



(b) Flow per hour

Figure A9: Histograms of hourly traffic flow based on loop data.

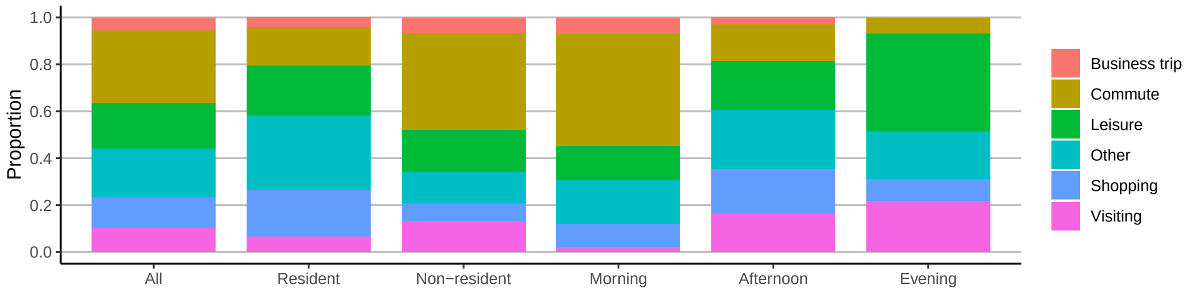


Figure A10: Purpose of car trips ending in Amsterdam excluding residential parking.

Traffic speed, as measured by the loop data, is also relatively uniform with only a small drop in average speed during the day when traffic flow is higher.

A.6. *Additional descriptives*

Figure A10 illustrates the stated purpose of car trips that end in the paid parking area of Amsterdam. We exclude trips by residents "returning home" as residents have access to permits and therefore these trips would generally not end in paid (hourly) parking. Overall, around one-third of trips are by commuters, which are more likely to be non-residents. These commuting trips may end in paid on-street parking however, commuters are likely to have access to (free) employer parking. The last three columns show that the proportion of non-work car trips is increasing throughout the day.

B. Additional results

B.1. *Identical trends on-street parking*

Our key identification is that in the absence of the policy, parking demand would have followed an identical trend as in the pre-period. In Figure 5 we show the estimated policy effect at the weekly level after including all controls. In this section, we show that the raw on-street parking trends show similar patterns to the estimated policy effect and that the effects for arrivals and duration are similar to the effect on parking volume. We also show the common trends for off-street parking demand and traffic flow.

Figure B1 shows that parking demand follows a very similar trend before and after the policy. Furthermore, the effect of the policy is clear from the sharp decline when the policy becomes active.

Figure B2 shows that the effect on arrivals is slightly more volatile than the effect on volume and duration, which show a sharper, more stable drop in demand. This is likely due to large events or activities around the city. While this may affect the precision of the policy estimate, it does not affect the consistency, under the assumption that the events are uncorrelated to the policy. This seems to be the case as the fluctuations appear to be random.

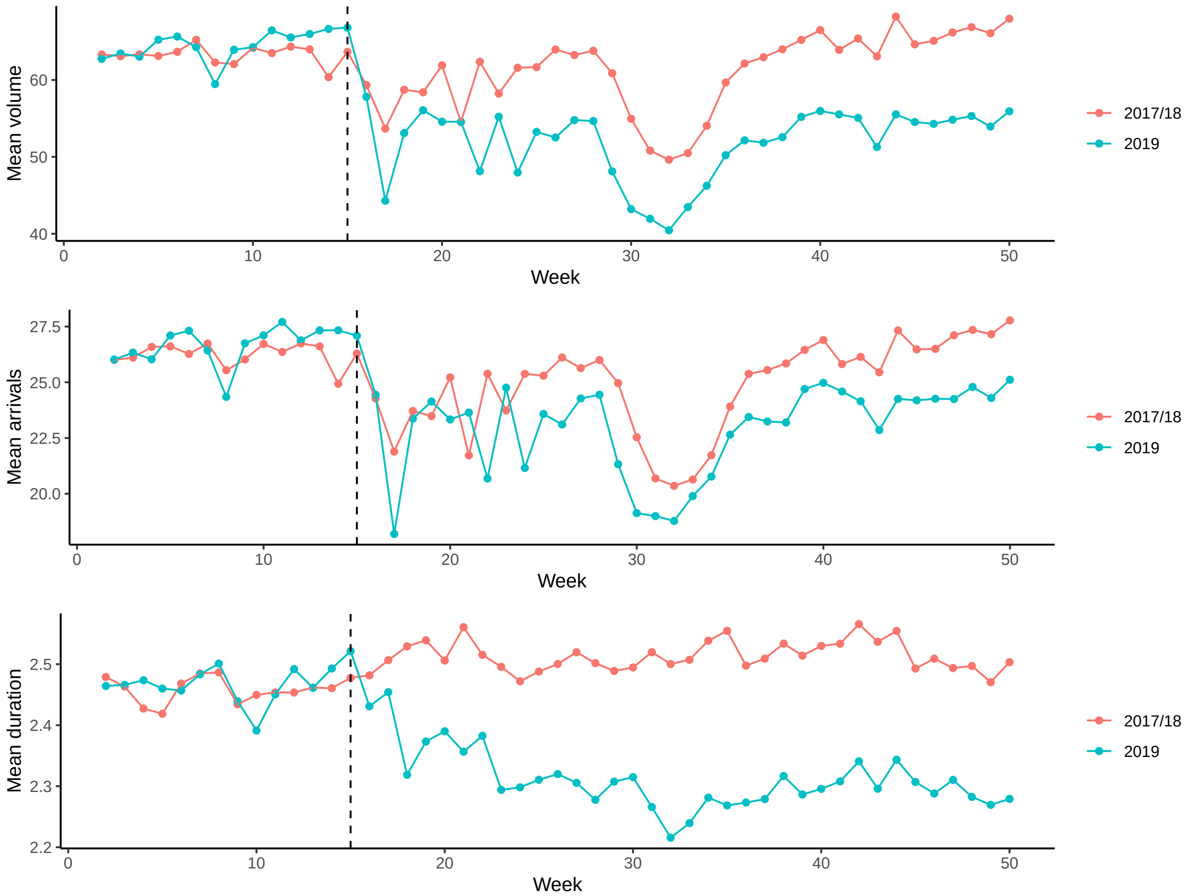
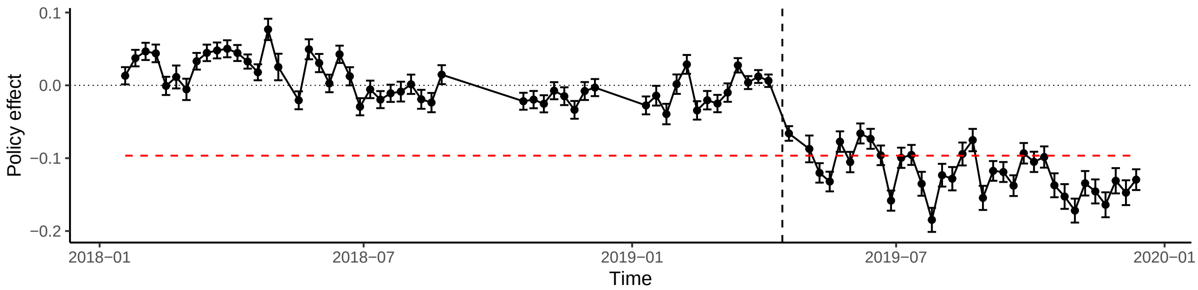
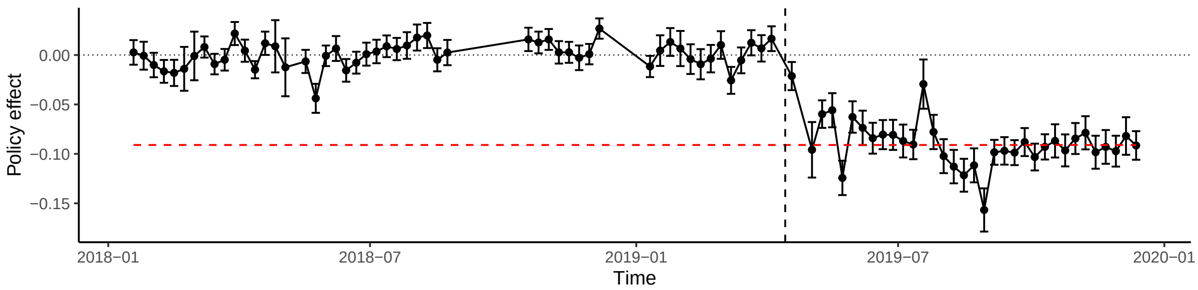


Figure B1: Mean on-street parking volume, arrivals, and duration per area.



(a) Arrival rate



(b) Duration

Figure B2: Estimated policy effect after including all controls.

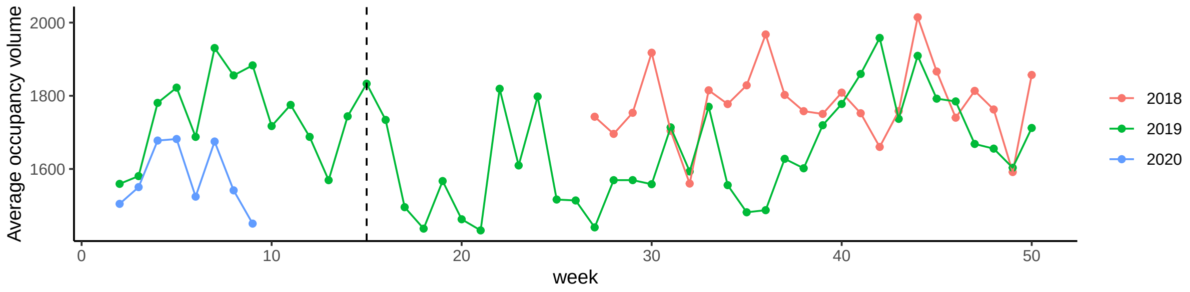


Figure B3: Commercial off-street parking identical trends.

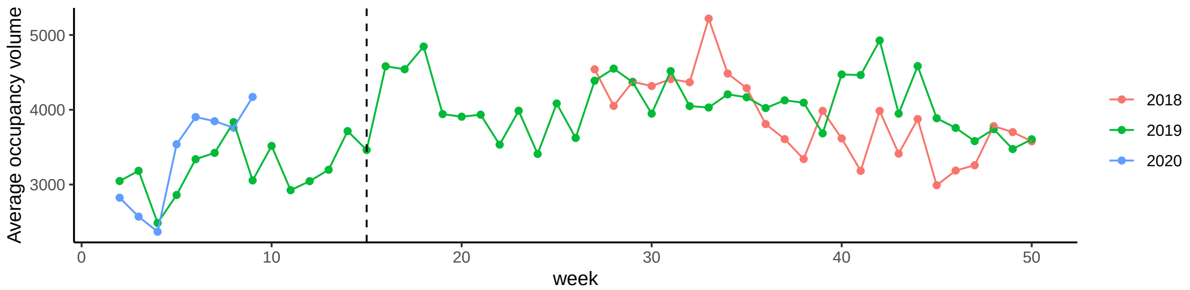


Figure B4: P&R off-street parking identical trends.

B.2. *Identical trends off-street parking*

Figure B3 and B4 show the raw trends in mean commercial off-street parking volume. The data is somewhat noisier because we have fewer observations as compared to the on-street data. However, there appears to be no discernible trend in commercial off-street parking, while demand is lower in the post period. Meanwhile, parking volume at P&R facilities appears to be declining over time, and there is a sharp increase when the parking policy is introduced. Demand then appears to shrink, and in early 2020, demand is similar to the same period in 2019. Note that due to the shorter time period for which we obtain off-street parking data, we cannot estimate the weekly policy effect after controls while including week fixed effects.

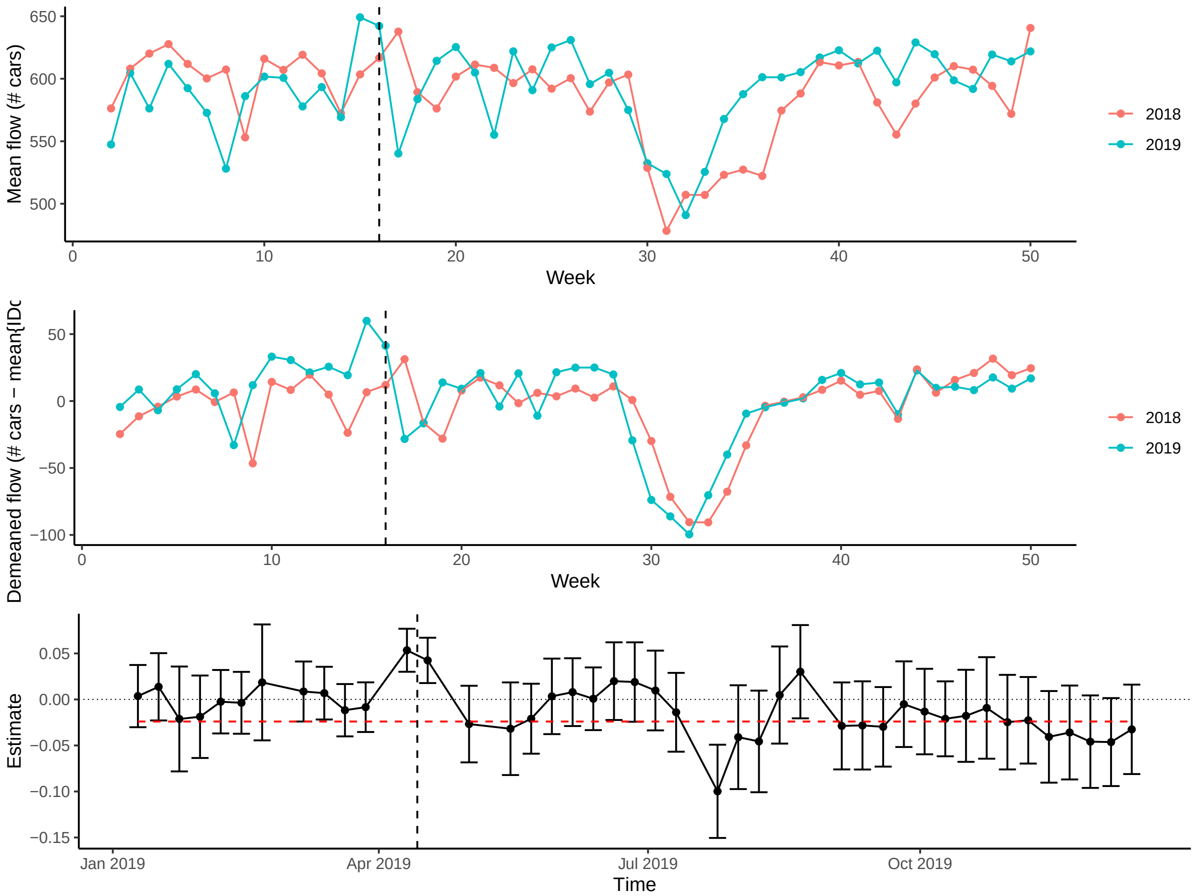


Figure B5: Aggregate traffic flow trends.

B.3. *Identical trends traffic flow*

Figure B5 presents the trends in traffic flow. The top plot indicates that flow appears to follow similar trends to on-street parking demand with a noticeable dip around the summer school holiday period. However, the aggregate data is quite noisy because the panel is unbalanced and road traffic is unequally distributed over the network so the mean is somewhat sensitive to missing data. Therefore in the middle plot, we demean the data by the average flow per traffic loop. The trend becomes clearer, although it is difficult to discern a significant policy effect. Therefore in the bottom plot, we control for all temporal and spatial factors as in Table 6 and find that the effect is approximately 2% however, we acknowledge that the effect is still quite noisy at the weekly level and is somewhat sensitive to summer vacations and other holidays.

Table B1: Sensitivity: spatio-temporal variation. Local results: On-street parking.

	Volume		Arrivals		Duration	
	Diff 500m	Excl 500m	Diff 500m	Excl 500m	Diff 500m	Excl 500m
	(1)	(2)	(3)	(4)	(5)	(6)
Price (log)	-0.434***	-0.377***	-0.217***	-0.224***	-0.218***	-0.190***
	(0.019)	(0.073)	(0.015)	(0.045)	(0.008)	(0.027)
Price difference (500 m)	-0.063***		-0.056***		-0.009	
	(0.019)		(0.016)		(0.007)	
Price difference^2 (500 m)	0.013		0.003		0.009*	
	(0.010)		(0.008)		(0.005)	
Price difference^3 (500 m)	0.007***		0.004***		0.003***	
	(0.002)		(0.001)		(0.0009)	
Area FE	Yes	Yes	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Public holiday FE	Yes	Yes	Yes	Yes	Yes	Yes
School holiday FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,709,707	349,429	2,709,707	349,429	2,654,913	341,875
Pseudo R^2	0.71699	0.70869	0.68185	0.64658	-21.0789	-18.42167

Notes: Estimated using Quasi-ML Poisson regression. Standard errors in parentheses are clustered at the parking meter level. Season FE include day-of-week, week-of-year, and public holidays. Weather controls include the average daily temperature, windspeed, and a dummy for whether there was rain or temperatures below 0 °C between 8-20hr.***, **, * indicate significance at 1%, 5%, and 10%.

B.4. *Robustness on-street parking*

B.4.1. *Local price effects and neighbouring prices*

The local estimates in Table 5 may be biased downwards (overestimate) if prices in neighbouring districts are lower, which may cause drivers to substitute over space. In Table B1 we show that controlling for differences in on-street parking prices within 500 m and excluding areas within 500 m of a price boundary has little effect on the results, suggesting that substitution over short distances is relatively minor. This is not surprising as prices decline gradually with distance to the city centre, also after the increase in prices. Therefore changes in price discontinuities over space are small.

B.4.2. *Specification of time trend*

In Table B2 we consider how time trends affect the results. In column (1) we interact the time trend with eight parking rate zones post policy, including €0.10 shopping areas,

Table B2: Sensitivity: long term trends. Citywide results: On-street parking.

	Arrivals					
	Zone × trend	Flex trend	Zone × flex trend	1 month	2 months	3 months
	(1)	(2)	(3)	(4)	(5)	(6)
Policy effect	-0.097***	-0.062***	-0.060***	-0.104***	-0.117***	-0.113***
	(0.005)	(0.005)	(0.006)	(0.004)	(0.005)	(0.005)
Year 2019	-0.037***	-0.004	-0.003			
	(0.006)	(0.006)	(0.006)			
Time trend		0.104***				
		(0.016)				
Time trend^2		-0.039***				
		(0.012)				
Time trend^3		0.003				
		(0.002)				
Area FE	Yes	Yes	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes			
Public holiday FE	Yes	Yes	Yes	Yes	Yes	Yes
School holiday FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,710,535	2,710,535	2,710,535	177,926	336,011	494,087
Pseudo R^2	0.68209	0.6812	0.68289	0.71678	0.70417	0.69892

Notes: Estimated using Quasi-ML Poisson regression. Standard errors in parentheses are clustered at the parking meter level. Season FE include day-of-week, week-of-year, and public holidays. Weather controls include the average daily temperature, windspeed, and a dummy for whether there was rain or temperatures below 0 °C between 8-20hr.***, **, * indicate significance at 1%, 5%, and 10%.

and add a separate category for residential permit zones. This captures potential linear differences in the attractiveness of parking areas over time, for example, because more tourists visit the city centre by car. The results suggest that the policy effect on arrivals is essentially the same and equal to 9.2%. In column (2) we include a flexible time trend by adding a third-order polynomial term and find that the arrivals rate effect declines to 6%. In column (3) we interact the flexible time trends with parking rate zones (as in column (1)) and find that the effect becomes 5.8%. In column (4) – (6) we examine the policy effects using a shorter time period event study approach in the spirit of regression discontinuity design. Therefore, we exclude week fixed effects and time trends. We gradually make the time interval larger from one-month pre-post to two and then three months pre-post. The results suggest that the short-run effects are around 10%, which is slightly larger than the estimated policy effect that takes longer-term trends into account.

Table B3: Sensitivity: Area. Citywide results: On-street parking.

	Incl North (1)	Centre (2)	Arrivals Centre (3)	Non-centre (4)	Non-centre (5)
Policy effect	-0.093***	-0.122***		-0.082***	
	(0.005)	(0.006)		(0.007)	
Price citywide (log)			-0.233***		-0.179***
			(0.012)		(0.015)
Year 2019	-0.034***	-0.029***	-0.029***	-0.040***	-0.040***
	(0.006)	(0.007)	(0.007)	(0.008)	(0.008)
Time trend (daily/365)	0.042***	0.024***	0.024***	0.047***	0.047***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Time trend (daily/365) × IDnewNoord	0.278***				
	(0.028)				
Area FE	Yes	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes
Public holiday FE	Yes	Yes	Yes	Yes	Yes
School holiday FE	Yes	Yes	Yes	Yes	Yes
Observations	2,867,996	1,093,002	1,093,002	1,617,533	1,617,533
Pseudo R^2	0.69644	0.61186	0.61186	0.70532	0.70532

Notes: Estimated using Quasi-ML Poisson regression. Standard errors in parentheses are clustered at the parking meter level. Season FE include day-of-week, week-of-year, and public holidays. Weather controls include the average daily temperature, windspeed, and a dummy for whether there was rain or temperatures below 0 °C between 8-20hr.***, **, * indicate significance at 1%, 5%, and 10%.

B.4.3. *Heterogeneity location*

In the main analysis, we exclude the North part of Amsterdam because they experienced an expansion in the parking area in July 2018. In Table B3, we include parking data from the North part of Amsterdam and a specific time trend for new areas which captures growth in demand in these areas over time. We find essentially identical results with parking arrivals decline by about 8.9% as a result of the policy. Furthermore, prices are the highest in the city centre and fall with distance to the periphery. Therefore, we also estimate the policy effect separately for central and non-central parking areas and find that the arrival effect is about 11.5% in central areas, which is around 50% larger than the effect outside these areas (7.9%) and is also reflected in a larger price elasticity.

B.4.4. *Heterogeneity discounted shopping and visitor permits*

We have included parking observations in discounted €0.10 shopping areas (with time limits of either one or three hours) and visitor permits in all our main on-street analysis. It is likely that the policy positively affected demand for these parking options as they became relatively cheaper. In Table B4 we examine to what extent drivers substituted to these options as a result of the policy. First, we examine to what extent the estimates change if we exclude observations of these two options. The first three columns indicate that the policy effect on arrivals is slightly stronger when excluding demand for visitor permits, but is much stronger when excluding demand for discounted shopping areas. This makes sense as only 1.3% of arrivals use residential permits while a relatively large proportion (13.5%) use shopping areas.

Columns (4) and (5) indicate that this result is mainly driven by an increase in demand for parking in inner-city shopping areas (which have one hour time restrictions) where arrivals increased by around 7%, while there was no increase in demand in the peripheral industrial parking areas which offer three hour time limits. This result is interesting as shopping areas generate substantially more traffic per parking space as they have a higher turnover. It follows that the policy effect would have been much larger in the absence of these discounted shopping areas, and would be much smaller in the hypothetical case that Amsterdam would have much more discounted shopping areas. Column (6) indicates that parking using visitor permits increased substantially as a result of the policy by around 65%.[47]

B.4.5. *Sensitivity to spatial aggregation*

In Table B5 we assess the sensitivity of our main results at various spatial scales and compare the estimates from a Poisson and log model. Columns (1) – (3) indicate that the policy effect on parking volume is identical when estimated using a Poisson model.

[47] This effect is a combination of the increase in on-street parking prices (so the discount increased in absolute value), more information about the availability of discounts, and an increase in the number of available hours from 10 or 30 to 40 hours per household per month.

Table B4: Sensitivity: substitutes. Citywide results: On-street parking arrivals.

	Arrivals					
	Excl 10c	Excl Res	Excl both	Only 10c 1hr	Only 10c 3hr	Only Res
	(1)	(2)	(3)	(4)	(5)	(6)
Policy effect	-0.116***	-0.104***	-0.126***	0.063***	0.0003	0.502***
	(0.005)	(0.005)	(0.005)	(0.022)	(0.021)	(0.050)
Year 2019	-0.034***	-0.036***	-0.034***	-0.050	-0.044	-0.048
	(0.005)	(0.006)	(0.005)	(0.042)	(0.035)	(0.040)
Time trend (daily/365)	0.046***	0.039***	0.047***	-0.089***	0.096***	-0.035
	(0.004)	(0.005)	(0.004)	(0.027)	(0.026)	(0.024)
Area FE	Yes	Yes	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Public holiday FE	Yes	Yes	Yes	Yes	Yes	Yes
School holiday FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,587,339	2,658,249	2,535,053	71,109	52,087	52,223
Pseudo R^2	0.64749	0.6789	0.64388	0.62668	0.83756	0.79011

Notes: Estimated using Quasi-ML Poisson regression. Standard errors in parentheses are clustered at the parking meter level. Season FE include day-of-week, week-of-year, and public holidays. Weather controls include the average daily temperature, windspeed, and a dummy for whether there was rain or temperatures below 0 °C between 8-20hr.***, **, * indicate significance at 1%, 5%, and 10%.

Meanwhile, the results from a log model are largest when estimated at the level of the parking meter and become smaller when areas are aggregated to the visitor permit zone and then to the aggregated parking zones. Furthermore, the estimates in the log model are most consistent with the Poisson model at a more aggregated level. We conclude from this exercise that the log model is more sensitive to the level of spatial aggregation and that the Poisson model is preferred as it does not suffer from aggregation issues and provides a conservative estimate of the policy effect.

B.4.6. *Standard errors*

Standard errors may be too small if parking demand is serially positively correlated (Bertrand et al., 2004). To address this issue, we cluster our standard errors at the time-invariant level of a parking area. In addition, we run a robustness check where we focus only on time-series variation around the policy introduction and aggregate our data into four periods, pre and post-policy in 2018 and 2019.[48] Table B6 presents the results.

[48] Therefore, for each parking area ID we have four observations.

Table B5: Sensitivity: Spatial aggregation. On-street parking.

	Meter	Volume Visitor permit	Agg zone	Meter	Volume (log) Visitor permit	Agg zone
	(1)	(2)	(3)	(4)	(5)	(6)
Policy effect	-0.184***	-0.185***	-0.185***	-0.208***	-0.193***	-0.187***
	(0.007)	(0.016)	(0.031)	(0.008)	(0.015)	(0.028)
Area FE	Yes	Yes	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Public holiday FE	Yes	Yes	Yes	Yes	Yes	Yes
School holiday FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,710,535	64,202	7,452	2,660,882	64,202	7,452
Pseudo R^2	0.71491	0.96301	0.99132	0.35161	0.74497	1.13052

Notes: Column (1) – (3) are estimated using Quasi-ML Poisson regression without weights. Column (4) – (6) is estimated using OLS and is weighted by the mean number of arrivals per parking area. Standard errors in parentheses are clustered at the parking area level.***, **, * indicate significance at 1%, 5%, and 10%.

Table B6: Sensitivity: Standard errors. On-street parking.

	Volume	Arrivals	Duration
	(1)	(2)	(3)
Policy effect	-0.175***	-0.093***	-0.090***
	(0.007)	(0.005)	(0.004)
Post week 15	-0.042***	-0.059***	0.024***
	(0.003)	(0.003)	(0.002)
Year 2019	0.028***	0.025***	-1.563×10^{-5}
	(0.007)	(0.006)	(0.003)
Area FE	Yes	Yes	Yes
Observations	19,707	19,707	19,707
Pseudo R^2	0.85468	0.76404	-21.96828

Notes: Estimated using Quasi-ML Poisson regression. Parking demand is aggregated into pre and post in 2018 and 2019, therefore we omit all time series variation other than the policy effect. Standard errors in parentheses are clustered at the parking area level.***, **, * indicate significance at 1%, 5%, and 10%.

The results are essentially identical to our main estimates, and the standard errors only slightly increase. This rules out any autocorrelation in error terms and highlights that our results and standard errors are hardly affected by serial correlation.

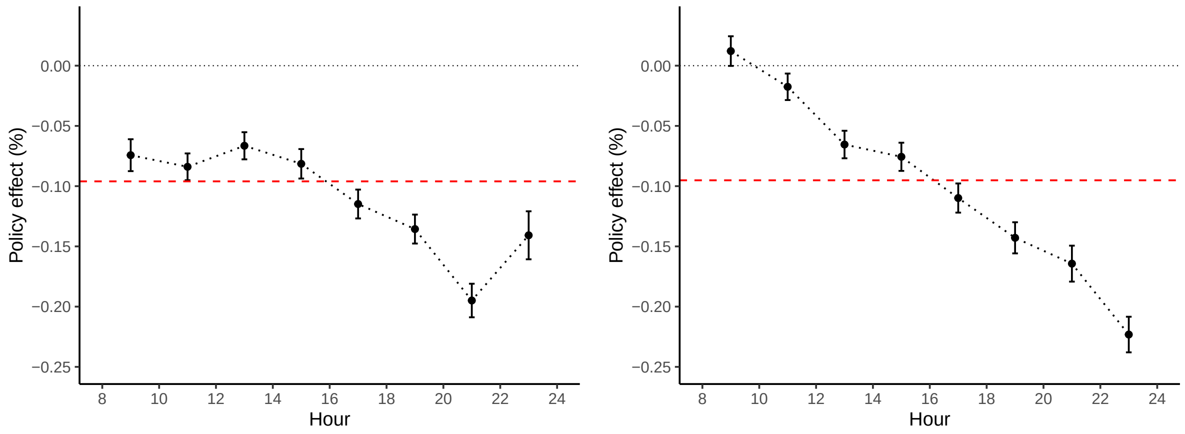
Table B7: Sensitivity: offstreet parking.

	City centre	Capacity	Volume Incl. 2020 (Off)	Incl. 2020 (P&R)
	(1)	(2)	(3)	(4)
Policy effect	-0.073***	-0.070***	-0.069***	0.057***
	(0.016)	(0.014)	(0.012)	(0.021)
Capacity (dynamic)		-0.002***		
		(0.0003)		
Year 2019				-0.009
				(0.021)
Area FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Public holiday FE	Yes	Yes	Yes	Yes
School holiday FE	Yes	Yes	Yes	Yes
Observations	5,713	6,514	7,269	3,126
Pseudo R^2	0.7563	0.73151	0.72393	0.44097

Notes: Estimated using Quasi-ML Poisson regression. Standard errors in parentheses are clustered at the year-week level. Season FE include day-of-week, week-of-year, and public holidays. Weather controls include the average daily temperature, windspeed, and a dummy for whether there was rain or temperatures below 0 °C between 8-20hr.***, **, * indicate significance at 1%, 5%, and 10%.

B.5. *Robustness off-street parking*

In Table B7 we further examine the sensitivity of off-street parking demand to other specifications. Column (1) shows that the effects are slightly larger when we exclude parking garages outside the city centre. In column (2), we also control for changes in short-term capacity throughout the week which may occur if commercial garages are also providing long-term parking to residents. The result also becomes slightly larger. In column (3) and (4) we include an extended period until February 2020, which also gives similar estimates to our main results.



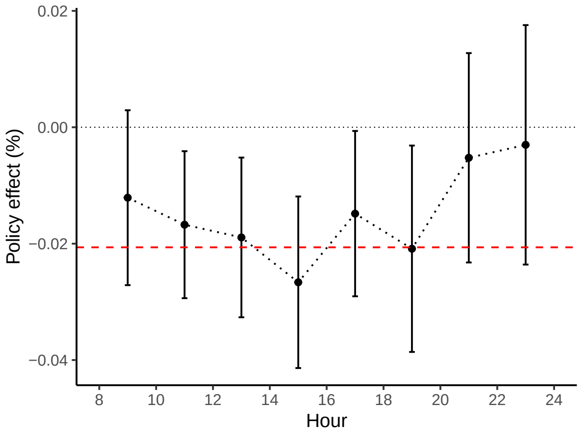
(a) Arrivals

(b) Exits

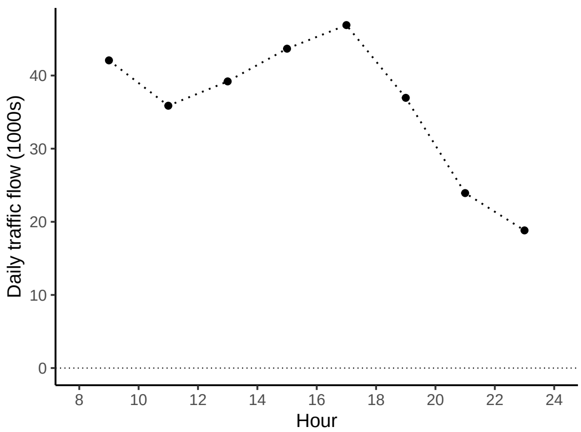
Figure B6: Policy effect (percentages) on arrivals and exits within the day.

B.6. *Heterogeneity on-street parking*

The effects of the policy on the number of cars are equal to the policy effect in percentage terms multiplied by the average daily number of cars arriving or exiting per hour in the preceding year. Figure B6 shows that the policy effect on arrivals in percentages is relatively uniform up to 18:00 and becomes stronger in the evening, while the exit effect in percentages becomes stronger throughout the day. This indicates that motorists typically arriving and leaving in the evening are more price sensitive, which makes sense as parking is not work-related. This is confirmed in Figure A10, which indicates that over 90% of trips in the evening are non-work related while in the morning it is less than 50%. Furthermore, Figure A7 shows how daily on-street parking arrivals and exits vary over the day just prior to the policy. Notably, the peak in implied on-street traffic (the sum of arrivals plus exits) is highest around 15:00.



(a) Policy effect



(b) Traffic flow

Figure B7: Policy effect (percentages) and daily implied traffic flow within the day.

B.7. *Welfare calculations*

In this section we document how we calculate the back-of-the-envelope welfare effects presented in Section 4.3.1.

B.7.1. *On-street market*

Given the rule of half, the change in consumer surplus equals $\Delta CS = 0.5(Q + Q_n)(P_n - P)$. Plugging in values, we get €$326,000$ in the on-street market $(0.5(213,000 + 177,000)(4.22 - 2.55))$.

The change in government revenues equals to the revenues under the new policy minus the revenues under the old price scheme, so $\Delta R = P_n Q_n - PQ$. Plugging in values gives €$204,000$.

We assume that the new pricing policy is socially optimal, therefore the reduction in total social costs equals to the change in parking demand multiplied by marginal social cost (i.e. the opportunity costs of the land), which is (by assumption) the new price level. This equals $\Delta TSC = P_n(Q - Q_n) =$ €$152,000$.

Adding the government revenues, the change in total social costs and subtracting the change in consumer surplus gives the welfare gain of €30,000. This can also be calculated using the rule of half $(0.5 \times dP \times dQ)$.

B.7.2. *Off-street market*

The change in consumer surplus in the off-street market equals: €$108,000$ $(0.5(106,000 + 101,000)(4.37 - 3.33))$.

Given that off-street parking is about half the size of the on-street market, 40% of off-street garage capacity is owned by the municipality, 20% is foreign-owned, and average prices off-street increased by around €1.00 we can calculate the change in profits as $\Delta\pi = P_n Q_n - PQ$ multiplied by the share of total capacity. Therefore, government revenues increase by about €35,000 (40% of total) and commercial operators gain €52,000 (60% of total), of which one third (€17,000) goes overseas.

In the off-street market, parking becomes idle and can not be replaced by other uses.

Therefore the reduction in demand off-street is a welfare loss (note maximum capacity off-street during the day is generally below 60%). Hence reductions in demand off-street results in a welfare loss of €3,000.

B.7.3. *Travel externalities*

The change in travel externalities approximately equals the reduction in the number of car trips (arrivals effect times two) multiplied by the average distance of a trip within Amsterdam and the marginal passenger vehicle externality per km. Therefore $\Delta E_{vkt} = (2 \times 7,800 \text{ trips})(7 \text{ km})(€0.12 - €0.09) = €3,000$. This excludes additional externalities from road traffic occurring outside of Amsterdam. Non-residents tend to travel longer distances (36 km) which may reduce an additional 226,000 km ((36 km − 7 km)($2 \times 7,800$ trips)) of road traffic.

This will be an upper bound estimate if drivers travelling longer distances are less sensitive to price changes and a lower bound if travel externalities are larger in urban areas and motorists that do not use the car to travel to Amsterdam do not substitute to alternative destinations. One may also argue that congestion costs are overestimated because they are mainly incurred during peak hours. Our estimates from Figure 6 imply that around 39% of the reduction in traffic due to the policy occurs during peak hours, so this is unlikely to significantly effect our main estimates.

B.7.4. *Cruising costs*

Before the policy off-street parking was 30% (€0.76) more expensive than on-street parking and it was reduced to 10% (€0.36). Given an average parking duration of 2.4 hours, this implies that drivers were willing to pay up to €0.96 to avoid parking on-street and have to search for parking.

Taking the average VOT of car travellers in the Netherlands of €15.40, this roughly translates to travel time savings of around 4 minutes, which would increase welfare by around €74,000 per day (€0.96 $\times$ 77,000 Arrivals). However, this is likely to be a large overestimate for four reasons. First, in a dynamic model, cruising does not occur in the morning when occupancies are still low. Second, we have ignored that the price differences between paid parking and discounted shopping areas which have increased because of the policy. Third, motorists may prefer off-street parking for reasons other than cruising. Finally, some off-street garages offer discounts for day parking, so this price difference (for longer durations) is likely to be smaller. Therefore it appears more reasonable that cruising costs are around one-quarter of the total amount (€18,000 per day).

B.7.5. *Overall*

Adding up the gains in the parking market (€27,000), the reduction in traffic externalities (€3,000), and the gains from less cruising (€18,000) implies an overall societal gain of around €48,000 due to the price increase.

As around half of all vehicle trips in the city are by residents, the gain to residents equals $\Delta W_R = 0.5(\Delta CS + \Delta E_{travel} + \Delta E_{cruising}) + \Delta R + \Delta TSC = €195,000$. Meanwhile, the change in welfare for non-residents is negative and equals $\Delta W_N = 0.5(\Delta CS + \Delta E_{travel} + \Delta E_{cruising}) = -€196,000$. Given that there are around 850,000 inhabitants in Amsterdam, this suggests that the annual gains per resident are around $(195,000 * 365 \text{ days})/850,000 = €84$.

B.7.6. *Alternative assumption social optimal price*

In the above analysis we assume that the new pricing policy is socially optimal from a land market perspective, conditional on parking supply. In the following analysis we relax this assumption, and alternatively assume that marginal social costs are equal to the old price level. This arguably provides a lower bound estimate of the welfare effects of parking policy in the on-street parking market because prices for close substitutes have increased strongly in the past 10 years while parking prices did not change.

Under this alternative assumption, the overall gain in the on-street parking market then become negative and equal to $-€30,000$. This implies an overall societal loss of around $€12,000 = \Delta W_{on} + \Delta W_{off} + \Delta E_{travel} + \Delta E_{cruising} = (-30,000) + (-3,000) + 3,000 + 18,000$, and a smaller annual net gain per resident of around €58, due to the price increase.

B.8. *Automated vehicles*

In this section we document how we calculate the back-of-the-envelope implications for AVs presented in Section 4.3.2.

We consider the potential impact of AVs in the city centre (25,928 daily arrivals) and in peripheral areas (49,651 daily arrivals) where hourly parking prices are currently around €6.75 and €3.50, respectively. We assume that the price elasticities we estimate are symmetric. Furthermore, we assume that cars can park outside the city in designated parking areas for a fee of €2.50 per hour (the lowest price in the periphery) and that the cost to travel to and from this area is €2.00 from the city centre and €1.00 from the periphery. The hourly and fixed costs are divided by parking duration, given the new hourly prices, to come to an 'effective' hourly price.

We consider two scenarios for AVs. On the one hand, if households own private AVs and parking costs at the destination are sufficiently high, it is likely that AVs will be parked at locations in the periphery, where parking costs are relatively low. At these locations, parking costs will approximately equal the current on-street parking price in the periphery plus additional costs of travelling to and from the parking area. Therefore in the private AV scenario, we assume parking costs approximately equal current parking prices in the periphery, €2.50, plus the travel costs. On the other hand, if AVs are shared, then cars will only need to be parked during the evening and parking costs will be almost zero as they are shared between many users. Therefore, in the shared AV scenario, we assume that car users incur a small fee to hail a trip of €2.00.

B.8.1. *Private AV scenario*

We first consider the private AV scenario where effective hourly prices become €3.20 in the centre and €2.90 in the periphery. Effective hourly prices are equal to the hourly price outside the city plus the travel costs to and from the periphery divided by the number of hours. We first calculate the expected number of hours parked using the hourly price only.

Our estimates for the price elasticity of arrivals and duration imply that car demand by motorists currently paying hourly on-street parking will increase by about 14% (4,000 car trips and 0.4 hours) in the centre and 4% (2,000 car trips and 0.2 hours) in the periphery. As each additional trip results in one car travelling to and from the periphery to park, this corresponds to twice the amount of traffic generated by one parking trip. Taking our estimate for the effect on traffic flow, this then implies an increase in traffic of around 8% and 2%, respectively.

Given that about one-quarter of traffic is related to on-street parking, additional traffic generated by empty cars travelling to and from the periphery would result in substantially larger effects. Assuming that each trip needs to be made twice, this roughly translates to an overall increase in traffic flow of about 27% – 33%, in the periphery and centre, respectively.

B.8.2. *Shared AV scenario*

In the shared AV scenario, effective hourly prices become around €0.40 and are the same in the centre and in the periphery. Hourly parking prices are essentially zero, so the effective hourly price is composed only of the trip fee divided by the duration of the trip. In our to calculate the expected change in duration using our log-log model, we take €0.01 for the hourly parking price.

Our estimates then imply that car demand by motorists currently paying hourly on-street parking increases by around 55% (14,000 car trips and 2.9 hours) in the centre and 42% (21,000 car trips and 2.6 hours) in the periphery. This corresponds to an increase in traffic of around 16% and 12%, respectively.