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Residential parking costs and car ownership: Implications for parking policy and automated vehicles[☆]

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ABSTRACT

Residents are often offered on-street parking at a fraction of the market price which may cause excess car ownership. However, residential parking costs are difficult to observe, so we propose an approach to estimate implicit residential parking costs and then examine the effect of these costs on household car ownership. We apply our approach to the four largest metropolitan areas of the Netherlands. Our results indicate that for city centres, annual residential parking costs are around €1000, or roughly 17 percent of car ownership costs, and are more than double the costs in the periphery. Our empirical estimates indicate that the disparity in parking costs explains around 30% of the difference in average car ownership rates between these areas and corresponds to a price elasticity of car demand of about −0.7. We apply these estimates to gauge the potential implications of automated vehicles which suggests that, if residents no longer require parking nearby their homes, car demand in city centres may increase by 8–14 percent.

1. Introduction

Parking has far reaching consequences on urban life. In cities, where land is scarce, the opportunity cost of parking is high, as on-street spots compete with pedestrian, cycling, commercial, residential and recreational uses. Nevertheless, cities devote a substantial amount of space to implicitly subsidised parking which may induce excess vehicle demand (Shoup, 2005). This raises an important open question, *to what extent do parking costs affect vehicle demand in cities?*[1] We address this question by estimating residential parking costs and examining to what extent these costs affect household vehicle demand.

Theory indicates that cheap residential parking reduces the (fixed) costs of owning a car and thereby increases vehicle demand (Shoup, 2005; Arnott, 2006). The empirical literature that quantifies this effect is scarce, but supports the idea that higher residential parking supply and lower residential parking rents are associated with higher car ownership (Guo, 2013; Seya et al., 2016).[2] Furthermore, waiting time for an on-street parking permit is shown to negatively affect vehicle demand. Residents in Amsterdam that have to wait an additional year are 2 percentage points less likely to own more than one car, corresponding to a

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1 Various other factors have been proposed to explain car ownership and car use in cities such as density, land use and accessibility. See, for example, Dargay (2002); Bhat and Guo (2007); Matas et al. (2009); Ewing and Cervero (2010) and Ding et al. (2017).

2 In their study for New York, Guo (2013) addressees endogeneity issues by instrumenting parking variables using housing and demographic characteristics in the neighbourhood. However, these instruments can be criticised as these characteristics are determined by demand factors, so the exclusion restriction is not fulfilled. Seya et al. (2016) study the impact of residential parking rents in Japan, ignoring simultaneity issues.

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price elasticity of demand for car ownership of −0.8 (De Groote et al., 2016).[3]

In order to estimate the impact of on-street parking costs on car ownership, one would like to observe market prices for on-street parking or close substitutes (for example off-street parking). In some countries, we are able to observe market rates for residential parking, as there is a thick rental market of privately-owned parking (for example Japan). However, in most countries, such a market is absent, as privately-owned parking is bundled with housing. Therefore, private off-street parking prices are not directly observed as residents mainly pay for parking through the purchase (or rental) of residential property or via regulated parking permits. Furthermore, in areas with excess demand, parking costs also include the time cost associated with cruising for parking.

This paper contributes to the literature on residential parking and car ownership by developing and applying a two-step approach which enables us to estimate local private parking costs and test to what extent these costs affect household car ownership.[4] In the first step, we identify the implicit price for parking through the effect of an outside private parking spot – arguably an almost perfect substitute for on-street parking – on house prices.[5] We exploit variation in the supply of private parking *within* a parking district to identify district-specific residential parking prices using semi-parametric hedonic house price methods.

Households considering car ownership face the same parking cost, on average, if they live in the same parking district. Hence, in the second step, we estimate the effect of residential parking costs on car ownership using variation in residential parking costs *between* districts. Endogenous parking costs are instrumented using the median construction year of properties in a district. Arguably, this instrument affects the supply of parking, while having no direct affect on parking demand, as it is determined in the past, often before cars were present.[6] We acknowledge that the construction year of properties is not random over space. Therefore, more precisely, we argue that, conditional on location controls, including, most importantly, distance to the nearest major train station, and household characteristics, historical supply decisions impact current building costs of a parking space, without directly affecting current demand for cars. We discuss this identifying assumption in more detail in the methodology section.

We focus on the Netherlands. In this context, residents who do not own private parking receive parking permits at very low fees and households with private parking are, in principle, not eligible for a parking permit. Hence, it is reasonable to assume that in equilibrium, *the residential parking price for households that own private parking is equal to the opportunity cost of parking on-street*, which equals the sum of the permit fee and cruising costs. The latter includes private search costs, walking time and uncertainty (Van Ommeren et al., 2011).[7] In case there is no cruising and street parking is not priced, residential parking prices should approach some underlying value of private parking, such as the security value or convenience of always having the car on hand. This approximately equals the value of private parking in locations where on-street parking is free.

We apply our approach to the four largest metropolitan regions in the Netherlands and estimate residential parking costs at the parking district level for owner-occupier households. On average, annual parking costs are around €1000 in city centres but are less than €400 in the urban periphery. We identify the impact of these costs on car ownership and find that owner-occupier households facing a one standard deviation increase (€503) in annual parking costs own 0.085 fewer cars on average, corresponding to a price elasticity of car demand of about −0.7. Our findings indicate that the disparity in parking costs between the city centre and the periphery explains around 30% of the difference in average car ownership rates between these areas.

Our results have implications for related literature on the urban spatial structure and transportation. Dense urban form is associated with lower vehicle ownership and kilometers travelled (Bento et al., 2005; Bhat and Guo, 2007; Duranton and Turner, 2018). Furthermore, transport infrastructure has been shown to affect residential location and mode choice, however parking is usually ignored (Baum-Snow, 2007; Garcia-López et al., 2015; Baum-Snow et al., 2017; Levkovich et al., 2017; Heblich et al., 2018). Our findings shed light on one of the mechanisms which explains why car ownership levels are lower in dense urban areas and indicates that residential parking costs are a significant determinant of mode choice.

Our findings also have implications for residential parking policy and relate to the growing literature on estimating the potential effects of automated vehicles (AVs).[8] We employ our estimates to consider the potential implications of raising fees of parking permits to the market value and eliminating parking costs from a widespread adoption of AVs. Increasing permit fees in the city centre of Amsterdam to the market value is expected to reduce average car ownership by 17–24 percent. Furthermore, the average annual gains per household from facing lower parking costs are estimated to be between €450 and €850 in city centres, depending on whether AVs are privately owned or shared. This is associated with an increase in average car demand between 8 and 14 percent. The effects are smaller in the periphery where parking costs are lower.

The paper proceeds as follows. In Section 2 we introduce the research context, data and provide some descriptives. In Section 3 we elaborate on the methodology. We report the main results in Section 4 and provide a counterfactual analysis in Section 5. Finally, Section 6 concludes.

2. Context and data

2.1. Parking and car ownership in the Netherlands

Dutch car ownership is low compared to most industrialised countries. Households own around one car on average, while in the UK and US they own around 1.5 and 2 cars, respectively (Clark and Rey, 2017). Moreover, in the Netherlands, as in other countries, car ownership is substantially lower in denser urban areas (see Fig. 1).

Our methodology relies on house prices and therefore we focus exclusively on households that own a residence. In the Netherlands, around 95% of owner-occupiers own at least one car while only 30% also own a private off-street parking spot, so most owner-occupiers park their car(s) on-street. Regulation of parking has shifted over the last 30 years. In metropolitan areas, paid on-street parking was introduced in the early 1990s to tackle the growing problem of excess demand for parking. Currently, most dense urban areas have paid parking (see Fig. 2). Due to scarcity of land in these areas, there has been an ongoing policy shift towards discouraging car use through parking policy (Antonson et al., 2017). These policies include increases in parking prices for visitors, introducing parking permits and fees for residents,

[3] Average waiting times are around three years in the city centre of Amsterdam.

[4] In our application, local is defined as administrative parking districts.

[5] Parking comes in different forms. In our data we observe garages, carports and outside parking spots.

[6] Supply-side instruments have also been used, for example, to investigate the effect of car ownership costs on the house price gradient in Singapore and housing supply elasticities in the US (Huang et al., 2018; Saiz, 2010).

[7] In waiting list districts, the implicit price also includes costs associated with waiting for a permit.

[8] See for example Fagnant and Kockelman (2014); Childress et al. (2015); Zakharenko (2016); Gelauff et al. (2019).

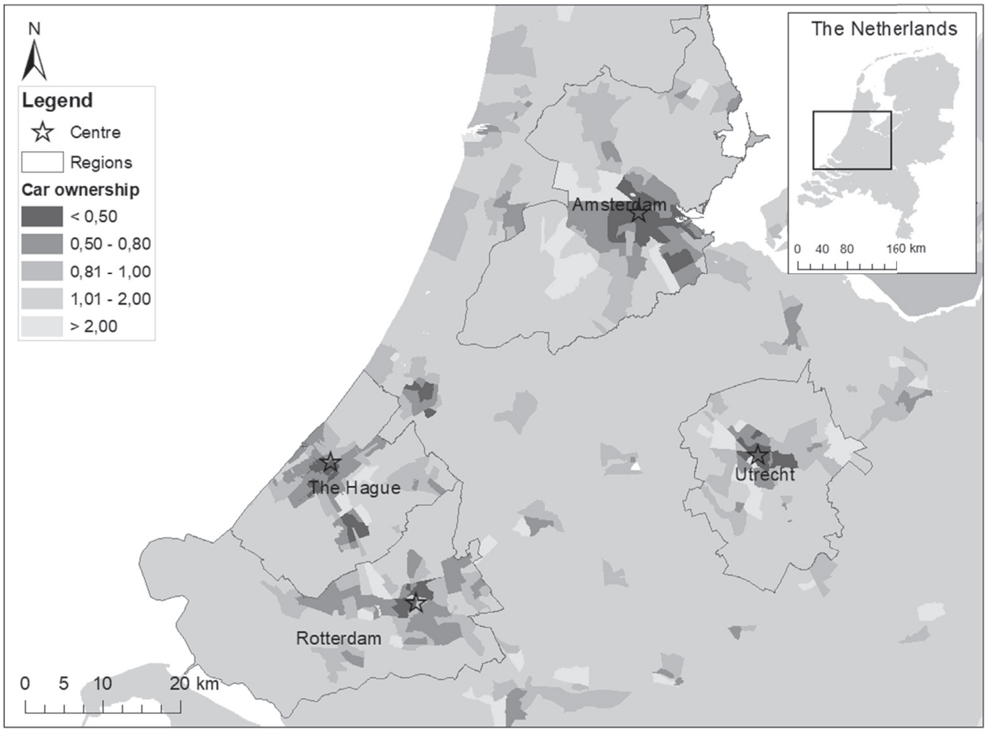

Fig. 1. Map of car ownership per household in the Randstad. *Note*: The spatial unit is the four digit post code area.

removal of on-street parking spots, lowering parking requirements for new buildings and developing fewer on-street spots (Mingardo et al., 2015; Gemeente Amsterdam, 2018).

Parking policy is determined at the municipal level and on-street parking is almost owned entirely by local authorities. Policies are geared towards charging high hourly prices to visitors and providing residents with the option to apply for a permit. In contrast to many countries, including the US, where on-street parking is generally cheap, prices for on-street parking in the Netherlands are comparable to commercial off-street garages and can cost up to €5 per hour. Paid parking generally starts early, between 8:00–9:00, and ends late, between 18:00–23:59. Permits cost less than €100 per year, except in Amsterdam (see Table 1). Compared to visitor tariffs and commercial off-street parking, the daily permit fee is a fraction of the cost. For example, in the city centre of Amsterdam, permit fees are the highest in the country, but still only cost €1.40 per day, while an identical on-street spot costs visitors around €45 per day. Therefore, as its costly, on-street parking without a permit is not a realistic option for most residents.

Residents with a car can choose to apply for an on-street parking permit except when they live in a property with private parking.[9] Depending on the location, households can apply for one or two parking permits. In Amsterdam almost all inner city locations allow only one permit and in some areas in the centre residents need to wait several years before obtaining a permit (De Groote et al., 2016). All metropolitan areas have good transport alternatives to the private car. These include a high quality public transport system of buses, trams, trains and in the case of Amsterdam and Rotterdam, a metro system. Furthermore cycling usage in cities is high, around 35% of all trips within 7.5 km are on the bike (Rietveld and Daniel, 2004).

[9] Renting a parking spot, for example from a private company, occurs seldom and prices of these parking spots reflect implicit parking prices paid for residential parking (Van Ommeren et al., 2011).

2.2. Data

We use three main datasets. In the first step we use transaction data on houses from the Dutch Association of Real Estate Agents (NVM). The dataset contains around 80% of all residential property transactions in the Netherlands between 2000 and 2016 and is recorded at a highly detailed level. It includes location coordinates for each unit, structural, historical and qualitative housing characteristics and transaction details. This data allows us to estimate private residential parking costs in the first step. We match the property data to administrative parking districts and select housing transactions within the four largest metropolitan regions of the Netherlands.[10] On average, each district has approximately 2000 properties, so parking districts are small. We remove districts with few observations and exclude large outliers from the remaining dataset.[11] After selections, the transactions dataset contains a total of 535,097 observations.

In the second step, we obtain household information from Bisnode and current building registry information from Building Characteristics Netherlands (GKN). Bisnode is a marketing firm that carries out representative surveys of households around the Netherlands, of which we have data between 2004 and 2014. The dataset distinguishes between zero, one and two or more cars per household.[12] Household location is

[10] Peripheral areas generally do not have paid parking (see Fig. 2). Therefore, in these areas we designate four digit post code units as parking districts.

[11] We select districts with at least 10 transactions of houses with outside parking and 10 transactions of houses without outside parking. This is explained in more detail in Section 3.1. Outliers are determined to be transactions above €2.5 million, €5000/m^2 property size, €5000/m^2 parcel size, 500 m^2 parcel size, 250 m^2 property size and 25 rooms. Similarly, we remove observations below €25,000, €500/m^2 property size, €400/m^2 parcel size, 50 m^2 parcel size and 40 m^2 property size.

[12] Only 4.2% of households own three or more cars in the Netherlands (Central Bureau of Statistics, 2015). This is likely to be much lower in the metropolitan areas we focus on. Therefore, any measurement error from not observing the exact number of cars is negligible.

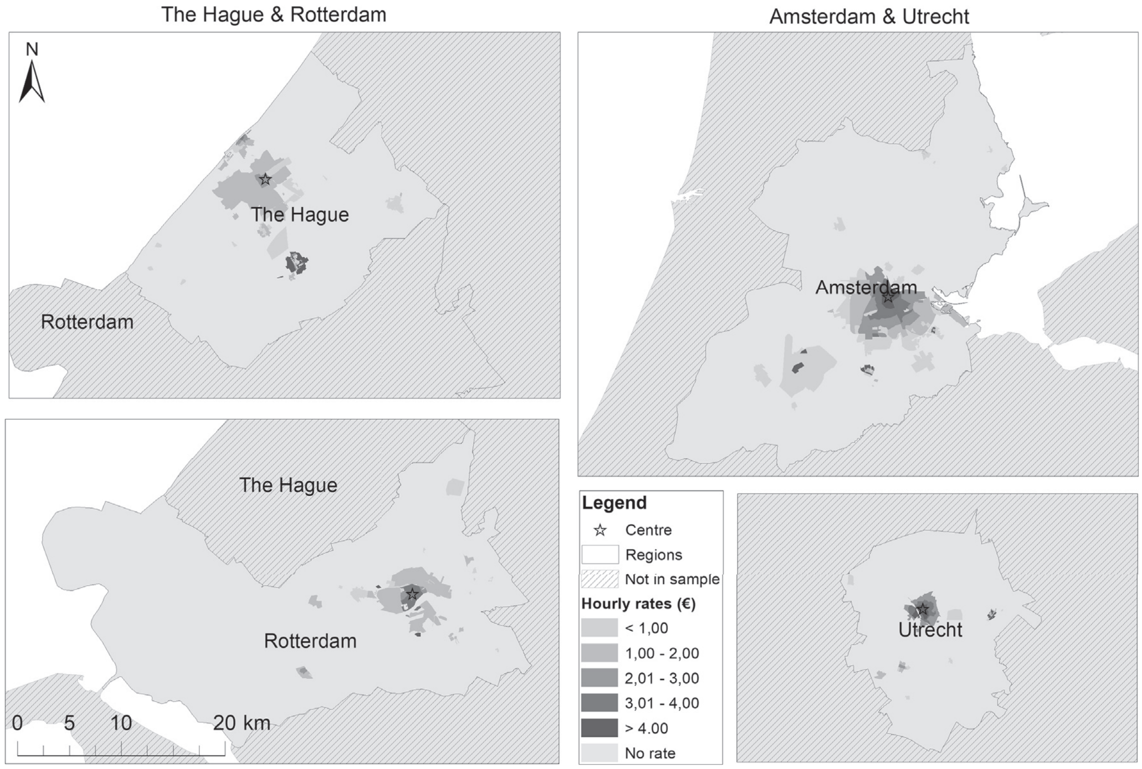

Fig. 2. Map of parking districts and hourly rates. *Note*: The rates in this _gure refer to visitor tari_s for non-residents.

Table 1
On-street residential parking permit fees.

	Amsterdam	Rotterdam	The Hague	Utrecht
Permit fee (€/yr)				
Centre (<2 km)	500	70	40	70
Urban ring (2–5 km)	200	70	40	30
Periphery (>5 km)	0	0	0	0

Notes: Fees are rounded averages for the areas indicated in 2018. During the period of study, 2000–2016, fees where lower.

precisely measured at the six digit post code (PC6) level, which contain around 20 properties on the same side of the street. Household characteristics include income, size, type, education, age and home-ownership status, which we use to select adult owner-occupiers.[13] We use the GKN dataset to construct geographical variables including the median construction year of residential properties in a parking district and building density in a PC6 area.[14] Finally, we also measure proximity to transport infrastructure and the city centre by calculating the distance from each PC6 area to the nearest train station, highway, highway ramp and metropolitan city centre. The availability of public transport is measured by the number of bus, metro and train stations within 100, 250 and 500 m buffers of the PC6 centroid.

2.3. Descriptives

Table 2 presents the main descriptive statistics for property transactions. The average transaction price is around €230,000, average size of a property is around 100 m^2 and the majority of properties are apartments (56%). Around 20% of properties have off-street private parking of which almost a third are outside, one fifth are semi-sheltered carports, half have a garage structure and very few have space for two cars.

Table 2
Descriptive statistics: Main transaction variables.

	Mean	Std. dev	Min	Max
Transaction price (€)	227,923	111,246	26,092	1,200,000
Size of property (m^2)	104.88	35.66	41	249
Size of parcel (m^2)	168.10	77.43	51	499
Distance city centre (km)	7.06	5.13	0	29
Apartment	0.56	0.50	0	1
Private parking	0.20	0.40	0	1
Outside	0.07	0.25	0	1
Carport	0.04	0.20	0	1
Garage	0.09	0.28	0	1
Carport & garage	0.00	0.06	0	1
Double garage	0.01	0.09	0	1
# Transactions	535,097			

Notes: We only observe parcel size for single family homes (234,395 observations). See Appendix A.1 for a full list of variables.

[13] Income is measured at the household level, while education and age is for the household head.

[14] The median construction year is truncated at 1900 as there is little variation in parking supply before 1900.

Table 3
Descriptive statistics: Main household variables.

	Mean	Std. dev	Min	Max
Number of cars	1.20	0.62	0	2
No car	0.11	0.31	0	1
One car	0.58	0.49	0	1
Two or more cars	0.31	0.46	0	1
Income (€)	46,052	21,954	15,178	120,750
Education low	0.27	0.44	0	1
Education middle	0.37	0.48	0	1
Education high	0.36	0.48	0	1
Age	46.75	15.00	18	90
Household size	2.80	1.24	1	6
Apartment	0.31	0.46	0	1
Distance city centre (km)	9.03	5.41	0	29
Within historic district	0.05	0.21	0	1
Building density (m^2/ha)	33,743	26,820	523	190,895
Median construction year	1966.33	21.85	1900	1999
# Households	98,659			

Note: See Appendix A.1 for a full list of variables.

Table 3 provides an overview of the main household characteristics. We have information about 98,659 owner-occupier households in 493 geographically distinct parking districts. The average household in the sample owns 1.2 cars, has an annual income of €46,000 and consists of 2.8 members.[15] Around 60% own one car, 30% own two or more cars, whereas few do not own a car (around 10%). Households live farther from the city centre than in the transaction dataset, 9 km vs 7 km and around 30% of households are apartment dwellers.[16] Most households live in highly built up urban areas, average building density is 33,700 m^2/ha, and the median construction year of properties is 1966.

3. Methodology

We develop a two-step methodology to estimate the effect of residential parking costs on car demand. In the first step we use hedonic house price methods to estimate implicit market prices for parking. To be more precise, we focus on local implicit prices for private outside parking spots which is a close substitute to on-street parking. In equilibrium, private parking prices should reflect (unobserved) outside parking costs. In the second step we investigate the effect of these prices on car ownership.

3.1. Step 1: Estimating parking costs

Our methodology exploits variation in the allocation of private parking *within* a parking district to identify district-specific residential parking costs using hedonic house price methods. As a household is only eligible for a parking permit when no private parking is available, spatial equilibrium theory predicts that for household utility to be the same in a given district, the implicit residential parking price should equal the costs of using a permit, i.e. the sum of the permit fee and cruising costs, capitalised in house prices (Van Ommeren et al., 2011).

We identify the implicit price of parking defined by the effect of having a private parking spot on house prices. Let us start with the following, naive, hedonic price regression:

$$P_{ijt} = \rho S_{ijt} + \boldsymbol{T}_{ijt}\alpha + \phi_t + \epsilon_{ijt}, \tag{1}$$

where P_{ijt} is the price for residential property transaction i in parking district j at time t, S_{ijt} is an indicator variable which equals one if the property has a private parking spot and zero otherwise. We also include four parking type dummies, $\boldsymbol{T}_{ijt}$, for carport, garage, carport and garage and double garage, which captures additional value of the building structure. Therefore, ρ can be interpreted as the implicit price (or cost) for a private outside parking spot. Lastly, ϕ_t is a vector of time fixed effects and ϵ_{ijt} is the error term.

We are interested in the causal effect of S_{ijt}, captured by ρ. It is unlikely that the estimate of ρ in (1) generates a causal estimate. For example, districts have different parking policies and may be attractive to car users for other reasons. Therefore we include parking-district fixed effects, ϕ_j, which absorb differences between parking districts and allow us to identify parking costs via variation *within* a parking district.[17] Moreover, there may be other housing or locational characteristics within a district that are correlated to property prices and parking allocation. For example, bigger properties are generally more expensive and are also more likely to have a parking spot. Hence we control for a large set of property and locational characteristics, $\boldsymbol{X}_{ijt}$.[18]

Parking costs are likely to vary locally, because supply and demand factors differ over space, so we allow ρ to vary at the parking district level j. Furthermore, the implicit price for housing and locational characteristics, as well as changes in property prices over time, are also likely to vary over space and may be correlated to local parking allocation.[19] Therefore we also allow the effect of housing and location characteristics $\boldsymbol{X}_{ijt}$ and time dummies ϕ_t to vary with j. This leads to the following regression:

$$P_{ijt} = \rho_j S_{ijt} + \boldsymbol{T}_{ijt}\alpha_j + \boldsymbol{X}_{ijt}\gamma_j + \phi_{jt} + \phi_j + \epsilon_{ijt}, \tag{2}$$

where the coefficients ρ_j, α_j and γ_j represent the implicit price for parking, the associated structure and other housing characteristics, respectively. The interaction ϕ_{jt} captures a district-specific time fixed effect.[20]

The coefficients, ρ_j, α_j and γ_j can be estimated by interacting S_{ijt}, $\boldsymbol{T}_{ijt}$ and $\boldsymbol{X}_{ijt}$ with parking district dummies. However, as most districts have few observations and there are many coefficients to be estimated, the variance of the implicit price estimates are high and outliers can lead to considerable variation in ρ_j (McMillen and Redfearn, 2010). To tackle this issue, we assume that districts neighbouring j have similar implicit prices as j which can be used to reduce the estimates' variance.[21] A semi-parametric approach can then be applied where neighbouring parking districts receive a higher weight than distant districts. To be more precise, we use the distance between the centroid of each

[15] Owner-occupiers tend to own more cars, are richer and have more individuals than an average Dutch household which owns one car, earns €45,000 and is composed of 2.2 people (Central Bureau of Statistics, 2015).

[16] This is less than in the transactions data, as apartments are generally sold more frequently than single-family houses.

[17] This implies that we can only identify ρ in districts where there is variation in the supply of *outside* parking.

[18] Property characteristics include; the log of size and parcel size (for single-family houses), the number of floors, rooms and bathrooms, and dummies for garden, balcony, central heating, new, monument, good inside maintenance, good outside maintenance, insulation (five levels), transaction year, construction year (nine interval dummies) and house type (apartment, terraced, detached, semi-detached, corner). Location characteristics include; distance to the metropolitan centre, closest train station and closest highway ramp and are specified in logs.

[19] For example, an additional meter of property size is likely to have a higher implicit price in the city centre than in the periphery as the demand for space is higher and the supply is fixed in the historic central part of most cities. This may lead to less allocation of parking as the space could be used for more valuable uses.

[20] As we perform local linear regression, a linear form for the dependent variable is preferable because implicit prices do not directly depend on average house prices.

[21] To prevent estimating ρ_j for districts without any outside private parking, we select districts with at least 10 transactions with outside private parking and 10 transactions without outside private parking.

parking district j, and any other district.[22] We estimate a partially linear regression model:

$$P_{ijt} = f_j(S_{ijt}, \boldsymbol{T}_{ijt}, \boldsymbol{X}_{ijt}, \phi_t) + \phi_j + \epsilon_{ijt}, \tag{3}$$

where the function $f_j(\cdot)$ is estimated in a non-parametric way. We estimate $f_j(\cdot)$ by locally weighted regression, implying:

$$f_j(\cdot) = \rho_j(u_j, v_j)S_{ijt} + \boldsymbol{T}_{ijt}\alpha_j(u_j, v_j) + \boldsymbol{X}_{ijt}\gamma_j(u_j, v_j) + \phi_t(u_j, v_j),$$

where (u_j, v_j) are the centroid coordinates of parking district j. The district-specific implicit parking costs ρ_j are then defined by $\rho_j(u_j, v_j)$.

Locally weighted regression techniques have been extensively used in the hedonic house price literature where parameters depend on geographic location (Sunding and Swoboda, 2010; Grislain-Letrémy and Katossky, 2014). For each parking district j, we estimate a weighted least squares (WLS) regression using an exponential distance decay kernel:

$$w_{jk} = \begin{cases} e^{-hd_{jk}}, & \text{if } d_{jk} < 5 \\ 0, & \text{otherwise,} \end{cases} \tag{4}$$

where w_{jk} is the weight applied to all property transactions in parking district k, the bandwidth h determines the speed of the decay and d_{jk} is the euclidean distance, in km, between the centroids of parking district j and k. Fig. A1 in Appendix A.2 illustrates the weighting function using various distance decay bandwidths. In our application, we estimate these partially linear regression models for each region separately as this makes the estimation procedure faster.[23]

As a part of the model is parametric, specifically the district fixed effect ϕ_j, we use a two-step estimation procedure (Bontemps et al., 2008). In the first step, the linear part of the specification, can be estimated using the Robinson (1988) approach. This method separately regresses P_{ijt} and the parametric part ϕ_j on the non-parametric part $f_j(\cdot)$ using local WLS and generates residuals, $\widetilde{P}_{ijt}$ and $\widetilde{\phi}_j$. The residuals $\widetilde{P}_{ijt}$ are then regressed on the residuals $\widetilde{\phi}_j$ using OLS and the coefficients $\widehat{\zeta}$ on $\widetilde{\phi}_j$ are captured.[24] In the second step, we then regress $P_{ijt} - \widehat{\zeta}\phi_j$ on the non-parametric part $f_j(\cdot)$ using local WLS to get the parking district specific coefficients of interest.

An important parameter in non-parametric estimation is the bandwidth. A lower bandwidth implies more bias, but lower variance, as the estimates are smoothed more over space. Meanwhile, a higher bandwidth implies less smoothing, therefore less bias and higher variance.[25] We will use a bandwidth of $h = 2$, which allows for a sufficient amount of variation in the estimates over space, while also having a variance that is economically meaningful. In Section 4 we show that lower bandwidths provide larger estimates of the price elasticity of car demand, so our approach is somewhat conservative, while higher bandwidths provide unrealistic estimates (for example negative parking costs and many large outliers).[26]

It is important to discuss the interpretation of the estimated implicit price, $\widehat{\rho}_j$. As parking is a discrete variable, those that own a private spot are willing to pay *at least* $\widehat{\rho}_j$, while households that do not own a private spot are *maximally* willing to pay $\widehat{\rho}_j$ (Bajari and Kahn, 2005).[27] Hence, we interpret the implicit price of a private outside parking spot as the (average) cost for an outdoor parking space for all residents living in district j.

3.2. Step 2: Parking costs and car demand

In the second step, we aim to estimate the effect of residential parking costs on vehicle demand. As mentioned in Section 3.1, implicit parking prices reflect parking costs, which are assumed to be the same for all households within a parking district. The identification strategy exploits spatial variation in implicit residential parking costs *between* parking districts to explain household vehicle demand using a multinomial logit (MNL) model. The MNL model assumes a random utility framework with k alternatives and i individuals, living in district j at time period t. As utility is not directly observed, we construct a model:

$$U^k_{ijt} = \lambda^k_{ijt} + \epsilon_{ijt}, \tag{5}$$

where the unobserved utility derived from alternative k, U^k_{ijt}, is composed of a deterministic component, λ^k_{ijt}, and a random component, ϵ_{ijt}, which is independently and identically distributed across alternatives with an Extreme Value Type I distribution. Therefore, the probability a household owns $C_{ijt} = k$ cars, where $k = 0, 1, \geq 2$, can be written as:

$$Pr[C_{ijt} = k] = \frac{e^{\lambda^k_{ijt}}}{\sum_{\tilde{k}=0}^{2} e^{\lambda^{\tilde{k}}_{ijt}}}. \tag{6}$$

We are mainly interested in how residential parking costs, $\widehat{\rho}_j$ affect the probability of owning k cars. Therefore, we specify the deterministic part λ^k_{ijt} as:

$$\lambda^k_{ijt} = \beta^k \widehat{\rho}_j + \phi^k_t, \tag{7}$$

where we control for year fixed effects, ϕ^k_t, and the error term is clustered at the parking district level, j, as parking costs are at a more aggregate level than household car ownership. The reference category is $k = 0$ cars, so we set $\beta^{k=0} = 0$.

One concern with equation (7) is that households with a higher (lower) preference to own a car may sort into areas with lower (higher) parking costs. Therefore β^k will be overestimated as parking costs and household characteristics related to vehicle demand are correlated. For example, larger families may want to own more than one car or live in a larger house and therefore choose to locate outside the densest areas in cities where parking costs are lower. Furthermore some households may have strong preferences for car ownership or urban amenities. Therefore, we control for household characteristics, $\boldsymbol{H}_{ijt}$, which include income, age, size, type and education.

The availability of substitutes and the ease of using a car may also correlate with vehicle demand and parking costs, so we add location characteristics, $\boldsymbol{L}_{jt}$, which include distance to transport infrastructure, the availability of public transportation, distance to the city centre, whether the household lives in a historic district and building density. Controlling for distance to the city centre is particularly important as it captures the stylised fact that in European cities, urban amenities are highly correlated with distance to the city centre and therefore may also be correlated to preferences for car ownership and residential parking

[22] To speed up the estimation, we set 5 km as the cutoff point. Therefore the weight for any observation i in parking district k greater than 5 km from j is set to zero. This does not materially effect the estimates of ρ_j as weights are approximately zero after 5 km (see Fig. A1 in Appendix A.2).

[23] This provides essentially the same results as estimating all regions simultaneously as most regions are more than 5 km apart, therefore observations of other regions are given a weight of zero.

[24] We estimate $\widehat{\zeta}$ by regressing: $\widetilde{P}_{ijt} = \zeta\widetilde{\varphi}_j + u_{ijt}$. Under regularity conditions, Robinson (1988) shows that the coefficient is a $\sqrt{n}$-consistent and asymptotically normal estimator for $\widehat{\zeta}$.

[25] A bandwidth of $h = 0$ implies each observation gets $w_{jk} = 1$ and we are back to specification (1), including more controls, where parking costs are assumed to be constant over space (causing high bias). A bandwidth of $h = \infty$ implies that we do not take into account the spatial correlation in ρ_j's as in specification (2).

[26] We detect any remaining large outliers as greater than or smaller than $mean(\widehat{\rho}_j) \pm 4 * std(\widehat{\rho}_j)$.

[27] The Bajari and Kahn (2005) approach has also been used to study car ownership, see for example Mulalic and Rouwendal (2015).

costs. Finally, as parking policy is determined at the municipality level, we include municipality fixed effects, ϕ_m^k, which also controls for other local unobserved characteristics of the built environment such as land use regulations that may influence vehicle demand and parking costs. This would suggest the following specification:

$$\lambda_{ijt}^k = \beta^k \hat{\rho}_j + \boldsymbol{H}_{ijt}\gamma^k + \boldsymbol{L}_{jt}\theta^k + \phi_m^k + \phi_t^k. \quad (8)$$

A major concern with (8) is that because residential parking costs are determined by supply and demand for parking, vehicle demand will be correlated to parking costs. Therefore, the specification suffers from reverse causality and the estimated coefficient β^k is inconsistent. We attempt to solve this problem by instrumenting $\hat{\rho}_j$ using the median construction year of properties in a district, B_j, similar to Van Ommeren et al. (2012). The median construction year of properties is a conditionally-valid instrument as it affects current parking costs via historical supply restrictions, reflecting historical land and building costs. Therefore the main assumption for identification is that, conditional on household and location controls, the median construction year of residential properties in area *j* only affects current vehicle demand *via* historical supply factors and is uncorrelated to the *current* demand for parking in area *j*.

It may be the case that households with preferences for car ownership sort into parking districts with newer buildings and lower costs. We argue that this is a minor threat to our identification as the lion's share of sorting is likely controlled for by the detailed set of housing characteristics, $\boldsymbol{H}_{ijt}$, and distance to the city centre. Furthermore, we exclude parking districts with a median construction year after 1999 and exclude households living in properties constructed after 1999 as parking costs in newer districts and houses may be affected by current parking demand. It is important to note that in the first-step the implicit parking costs are estimated conditional on construction year of the property, so the cost should not be influenced by its own construction year.

There are two additional advantages of instrumenting for $\hat{\rho}_j$, compared to using a standard MNL model. Firstly, because we identify the impact of changes in parking costs due to a shift in supply, conditional on controls, we address the issue that random measurement error is introduced during the estimation of costs in Step 1 which usually causes a downward bias in the estimated β^k coefficient. Secondly, it mitigates issues from any other omitted factors, correlated to vehicle demand and parking costs.

As a MNL model is non-linear in parameters, 2SLS estimators are inappropriate, so we apply a control function approach (Petrin and Train, 2010; Wooldridge, 2015). In the first stage we estimate:

$$\hat{\rho}_j = \eta B_j + \boldsymbol{H}_{ijt}\gamma + \boldsymbol{L}_{jt}\theta + \phi_m + \phi_t + \upsilon_j, \quad (9)$$

where B_j is the median construction year of residential properties in parking district *j* and υ_j is the residual. In the second stage, we plug in $\hat{\upsilon}_j$ linearly as an additional control and specify:

$$\lambda_{ijt}^k = \beta^k \hat{\rho}_j + \boldsymbol{H}_{ijt}\gamma^k + \boldsymbol{L}_{jt}\theta^k + \phi_m^k + \phi_t^k + \hat{\upsilon}_j, \quad (10)$$

where standard errors are bootstrapped (250 replications) over both steps and clustered at the parking district level *j*.

The parameters of a MNL model represent the probability one alternative is chosen as compared to the base category. Therefore, the directionality and magnitude of the coefficients are not straightforward to interpret. In light of this, we calculate and present the average marginal effect (AME) for the variables of interest on the choice probabilities of each car ownership alternative (Bhat and Pulugurta, 1998). The marginal effect of a continuous variable, for example parking costs $\hat{\rho}_j$, on the probability a household i chooses k cars, $\pi_{ijt}^k = Pr[C_{ijt} = k]$, can be written as:

$$\Delta Pr[k] = \frac{\partial \pi_{ijt}^k}{\partial \hat{\rho}_j} = \pi_{ijt}^k (\hat{\beta}^k - \sum_{\tilde{k}=0}^{2} \pi_{ijt}^{\tilde{k}} \hat{\beta}^{\tilde{k}}). \quad (11)$$

We take the average of the marginal effects over all households to get the AME, denoted as $\Delta Pr[k]$. Using the AMEs, we can calculate the change in average car ownership as:

$$\Delta E[C] = 1 \cdot \Delta Pr[1] + 2 \cdot \Delta Pr[2]. \quad (12)$$

When estimating a MNL model, one does not impose restrictions on the marginal effect of a variable on the probability an alternative is chosen. If parking costs have a larger impact on the demand for a second car because it is for example less essential than the first car for mobility, we can test whether the effect of parking costs varies over each car ownership alternative. When the AME on $k = 1$ car, $\Delta Pr[1]$, is zero, it indicates that the number of households switching from $k = 1$ to $k = 0$ cars is the same as from $k = 2$ to $k = 1$ cars. This suggests that the assumption of a linear restriction holds and therefore, we can apply linear regression techniques, such as 2SLS, which are more efficient. We therefore also estimate 2SLS models.

4. Results

In this section we present the results from estimating implicit parking costs (Section 4.1), the impact of these costs on household vehicle demand (Section 4.2) and additional sensitivity checks (Section 4.3).

4.1. Step 1: Estimating parking costs

In Table 4 we present the average implicit parking prices, or costs, of various parking types for each region obtained by estimating equation (3). The implicit parking price can be interpreted as the average price for a private outside parking spot. This represents the net present value of future benefits from private parking as compared to parking on-street with a permit. The average price for an outside private parking space is around €12,000 and is highest in the Amsterdam region. Prices are generally higher for parking spaces with structure, such as garages, and for larger lots which suggests higher construction costs and other uses such as storage.[28] Prices vary slightly between regions which suggests different supply and demand conditions. As we are interested in estimating the effect of parking costs on car ownership, we derive annual parking costs by assuming zero depreciation costs and an annual discount rate of 5%.[29] Hence, we multiply the implicit price $\hat{\rho}_j$ by 0.05.

Table 5 presents the average annual implicit outside parking costs. There are a total of 542 parking districts in the sample. On average, annual parking costs are around €600 and seem to follow an approximately normal distribution (see Fig. A2 in Appendix A.3). Around 13% of the estimates are negative, most of which are close to zero and statistically insignificant. Furthermore, another 21% of the estimates are positive and not significantly different from zero (see Table A3 in Appendix A.3). Hence, for about one third of the estimates, parking costs are essentially zero. This makes sense as outside parking costs are close to zero in peripheral areas.

We also separate the results by distance to the metropolitan centre and present the results graphically. Table 5 and Fig. 3 show that there is substantial heterogeneity in annual parking costs over space with higher costs generally in central city areas, especially in Amsterdam where annual costs are around €1600 within 2 km from the city

[28] Implicit prices for large parking spots are based on few observations (see Table 2), therefore estimates are less precise (have large standard errors) and should be interpreted with caution. A priori, it is not clear whether carports should be more or less expensive than garages as carports may have space for more than one car while garages include a physical structure. Our findings indicate that garages are more expensive than carports in general, however carports seem more valuable in Utrecht.

[29] Outside parking is unlikely to depreciate as it does not include any building structure. This discount rate gives realistic parking cost estimates, as discussed at the end of this section.

Table 4
Average implicit parking costs (€).

	Amsterdam	Rotterdam	The Hague	Utrecht	Overall
Outside parking	14147	12747	9264	10422	11914
	[12825]	[11010]	[9992]	[8089]	[11188]
Carport	18353	15816	17996	20200	17990
	[13990]	[15485]	[16336]	[15419]	[15281]
Garage	21384	18683	20486	10851	18788
	[10051]	[8542]	[9689]	[9310]	[10194]
Carport & garage	21042	27973	31542	14569	24331
	[21242]	[26953]	[30522]	[23034]	[26282]
Double garage	22651	29765	16886	10907	20781
	[27077]	[27730]	[25906]	[15945]	[26173]
# Transactions	182,958	121,128	142,303	88,708	535,097

Notes: Costs are a representative average for all transactions over the time period 2000–2016. Standard deviation in brackets. Full table of implicit prices are available upon request.

Table 5
Average annual implicit outside parking costs (€/yr).

	Amsterdam	Rotterdam	The Hague	Utrecht	Overall
Overall	707	637	463	521	596
	[641]	[550]	[500]	[404]	[559]
Centre	1609	826	953	771	1023
	[215]	[181]	[347]	[422]	[463]
Urban ring	1060	1122	535	420	792
	[513]	[669]	[365]	[354]	[552]
Periphery	354	476	322	455	395
	[481]	[475]	[554]	[370]	[487]
# Parking-districts	147	141	155	99	542

Notes: Costs are a representative average for all parking districts, weighted by the number of transactions in a parking district, over the time period 2000–2016. As in Table 1, we define the ‘centre’ as <2 km radius from the city centre, the ‘urban ring’ is between 2 and 5 km and the ‘periphery’ >5 km. Standard deviation in brackets.

centre and fall with distance. Costs in the periphery level off at around €300 to €500. Parking costs in Rotterdam are slightly different from the general trend and are higher surrounding the city centre. This is likely because the city centre of Rotterdam was re-built after the bombings in WWII and therefore has a higher supply of parking than the historic neighbourhoods surrounding the centre (Koster et al., 2012). Overall, the estimated implicit parking costs appear realistic.[30]

4.2. Step 2: parking costs and car demand

The maps of car ownership and parking costs in Figs. 1 and 3 suggest that there is an inverse relation between vehicle ownership and residential parking costs. This relation is investigated in more depth in this section. Table 6 presents the main results.

Firstly, in columns (1) and (2) we present the average marginal effects (AME) from estimating specification (7) and (8) using MNL, hence we still ignore a range of endogeneity issues. We see that there appears to be a small, negative effect of parking costs on car ownership, with a smaller effect size when controlling for household and location characteristics. These results are however difficult to interpret as causal estimates because reverse causality and measurement error will likely bias the estimates towards zero. Owning a vehicle creates demand for parking and thereby raises prices, resulting in a positive bias in the coefficient for parking costs on vehicle demand, whereas if there is (random) measurement error in step 1, results will be biased towards zero.

In columns (3) and (4) we estimate specification (10), using a MNL control function approach, where parking costs are instrumented with the median construction year of buildings in a parking district. It is useful to discuss the sign of the instrument. In the Netherlands, car ownership has grown over the last century. Hence, we expect that, ceteris paribus, parking supply will be higher in areas where buildings have been constructed more recently, as parking does not need to be redeveloped from pre-existing land uses which is costly in built-up areas. Therefore we should see a negative relation between the median construction year of residential properties in a parking district and parking costs. Results from the first stage show that the instrument is strong, the Kleibergen-Paap First stage F-statistic is 51.55 and 15.64, respectively, and indeed has the expected negative sign (see Table A5 in Appendix A.2.2).

The results from column (4) indicate that the AME of residential parking costs on the probability of owning one car is zero, while for the second car it is negative. This indicates that as parking costs increase, around the same number of households switch from two to one car as the number that switch from one to zero cars, implying that the effect of parking costs on vehicle demand is approximately linear and therefore 2SLS can be applied. Comparing the effect of parking costs on average car ownership, $\Delta E[C]$, with and without control variables in columns (3) and (4) suggests that controlling for household and location characteristics are important for the conditional validity of the instrument.

[30] Based on current list prices from Funda, the largest online multi-listing housing market platform in the Netherlands, rental prices in 2019 for private parking spots in city centres are around €3000 in Amsterdam and are around €1500 in Rotterdam, The Hague and Utrecht (Funda, 2019). Note, these prices are not directly comparable as housing prices have almost doubled since 2008 (the average year in the data), private rental spots are generally garages which are more expensive and because implicit prices should be lower than market prices due to permits.

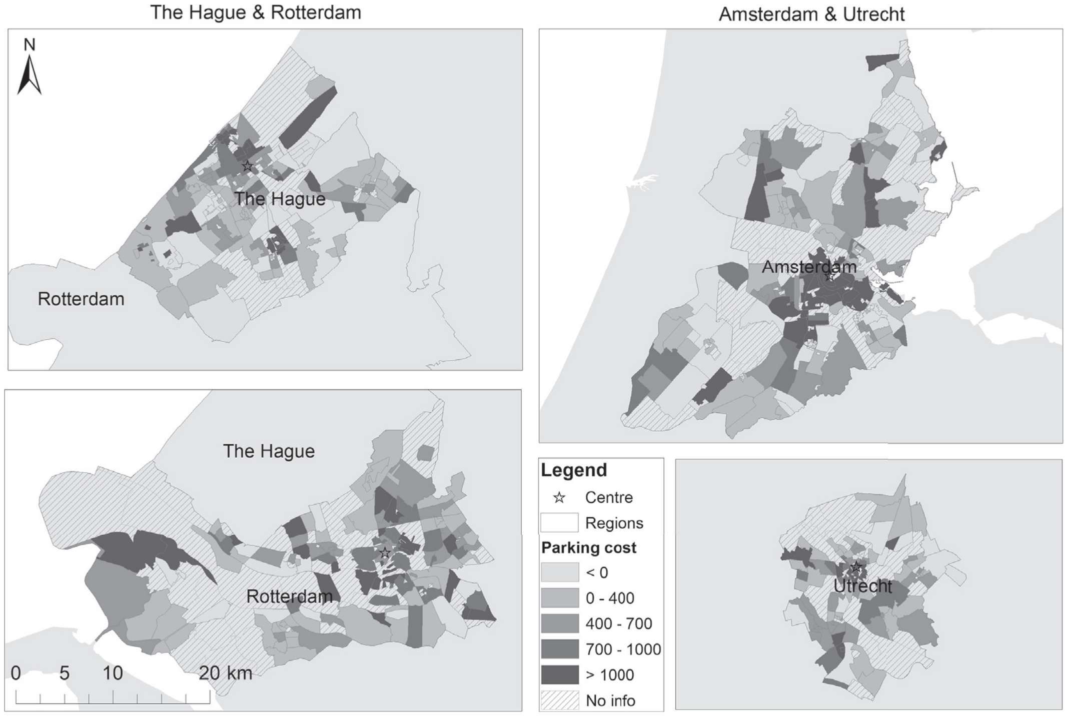

Fig. 3. Map of annual residential parking costs (€/yr).

Table 6
Main results.

	MNL		MNL-CF		2SLS	
	(1)	(2)	(3)	(4)	(5)	(6)
Parking cost (€100/yr)						
Pr[0 car]	0.00356***	0.00120***	0.0126***	0.00597**		
	(0.000548)	(0.000351)	(0.00179)	(0.00241)		
Pr[1 car]	−0.00170**	−0.00131**	0.00516**	0.00269		
	(0.000682)	(0.000597)	(0.00210)	(0.00379)		
Pr[2 cars]	−0.00186**	0.000105	−0.0177***	−0.00866*		
	(0.000929)	(0.000606)	(0.00331)	(0.00501)		
$\Delta E[C]$	−0.005***	−0.001	−0.030***	−0.015**	−0.035***	−0.017***
	(0.001)	(0.001)	(0.005)	(0.007)	(0.005)	(0.005)
ε_P^C	−0.23***	−0.05	−1.26***	−0.61**	−1.45***	−0.70***
	(0.06)	(0.03)	(0.20)	(0.29)	(0.21)	(0.20)
Controls (18)	N	Y	N	Y	N	Y
Year FE's (10)	Y	Y	Y	Y	Y	Y
Mun FE's (45)	Y	Y	Y	Y	Y	Y
First stage F-statistic			51.55	15.64	65.68	22.00
# Parking-districts	493	493	493	493	493	493
# Households	98,659	98,659	98,659	98,659	98,659	98,659

Notes: Dependent variable is the number of cars per household. Standard errors are in parenthesis and are clustered at the parking-district level. For MNL specifications, AMEs and two-stage clustered bootstrapped standard errors and (Kleibergen-Paap) First stage F-statistics (250 replications) are presented. MNL-CF refers to MNL model with a control function approach. $\Delta E[C]$ represents the change in average car ownership from a €100 increase in parking costs and is calculated as in equation (12). See Appendix A.2.2 for calculation of ε_P^C, the implied price elasticity of car ownership, standard errors are calculated using the delta method. See Tables A4 and A5 for full table with controls and first-stage regression results. Stars denote *p < 0.1, **p < 0.05, ***p < 0.01.

In columns (5) and (6) we present the results using 2SLS, which allows us to immediately estimate the average effect on car ownership, $\Delta E[C]$.[31] Our preferred estimate in column (6) indicates that the marginal effect of parking costs on car ownership is statistically significant at the 1% level and can be interpreted as an increase in parking costs of €100 is associated with a reduction in average car ownership of 0.017.[32] This is qualitatively the same as the outcome in column (4) using the MNL-CF approach and is larger than the estimate in column

[31] Results from a control function ordered logit model are essentially the same and are available upon request.

[32] In general, the control variables have plausible signs. Income, household size, age, level of education and distance to the nearest major train station have a positive effect on car ownership while building density and the availability of public transport in the near vicinity have a negative affect. Table A4 and A5 in Appendix A.3 suggest that the most important control variables are household type and location characteristics such as distance to the nearest major train station, distance to the metropolitan city centre and building density.

Table 7
Sensitivity: Heterogeneous effects.

	(1) Flats	(2) Houses	(3) Renter	(4) Amsterdam	(5) Rest
$\Delta E[C]$	-0.0130^{***}	-0.0185^{**}	-0.00734^{*}	-0.0287	-0.0152^{***}
	(0.00443)	(0.00829)	(0.00379)	(0.0186)	(0.00526)
ε_p^C	-0.66^{***}	-0.71^{**}	-0.54^{*}	-1.53	-0.62^{***}
	(0.22)	(0.32)	(0.28)	(0.99)	(0.22)
Controls (18)	Y	Y	Y	Y	Y
Year FE's (10)	Y	Y	Y	Y	Y
Mun FE's (45)	Y	Y	Y	Y	Y
Mean car ownership	0.99	1.30	0.68	0.94	1.22
KP F-statistic	33.60	9.30	35.24	3.76	16.86
# Parking-districts	484	480	492	49	445
# Households	29,222	65,700	52,871	7517	91,142

Notes: Dependent variable is the number of cars per household. Standard errors are in parenthesis and are clustered at the parking-district level. 'Ams' refers only to the municipality of Amsterdam while 'Rest' refers to all other municipalities. All models are estimated using 2SLS. Kleibergen-Paap First stage F-statistic is presented. We directly estimate the change in average car ownership, $\Delta E[C]$, from a €100 increase in parking costs as the marginal effect of parking costs on car ownership. See Appendix A.2.2 for calculation of ε_p^C, the implied price elasticity of car ownership, standard errors are calculated using the delta method. The elasticity is corrected for differences in mean car ownership between groups, as indicated above. See Table A5 for first stage results. Stars denote $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

(2) where parking costs are not instrumented.[33] Given the result in column (7), this suggests that the implied price elasticity of car ownership is: $\varepsilon_p^C = -0.7$.[34] The results can also be interpreted in standard deviations (see column (3) of Table A8 in Appendix A.3). A one standard deviation increase in parking costs (€503) is associated with a reduction in average car ownership of 0.085.

The implied elasticity is within the range (but at the higher end) of estimates from the literature, which ranges between $[-0.3, -0.8]$.[35] Car ownership elasticities with respect to fuel prices are generally below -0.3, so parking costs seem to have a stronger effect on car ownership than variable costs such as fuel prices (Goodwin et al., 2004; De Jong et al., 2009). This suggests that, at least for the Netherlands, permit fees may be an effective tool to reduce car ownership. This likely reflects the availability of close substitutes to cars, such as public transport and bicycles, in the dense metropolitan regions we focus on.

It is important to put this result into context. Average car ownership in the city centres is around 0.90, while in the periphery it is 1.27, so the difference is 0.37 (see Table A9 in Appendix A.4). Meanwhile parking costs in these areas are €1023 and €395, respectively, so the difference is around €630 (see Table 5). This suggests that, conditional on household and location characteristics, parking costs explain $-0.017 \times \frac{630}{100} = 0.11$ or around 30% of the difference in car ownership between the centre and periphery.[36] This seems realistic given how large parking costs are, relative to ownership costs. The remaining difference in car ownership rates can likely to be explained by substitutes to cars available in the city centre such as walking and cycling, sorting of households and the difficulty of driving in the city centre, which are controlled for in our regressions.

4.3. Sensitivity

The results indicate that an increase in residential parking costs of €100 is associated with a reduction in average car ownership of around 0.017, indicating an implied price elasticity of car ownership of -0.7. In this section we perform a range of robustness checks.

In Table 7 we test the robustness of the specified demand for cars over various sub-groups.[37] In columns (1) and (2) we estimate specification (10) separately for households living in flats and single-family houses and find that the elasticities are the same. In the analysis above, we exclude renters because our estimated parking costs (using house prices) most likely reflect prices faced by owner-occupiers which may differ from parking prices faced by renters. In the Netherlands, the majority of urban renters live in public housing which generally does not have private parking. Therefore, these residents will mainly park on-street using a parking permit. If (public) renters respond less to cruising (time) costs, as they have lower incomes on average, the elasticity may be smaller. In column (3), we check whether renters have a different car demand function as compared to owner-occupiers. The results suggest that renters may be slightly less responsive to changes in parking costs, however the elasticity is not statistically different.

In the municipality of Amsterdam, most districts allow a maximum of only one permit, while some districts also have waiting lists and permit fees are substantially higher than in other metropolitan areas. Therefore, households may be willing to pay more for a private spot and also may respond more strongly to permit fees. Therefore, in columns (4) and (5) we estimate the model separately for Amsterdam and all other municipalities. The effect of parking costs on average car ownership is roughly twice as high in Amsterdam. However, because it is imprecise, the estimate is statistically indistinguishable from the effect in other municipalities.

We also test the sensitivity of the results to various functional form assumptions and bandwidth sizes (see Table A7 in Appendix A.3). We specify the functional form of control variables more flexibly by measuring income, age, distance to the city centre and availability of public transport using more detailed categories.[38] The average change in car ownership increases slightly to -0.018. We also test whether changing the functional form of the instrument from linear to quadratic affects the results. Column (2) suggests that the marginal effect declines slightly to -0.014. In column (3) and (4) we test the sensitivity of

[33] This suggests that reverse causality and measurement error indeed cause a bias towards zero.

[34] Annual average car ownership costs, excluding parking, are assumed to be €5000 (Nibud, 2017). See Appendix A.2.2 for the full calculation. If $\Delta Pr[1]$ is zero, $\Delta E[C] = -0.017$ while if we include $\Delta Pr[1]$, $\Delta E[C] = -0.015$.

[35] Note the range presented is based on the elasticities with respect to purchase or fixed costs. See Dargay (2002); De Jong et al. (2009); De Groote et al. (2016); Seya et al. (2016).

[36] The magnitude is slightly higher for Amsterdam and The Hague at around 40%, while in Rotterdam and Utrecht it is around 15%.

[37] Note the elasticity takes into account differences in mean car ownership between groups.

[38] Income is split into 6 categories: <20k, 20-40k, 40-60k, 60-80k, 80-100k and >100k. Age is split into 4 categories: <26, 26–45, 45–65 and >65. Distance to city centre is split into ten 1 km bands and public transport availability is split into number of bus, metro and train stops within 100, 250 and 500 m.

the implied elasticity to alternative discount rate assumptions. Lower (higher) discount rates are associated with larger (smaller) elasticities, suggesting our estimate is conservative.

Lastly, we test the effect of adjusting the bandwidth used to estimate parking costs in Step 1. Table A8 in the Appendix A.3 indicates that a one standard deviation increase in parking costs has a similar effect on vehicle demand with lower bandwidths implying larger elasticities. We decide to take a conservative approach and use the implied elasticity for $h = 2$.

5. Counterfactual analysis

In order to apply our estimates, several assumptions are required. Most importantly, we assume a *partial equilibrium* setting where residence and job locations are fixed, therefore commuting patterns remain unchanged. We also assume that households respond to changes in (monetary and time) costs in the same manner, that vehicle externalities are zero and that the implicit price for a *marginal* parking spot applies to all households. Additionally, we assume that cruising costs are zero in the periphery, where there is no paid parking. Therefore the value of a private off-street parking spot in the periphery captures the security value attributed to private parking, which we assume does not vary systematically over space. As such, we can calculate annual cruising costs per district, ζ_j, as the difference between the implicit parking cost, $\hat{\rho}_j$, minus permit fees, F_j, and the parking cost in the periphery, $\hat{\rho}_p$ or $\zeta_j = \hat{\rho}_j - F_j - \hat{\rho}_p$.

We follow De Groote et al. (2016) and assume a constant-elasticity inverse demand function: $D(Q) = P_c(Q/Q_c)^{\frac{1}{\epsilon}}$, where P_c is the total current annual cost of owning a car, Q/Q_c is the average number of cars in the new scenario, Q, relative to the initial average number of cars, Q_c, and ϵ is the price elasticity of car ownership which is assumed to be constant over space. This functional form better accounts for the non-linearity in demand responses, which is important as we may want to consider large changes in parking costs.[39] We assume that the supply curve is fully elastic. Therefore the marginal cost of adding or removing a car is roughly constant and equal to the total average car costs excluding parking, which are around €5000, plus parking costs, $\hat{\rho}_j$. This would imply a supply curve: $S(Q) = 5000 + \hat{\rho}_j$. As we assume zero externalities, welfare effects in the car market can be calculated as the difference between the inverse supply and demand function.

Given these assumptions, we use information about current parking and vehicle markets to provide back-of-the-envelope calculations that approximate the effect of changes in parking costs (see Appendix A.4 for calculations and an example). Estimates are based on a cross-section of transactions and households, therefore represent long run effects. We discuss the main implications of these assumptions in Section 5.3.

5.1. Implications for parking policy

Residential parking permits are offered at a fraction of the cost in the Netherlands. Currently, the highest annual permit fees in the country are in the centre of Amsterdam and cost €500 while the market value of a parking permit is around €3600 (Van Ommeren et al., 2011).[40] We apply our estimates to gain insights into the potential implications of raising residential permit fees in the city centre of Amsterdam to the market value estimated in Van Ommeren et al. (2011).

Increasing permit fees will likely raise overall parking costs in the short run, however, the effect on car ownership is likely to be smaller in the long run as higher costs induce households to give up their car which results in less cruising and shorter waiting lists.[41] We deal with this by considering two extreme cases, assuming; (A) that private cruising costs are unchanged and (B) that private cruising costs are zero when permit fees equal the market value.

In case (A), raising permit fees by €3100 (an increase in the total annual car ownership costs from around €6600 to €9700), is expected to reduce car ownership by approximately 24 percent and is associated with a welfare gain of around €300 per household (see Appendix A.4 for calculation). In case (B), cruising costs, which account for around €800 in private time costs, fall to zero. This results in an increase in car ownership of around 5 percentage points, corresponding to a rebound effect of 20%. Therefore, the decline in car ownership is lower overall, 19 percent, and is associated with a lower annual welfare gain of around €245 per household.

5.2. Implications of automated vehicles

In the near future, automated vehicles (AVs) may not necessarily require parking which has implications for vehicle demand in cities. In a residential context, if households do not need parking anymore, there will likely be three types of welfare effects from: (1) not facing cruising costs, (2) increases in vehicle demand and (3) the value of re-purposing land currently designated to parking (Fagnant and Kockelman, 2015; Zakharenko, 2016). Our results allow us to provide estimates for (1) and (2).

We consider two scenarios for AVs. On the one hand, if households own private AVs and parking costs at the residence 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 reservation value of land plus additional costs of traveling to and from the parking area (Zakharenko, 2016). Therefore in scenario (A), we assume parking costs approximately equal implicit parking costs in the periphery, $\rho_j^A = \hat{\rho}_p$. 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 scenario (B), we assume households incur zero parking costs, so $\hat{\rho}_p = 0$ and $\rho_j^B = 0$.

To calculate (1), the welfare effect from not facing cruising costs, we compute the annual cruising costs per car, ζ_j, and transform this into an average welfare effect per household by multiplying ζ_j by the average number of cars per household, $\overline{C}_j$. Therefore, $\Delta W_{1j} = \zeta_j \cdot \overline{C}_j$. The welfare effect (2), from additional vehicle demand, is calculated as $\Delta W_{2j} = \int_{Q_c}^{Q'} (D(Q) - S(Q))dQ$, where Q' equals the average number of cars, given parking costs as specified in scenario (A) and (B).[42]

The counterfactual results are shown in Table 8. We focus on the "Overall" effects for an average owner-occupier household in the far right column. In scenario (A), AVs are privately owned and therefore parking costs equal the implicit cost in the periphery. This is expected to increase car demand by around 8 percent in the centre, 5 percent in the urban ring and there is no change in the periphery. This is associated with annual gains per household of around €450 in the city centre, €300 in the urban ring and zero in the periphery.

[39] Note assuming a linear demand function, whereby the change in car ownership equals $\Delta C = -0.017 \cdot \Delta P$ will likely overestimate the impact for large changes in P.

[40] Note, we estimate the implicit parking cost, conditional on the current number of permits which is likely to be an underestimate of the market value of a parking permit. Meanwhile, €3600 is likely to be an upper bound estimate of the market value as the average residents value for a permit is likely to be lower than a household with private parking.

[41] Note for simplicity we include all additional costs such as waiting times under the header cruising costs.

[42] We note that car ownership is *currently* a pre-requisite for car use. However, in the future, this is unlikely to be the case as AVs can be shared and used on demand. Therefore we consider our estimates for the effect of residential parking costs on car ownership (2) as providing an indication of the effect of parking costs on the extensive margin, i.e. whether households use a car.

Table 8
Implications of AVs.

	Amsterdam	Rotterdam	The Hague	Utrecht	Overall
Scenario A: Private AV					
ΔCar demand (%)					
Centre	16	4	8	4	8
Urban ring	9	8	3	0	5
Periphery	0	0	0	0	0
ΔWelfare (€/yr)					
Centre	641	256	623	235	445
Urban ring	484	632	187	0	321
Periphery	0	0	0	0	0
Scenario B: Shared AV					
ΔCar demand (%)					
Centre	22	11	13	11	14
Urban ring	14	15	7	6	11
Periphery	5	7	4	6	5
ΔWelfare (€/yr)					
Centre	962	714	985	690	832
Urban ring	843	1194	546	422	760
Periphery	450	629	415	610	515

Notes: In scenario (A), parking costs equal the implicit cost in the periphery. In scenario (B), parking costs are zero. As in Table 1, we define the 'centre' as <2 km radius from the city centre, the 'urban ring' is between 2 and 5 km and the 'periphery' >5 km. Δ Welfare represents the annual gain for an average owner-occupier household. See Table A9 in Appendix A.4 for additional information.

In scenario (B), AVs are shared and therefore parking costs approach zero. As a result, car demand is predicted to increase by around 14 percent in the centre, 11 percent in the urban ring and 5 percent in the periphery. Annual gains per household are around €850 in the city centre, €750 in the urban ring and €500 in the periphery.

Overall, it appears that car use is likely to increase substantially if residents no longer face parking costs, with larger effects in denser urban areas where parking costs are high. Given that annual average travel distances per car are approximately 13,000 km, additional vehicle demand may result in up to 1600 km of additional annual car use by households in city centres.[43] The largest welfare gains arise from eliminating cruising costs, which are larger in areas with higher parking costs and higher car ownership. Meanwhile, the welfare gains in the car market, ΔW_{2j}, which are small, are likely to be lower due to vehicle externalities, such as congestion, pollution and injury, which are assumed to be zero in this application (Glaeser and Kohlhase, 2004; Sovacool, 2009).

In a realistic future scenario, one would expect that there will be both private and shared AVs, therefore the effects of reduced parking costs are likely to be somewhere in between the two cases presented.

5.3. Discussion

It is important to discuss the uncertainties from our application and implications of our assumptions as there may be reasons to believe that the effects could be over or under-estimated. Implicit prices from a hedonic model are an outcome of both supply and demand. Therefore, parking costs may be measured with error when considering a *large* change in parking demand. Additionally, estimated parking costs in the first step may be overestimated if off-street is preferred to on-street parking, conditional on search, or if parking policy is not binding. We are however not concerned with measurement error for our estimates of parking costs in the first step because we use an instrumental variables approach to estimate the elasticity in the second step. In our analysis, we focus on owner-occupiers which, as we show in the sensitivity analysis, may respond more strongly to parking costs than renters.

It is more likely however that the estimated welfare changes for owner-occupiers are conservative. Firstly, the elasticity may vary over space. As there is a higher availability of substitutes in the city centre, the average elasticity may underestimate the effect in the dense urban areas which we focus on. Secondly, residential locations may change. Sorting of households with a high propensity to drive, such as high income families, into currently expensive parking districts may also result in larger changes in vehicle demand. Finally, we do not consider additional traffic congestion externalities associated with cruising and vehicle use. This would cause an underestimate for the welfare gains from eliminating cruising and raising permit fees while overestimating the (small) gains from additional vehicle demand in the case of AVs.

6. Conclusions

This paper provides an approach to estimate local residential parking costs and examines to what extent these costs affect vehicle demand, taking endogeneity issues into account. We apply the methodology to the four largest metropolitan regions of the Netherlands. The findings suggest that parking costs vary substantially over space. For example, in the city centre of Amsterdam, the annual implicit cost of an off-street, outside, parking spot is around €1600, which is over 20% of total average car costs and four times higher than in the periphery. Average car ownership for owner-occupier households in districts with one standard deviation (€503) higher annual parking costs decreases by around 0.085, corresponding to a price elasticity of car demand of about −0.7. The disparity in parking costs between the city centre and the periphery explain around 30% of the difference in average car ownership rates between these areas, providing an additional explanation for why car ownership is lower in dense urban areas.

We employ the estimates above to investigate the implications for parking policy. The municipality of Amsterdam is currently determined to reduce private car ownership and promote more sustainable modes

[43] Assuming that residential parking costs do not affect the number of km travelled per vehicle and that new users utilise the car as intensively as an average current user.

of transportation in the city (Gemeente Amsterdam, 2018). One tool at their disposal is permit fees. The results, applied to the city centre of Amsterdam, indicate that raising annual permit fees in the city centre to the market value, an increase from €500 to €3600, is expected to reduce average car ownership between 19 and 24 percent, depending on whether the rebound effect from eliminating cruising is taken into account.

These estimates can also be useful to gauge the potential implications of AVs as households will no longer require parking directly outside their residence. Our estimates provide long run approximations for the effect of fully AVs on cruising costs and vehicle demand considering different assumptions about changes in parking costs. The findings indicate that the average annual welfare gain per household from not incurring residential parking costs is between around €450 and €850 in the city centre, depending on whether AVs are privately owned or shared. This is associated with an increase in car demand in the city centre by 8–14 percent. These effects are smaller outside the central urban areas where parking costs are lower.

While this paper focuses on the effects of parking costs on car ownership, further research should consider the value of re-purposing on and off-street parking in cities as the land value is likely to be large. Furthermore, additional attention should be placed on estimating the effect of parking policy on cruising costs to get a better understanding of the rebound effect from policies aimed at raising parking fees. Finally, further research should consider how the elasticity of car ownership with respect to parking costs is related to the availability of substitutes for the private car.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.regsciurbeco.2019.05.005.

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