The welfare implications of parking policy

Cover pictures:

Front cover:

Smith, J. (2009, 8 November). Parking Lot [online photograph]. Retrieved from https://www.flickr.com/photos/jmsmith000/4088871694.

Back cover:

Jastremski, M. (2004, 2 November). Empty Autumn Parking Lot [online photograph]. Retrieved from https://openphoto.net/gallery/image/view/6659.

VRIJE UNIVERSITEIT

The welfare implications of parking policy

ACADEMISCH PROEFSCHRIFT

ter verkrijging van de graad Doctor of Philosophy
aan de Vrije Universiteit Amsterdam,
op gezag van de rector magnificus
prof.dr. V. Subramaniam,
in het openbaar te verdedigen
ten overstaan van de promotiecommissie
van de School of Business and Economics
op vrijdag 13 september 2019 om 11.45 uur
in de aula van de universiteit,
De Boelelaan 1105

door
Jesper de Groote
geboren te Amsterdam

promotor: prof.dr. J.N. van Ommeren

copromotor: dr. H.R.A. Koster

Contents

Preface

I met my supervisor Jos van Ommeren at the end of 2010 while doing the STREEM master. Both he and Jasper Knockaert taught the suspiciously unpopular course called *Applied Transport Economics*. The course was held in one of the tiniest rooms of the whole university and on bad days only a few students would turn up, which provided me with the opportunity to get to know the teachers better. Jos came across as a very accessible teacher and a few months later I decided to write my master thesis under his supervision, so that is how I got involved in parking. After finishing my thesis, Jos offered me a PhD position at the VU. Now, seven years later, I am about to finalize my dissertation.

My PhD has been a long and wonderful journey. When I started, the Department of Spatial Economics was located on the fourth floor of the main building. In the summer of 2014 we moved to the ninth floor, which unexpectedly proved to be a boost to my social life. In the reshuffle I met Xinying Fu, one of the most intelligent people I have ever met, and Jamie (Mei) Chen, my "Chinese sister". I became part of a group of predominantly international PhD students, who decided to have a good time in the Netherlands, and therefore regularly organized out-of-worktime activities. Occasionally I would join, but I still missed out on a lot of these events.

I did not miss out on yoga, which Xinying thought was good for our posture, given that we were sitting behind a desktop almost all day. She convinced me and Jamie to join the yoga class, and soon we were practicing downward-facing dogs and sun salutations every week. Even though the exercises were often physically challenging to me, they were a little more manageable because of Anouk, our wonderful yoga teacher, who talked us through every pose. Almost every time we had a different teacher my muscles were sore for the next three days.

Early 2016 Jamie and I joined the *Party Committee*, as it proved difficult to find volunteers in the department to replace *the Spacecakes* after three years of service. Even though we could not find a third committee member, Jamie's tremendous energy more than made up for this small deficit. As a member of the Party Committee I had the pleasant task to make possible the monthly birthday celebrations and the great responsibility to organize the Christmas dinner. We had a great time testing cakes and tasting chocolate, but after a year, Jamie temporarily left our department. She got replaced by Francis Ostermeijer and Sanne Hettinga, and as a result, we changed our name from *Cookie Monster* to *Party Crew*. We kept celebrating birthdays and other special events, although perhaps slightly less frequent than before.

In the meantime, I managed to write the four papers on parking policy that make up this dissertation. Doing research was not always easy and quite a few times I felt lost. Luckily, my supervisors Jos van Ommeren and Hans Koster always had creative ideas and helpful comments. I learned a lot from them and without them I would not have been able to write this dissertation. As expected, the writing down the results in a scientific way was challenging, but it was well worth the effort, as most papers so far have been published. My paper on car ownership was even mentioned in *Ad Valvas*, the university magazine, which was really a highlight of my scientific career. Apparently, the result of all this number-crunching can even be meaningful in everyday life.

Perhaps not as meaningful was the number-crunching used for my Formula 1 research. Following Formula 1 has become a bit of a hobby that got out of hand. Having watched and analyzed countless races I decided to write a popular-scientific book on Formula 1 in 2015. Last year, I wrote a mathematics book targeting high school students. This means that this dissertation will be my third physical publication.

All in all, the past decade has been quite productive and instructive in many ways. The time has come to start a new chapter in my life. I just started working at the *Ministry of Social Affairs and Employment* as a data analyst and I am convinced that I can use the knowledge acquired during my PhD trajectory to become very good at this job.

Jesper de Groote,

January 2019

1. Introduction

Parking requires space. This is especially noticeable in the US, where retail stores are generally surrounded by oceans of tarmac. These parking lots provide enough parking space to accommodate parking demand during the busiest hours of the year. Even though parking is usually free to users, there are still costs associated with the provision of parking space, such as construction and maintenance costs, on top of land rents. This point was made by Donald Shoup in his groundbreaking 2005 book *The high costs of free parking*, in which he claims parking space should be considered an economic good, which should be priced in accordance with demand and supply.

This is usually not the case, as the parking market is highly regulated, which means that parking prices do not capture all costs. For example, in many cities in the world developers are required to provide considerable amounts of parking space next to the building, which increases construction costs. According to Shoup, the abundance of parking space has removed the incentive to charge parking prices, which in turn creates parking demand that needs to be accommodated. As parking is generally free, these additional costs are not passed on to car drivers, but they are passed on to consumers for example in the form of higher prices of goods. This means that distortions in the parking market may distort other markets as well.

Local governments usually have strong motives to intervene in the parking market. For example, they want to make sure there is enough parking space available to their residents or customers of local shops. These policies usually do not adhere to the recommendations made by economists, so they often result in inefficient market outcomes. Government intervention can affect the parking market through both the demand and the supply side of parking. Parking subsidies to car owners affect the demand side, whereas mandatory parking requirements affect the supply side. Both interventions will cause parking space to be underpriced and overconsumed from an economic perspective, which induces welfare losses to society.

According to economic theory, demand equals supply in the market equilibrium. The *unregulated* equilibrium is then welfare-optimal (in the absence of external effects, market power, etc.), as the consumers have a willingness to pay that is equal to or exceeds the costs of producing the good. Therefore, in the market equilibrium the construction costs of the *final* (and most expensive) parking space are equal to the *lowest* value attached to it by the users, which is equal to the market price. However, in the *regulated* equilibrium parking space is too cheap and therefore the value attached to the parking space by the marginal (newly-attracted) consumers is *lower* than the construction costs of the additionally constructed parking space. This negative difference between consumers' demand curve and the producers' supply curve is the so-called *deadweight loss*, the welfare loss to society.

The size of the deadweight loss is useful to evaluate government policy. A substantial loss warrants a change in policy. It is important to note that the deadweight loss of parking policies can easily be estimated in the absence of *external effects*, the costs incurred to users outside of the parking market. Car usage is usually associated with a lot of external effects, such as congestion, noise and pollution. However, in the Netherlands, where this dissertation focusses on, car and fuel taxes are fairly high, so it is reasonable to assume that these external effects are already *internalized*; they are passed on to car users in the form of additional taxes.

Car parking induces an additional form of externality, caused by cruising for a parking space. In this process, car drivers are wasting time and fuel searching for a vacant parking spot, thereby delaying other traffic as well. Cruising for parking is especially severe in the US, where street parking is usually free, unlike garage parking (Shoup, 2006). This makes street parking the much more attractive option and leads to a lot of wasteful cruising. Economic theory suggests that in this case raising the street parking prices to reduce cruising for parking is clearly beneficial, as it reduces travel time and congestion, and yields additional tax revenues (Arnott, 2006).

Cruising for parking is much less of a problem in the Netherlands, where street and garage parking are roughly equally priced, which almost completely eliminates cruising for parking (Van Ommeren et al., 2012). Therefore, in this dissertation, which focuses on parking in the Netherlands, cruising for parking is largely ignored, though some results imply it may have had an impact in city centers before the introduction of paid parking.

Even in the absence of cruising for parking, there are still distortions in the Dutch parking market through non-optimal regulations. In the Netherlands, paid parking is common in most city centers and the parking tariffs can be as high as € 5 per hour. Most likely, these tariffs are close to welfare-optimal. However, these tariffs are not paid by residents, who can almost always apply for parking permits. Residential parking permits cost on average about € 100 per year, or less than a euro per day, which means that residents pay a much lower price than nonresidents for the same parking space. This ensures that the available parking space is poorly allocated: it is overused by residents and likely underused by nonresidents. In short, residents with cars are subsidized to the detriment of residents without cars (or fewer cars) as well as nonresidents. This induces costs to society, as nonresidents with a high willingness to pay for parking are replaced by residents with a lower willingness to pay.

This dissertation focusses on the welfare losses induced by too low parking prices. This is most apparent when looking at residential parking permits. These permits create excess parking demand, which induces additional parking construction costs (Chapter 2) and increases car ownership (Chapter 3). Despite the provision of parking permits, the introduction of paid parking can either be favorable or detrimental to residents, depending on the initial severity of the parking problems. To examine this further, Chapter 4 examines the effect of the introduction of paid parking on residents using house prices. Finally, Chapter 5 analyzes the effect of a parking price increase on parking demand in the context of employer parking.

The calculation of these welfare losses in these chapters require information on the shape of the demand and supply curve of parking. This can be problematic, as these curves cannot be observed directly, but only indirectly via market outcomes. In this dissertation I will deal with this problem in several ways.

In Chapter 2 I will estimate the parking supply curve in residential areas near downtown shopping malls In these areas both residents and shoppers use the same parking space, but as residents can apply for parking permits, they face lower tariffs. Because residential parking is subsidized, residents consume more parking than would be optimal, which then increases parking supply. This will lead to welfare losses if parking supply is not perfectly elastic.[1]

I estimate the shape of the supply curve using the price and quantity of parking at every mall. In this case, the observed parking prices and quantities are the result of shopping mall-specific demand curves intersecting with the unknown supply curve. I estimated these demand curves using an *instrumental-variables approach*. The main idea here is to use floor shopping area of the mall (the instrument) to predict parking demand in the first stage. I then use the predicted parking demand to estimate the (inverse) supply curve in the second stage. Finally, I use the estimated supply curve to calculate the welfare losses of residential parking permits.

The possibility of underpriced parking affecting other markets as well was ignored in Chapter 2. For example, underpriced residential parking may increase car ownership, a possibility which I will analyze for the city of Amsterdam in Chapter 3. Car congestion is usually a problem in cities, so increases in car ownership will only make the problem worse. Interestingly, in contrast to the rest of the country, car ownership has remained constant in the city center of Amsterdam over the last 30 years. Nowadays, its city center has one of the lowest car ownership rates of the Netherlands.

The main explanation for this low car ownership in the city center is the rather fixed amount of parking space. As a result of the high parking demand, paid parking was introduced to reduce parking by nonresidents, but at the same time residents could apply for parking permits. The maximum number of parking permits in each parking district is limited by the number street parking spaces. Because the permit price was very low compared to the market price of parking or the on-street parking tariff, waiting lists for these permits soon started to form. In effect, these waiting lists increased the costs of a permit, as residents had to pay the market price for parking (or the on-street tariff) until they got the permit. As a result, the waiting-list duration increased parking costs.

---

[1] Parking demand has been extensively studied in literature, yet parking supply has been largely neglected (see, for example, Axhausen and Polak, 1991; Feeney, 1989; Hensher and King, 2001; Kelly and Clinch, 2006; 2009). Parking supply is sometimes thought to be *perfectly elastic*, which means that the costs per parking space supplied remain constant. However, this may only be true for when there is a sufficient supply of street parking to meet demand. When there is insufficient street parking, garage parking is then a common alternative. As the construction of parking garages entails huge costs, the transition from street to garage parking most likely increases the cost per parking space.

In Chapter 3, I will estimate the impact of the increase parking costs via waiting-list duration on car ownership. In the analysis, I compare car ownership of households in paid-parking districts with different waiting-list durations using a *boundary-discontinuity design*. In order to mitigate the problem of heterogeneity between inhabitants of different districts, I will focus on households close to the district borders. Using the estimated drop in car demand (and information on the additional costs of car ownership), I estimated the parking demand curve. In this chapter, to estimate the welfare effects of waiting lists for parking permits, I do not estimate the supply side, but I used a combination of information on fixed car usage costs and information on the upward-sloping parking supply curve estimated in Chapter 2.

As mentioned before, the introduction of paid parking may be beneficial to a city as a whole, as the parking fees yield government revenues while reducing congestion, but its effect on residents is unclear. On one hand, they will directly benefit from the reduction in parking-related congestion (cruising for parking), but on the other hand they face higher parking prices, even though they can apply for parking permits. In Chapter 4 I will estimate which of these effects dominates by analyzing house prices.

House prices not only depend on the characteristics of the house, but they are also influenced by location. If a location becomes more attractive, residents are willing to pay more for the same house, hence, the house price increases. House prices can therefore be used to determine the effect of parking policy on the attractiveness of the neighborhood. As a result, the effect of parking policy changes on the attractiveness of the neighborhood will be absorbed in the house prices. This effect can then be estimated using a *hedonic house price regression*.

In Chapter 4, I will estimate the causal effect of the introduction of paid parking on house prices in Amsterdam and Utrecht. Both cities had paid parking in their city centers as early as the 1960s, but only in the 1990s paid parking became more common outside the city center. Using house transaction data from the mid-1980s I estimated the effect of the introduction of paid parking on house prices. Maybe surprisingly, I find little effect of the introduction of paid parking on house prices.

Nowadays, on-street paid parking in cities is quite common. However, due to tax incentives, paid parking for employees is not very common, even for expensive locations in the city. Hospital employees are a notable exception. This phenomenon can be used to estimate hospital employees' price sensitivity of parking, which is useful information to estimate the deadweight loss of underpriced parking but is also useful if one wants to reduce commuting by car by taxing employer parking. Chapter 5 focusses on the effect of a price increase on parking demand of the employees of the Maastricht University Hospital, a large hospital in the Netherlands.

The parking price increase at this hospital was triggered by a sudden decrease in available parking space, as the parking space was needed for other hospital practices. Hence paid parking was introduced not because of excess demand, which is usually the case. This is useful for the empirical investigation, as we can regard the price increase as a *natural experiment* in which we observe the same employees before and after the price increase. As a result, we can interpret the change in parking demand as a causal effect of the price increase.

In the new parking regime, employees were faced with three different price changes: 1) a price increase depending on commuting distance, 2) a subscription fee depending on commuting distance, and 3) a subsidy if they travelled to the hospital by bike during the winter months. Hence, in Chapter 5, I will estimate the effect of the parking tariff increase and the bicycle subsidy on *daily* peak-parking demand, as well as the effect of the subscription fee on *monthly* peak-parking demand. The new parking regime may or may not have led to a uniform decrease in parking demand. I will perform *quantile regressions* to analyze if parking demand was reduced more on busy or calm days to further test the effectiveness of the policy change. The welfare effects of the old and new parking policy were then calculated based on the estimated parking demand curves and information on the parking construction costs.

This dissertation shows that suboptimal parking prices induce welfare losses in several ways: they may lead to increased parking provision costs, to inflated car ownership levels and likely to more cruising for parking. Unfortunately, improving the efficiency of the parking market often entails additional costs to the car user, whereas the gains may be more subtle, which makes it harder to implement welfare-improving policies. However, this dissertation shows that, as parking is so widespread, the welfare gains can be significant and in the order of millions of euros per year, which should be a convincing argument for policymakers to start charging the right parking prices.

2. Residential parking permits and parking supply[2]

2.1 Introduction

On-street parking pricing receives much attention in economic theory (e.g., Arnott et al., 1991; Verhoef et al., 1995). Theory recommends that parking prices should be used to allocate on-street parking places to users with the highest willingness to pay (Vickrey, 1954). In many parts of the world, this recommendation is not followed. For example, in the US, minimum parking requirements and below-market street parking prices are the norm. In the Netherlands, this principle is widely used, particularly in downtown cities, except when it comes to residential parking. Dutch cities allocate street parking to downtown residents by supplying residential parking permits almost free of charge to all residents in paid-parking areas. As a consequence, the number of residential parking permits is non-negligible. For example, in the historic city center of Amsterdam, the number of residential parking permits is almost equal to the number of street parking places (about 100,000), see Gemeente Amsterdam (2000). Arguably, the provision of residential permits distorts the parking market through demand, because (street) parking places are occupied by residents with a willingness to pay for parking that is lower than the visitors' willingness to pay, and through supply, as it encourages supply of expensive (garage) parking to address visitors demand.

Residential parking permits are not only common in the Netherlands but can be observed in many European countries. For example, in the UK, ‘residential permit holders only’ districts, where nonresidents are not allowed to park, can be observed in the smallest villages as well as in the main cities. A good example is the wealthy borough of Kensington and Chelsea (London, UK), where 82 percent of the 34,000 on-street parking places are allocated to residential permit holders only, and the number of permits exceeds the number of street parking places. While residents pay £ 0.30 per day for a parking permit, the parking costs for nonresidents are £ 30 per day (Kensington and Chelsea, 2012).[3]

We can only speculate why we observe parking permit policies which make parking cheap for residents but not for nonresidents. One potential explanation is that residents are voters, whereas visitors do not vote. It then makes sense for local governments to maximize residents' welfare at the expense of nonresidents by differentiating parking

---

[2] This chapter is based on joint work with Jos van Ommeren and Giuliano Mingardo. It has been published as Van Ommeren, J., De Groote, J., Mingardo, G., 2014. Residential parking permits and parking supply. Regional Science and Urban Economics, 45, 33-44.

[3] Residential parking permits are apparently not extremely common in the US, perhaps because minimum parking requirements usually induce an oversupply of off-street parking (Shoup, 2005; Cutter and Franco, 2012). Nevertheless, they can be found in San Francisco, Chicago and Boston and have recently been approved in New York. In New York politicians are concerned that the recently opened Brooklyn Barclays Centre, a sports arena with limited parking, might have negative consequences for residents parking (CBS New York, 2011).

tariffs. Our empirical results later on are consistent with this. We find that residential parking permits decrease the consumer surplus of nonresidents. Note that we ignore general-equilibrium effects, which may occur because high nonresidents' tariffs might be detrimental to profits of downtown shops.

We are not aware of any estimates in the literature about the induced welfare losses of residential permits. In the current paper we aim to derive these costs for parking permits that are offered to Dutch residents who live within large shopping districts that are predominantly downtown. These districts are usually mixed in the sense that they contain both shops and residential housing, so shoppers and residents both have a demand for parking in the same location. Frequently, the parking demand by shoppers and residents occurs at the same time. A recent poll for the West of Amsterdam indicates that 50 percent of households with a residential parking permit use the car at most one day per week (Trajan, 2009), suggesting that their cars remain parked for most of the time.

Residential parking permits are particularly distortionary if the parking supply is not fully elastic, because residents consume more on-street parking and shoppers consume less on-street parking than would be optimal. Knowledge of the parking supply function within shopping districts is then useful to derive the order of magnitude of the welfare effects of residential parking permits. In the current paper, we estimate the long-run (inverse) parking supply function using a dataset of about 300 of the largest shopping districts in the Netherlands, most of them (about 80 percent) being downtown shopping districts. Importantly, we employ a unique dataset with detailed information about street and garage capacity. Our main finding is that parking supply is quite elastic in downtown shopping districts, but possibly perfectly elastic in suburban and out-of-town shopping districts. This suggests that parking policies that provide parking permits to residents increase parking costs for nonresidents in downtown shopping districts, which has negative implications for welfare.[4] Our results suggest that the Dutch residential parking permits policy induces an annual welfare loss of about € 100 to 140 million per year, which is about 15 percent of the parking supply costs in downtown shopping districts. 80 to 90 percent of this loss is borne by nonresidents.

The outline of the rest of the paper is as follows. In section 2.2, we will discuss the main theoretical considerations to estimate the welfare losses of a residential parking permit policy. In section 2.3, we discuss the institutional context and will focus on the empirical results. Section 2.4 discusses the welfare implications and section 2.5 concludes.

[4] In this paper, we ignore the effect of residential parking permits on car ownership. As the costs of car ownership decrease, car ownership and car use may increase, which may cause additional parking and traffic congestion problems.

2.2 Theory and welfare

2.2.1 Theoretical considerations

The welfare loss of a residential parking permit policy depends on the properties of the residents' and nonresidents' demand and supply functions. In the current paper, we will estimate the (inverse) supply function relevant to nonresidents. By making assumptions on the demand function we are able to determine the boundaries of the welfare loss.

There is a large empirical literature on parking demand.[5] However, as far as we know, there is only one empirical study about parking supply which does not apply to shopping districts.[6] Parking supply is likely perfectly price elastic in out-of-town shopping malls with large outdoor car parks (Hasker and Inci, 2014), but this is unlikely to be true for parking within mixed downtown shopping districts which combine street and garage parking places. When parking supply includes garage parking, it is unlikely that parking supply is perfectly elastic.[7] Note that it is a misconception that street parking is perfectly inelastic, even within historical city centers, because parking places may be converted into pedestrian areas or street lanes, which reduces traffic congestion (Arnott and Inci, 2006).

In order to identify the parking supply curve, we make a few strong assumptions. First of all, we assume that street and garage parking are perfect substitutes for nonresidents. Furthermore, we assume that parking suppliers are free to set parking prices and that they apply marginal cost pricing.

One may argue that street and garage parking are not perfect substitutes, for example because they are not at exactly the same location. This is consistent with Kobus et al. (2013), who show that drivers have a preference to park on street. However, the average drivers' willingness to pay to park on street is small and equal to only € 0.25, so the perfect-substitution assumption is a reasonable approximation. Arguably, garage parking represents a safer place to park the car compared to on-street parking. So, drivers with more expensive cars might prefer off-street parking. As far as we are aware, this issue does not play a role in shopping districts particularly during shopping hours. When street and off-street parking are perfect substitutes (and freely compete with each other within a shopping district), then, despite any difference in construction costs, their prices are equal to each other (Calthrop and Proost, 2006). So, we will estimate the parking cost function ignoring the type of parking (garage or street parking) that is supplied.

---

[5] About 25 years ago, reviews by Feeney (1989) already revealed 20 revealed parking-demand studies. For more recent contributions, see for example, Kelly and Clinch (2006; 2009). Stated-preference studies are also common, see e.g. Axhausen and Polak (1991) and Hensher and King (2001).

[6] This study reports that the long-run supply function of employer-owned parking near office buildings is perfectly elastic (Van Ommeren and Wentink, 2012).

[7] Garage parking implies substantial fixed cost. In addition, marginal building costs for underground parking increase steeply with the number of parking levels. Arguably, there are constant returns to scale in terms of number of garages. So, in districts that contain *only* garage parking, parking supply may be perfectly elastic (see Arnott and Inci, 2006). These districts are rare in our dataset.

There are many reasons to believe that the marginal cost pricing assumption does not hold. One fundamental criticism of the marginal cost pricing assumption is that local monopolistic behavior by commercial parking garages is likely present when local governments keep street prices low (Arnott, 2006; Arnott and Rowse, 2009). As we shall see, the consequences for pricing of this behavior is not important in the Netherlands, because on-street and garage prices are roughly equal, and street parking is the dominant form, so as a simplifying assumption we believe that the marginal cost pricing assumption is reasonable.

Another criticism is that the presence of second-degree (nonlinear) price discrimination is strongly suggested by the well-known observation that parking usually occurs at a price discount for longer parking durations (National Parking Association, 2009).[8] Prices for short durations then exceed marginal costs, whereas prices for long durations equal marginal costs.[9] However, particularly when parking duration restrictions are applied, parking may be free for the first hour(s), the opposite may be true. Hence, to deal with second-degree price discrimination, we will use prices *per day* rather than per hour. There are, however, also other reasons to use prices per day. In particular, it does not require additional information about the average daily occupancy rate. As we lack this information, it makes more sense to focus on day prices. In the sensitivity analysis, we will show that using prices of the first hour parking generates almost identical results.

So, given the strong competition of suppliers within and, in particular, between shopping districts, the marginal cost pricing assumption seems reasonable.[10] However, differences between price and marginal costs are expected to exist, for example due to unexpected strong or weak demand. When these differences are random, we will still obtain consistent estimates of the inverse supply function. So, the marginal cost pricing assumption generates consistent estimates when parking is not systematically over- or undersupplied.

The welfare loss of a residential parking permit policy depends not only on the number of residential parking permits issued, but also on other local government policies, like the setting of on-street prices and the regulation of commercial parking prices. It is well known that setting the street prices far below garage prices will induce cruising for parking (Shoup, 2005; Calthrop and Proost, 2006). Although price regulation does occur in the Netherlands, it is rare, as commercial suppliers hardly ever have a dominant position, so they have little market power. Price regulation only occurs in shopping

---

[8] The observation that prices vary within the day (e.g., night prices are often zero) is *not* evidence of third-degree price discrimination, because the daily parking supply costs are fixed.

[9] Local governments may set parking charges above marginal costs for shorter durations for a completely different reason: i.e. to charge for car congestion, (see Glazer and Niskanen, 1992).

[10] The empirical finding that shoppers' choice of parking is very price elastic for longer parking durations (Kobus et al., 2013) also suggests that monopolistic competition is not so much an issue when using parking prices for long durations.

districts with only one or two dominant commercial garage parking suppliers and little street parking (e.g., within the inner cities of Almere and Maastricht). In these shopping districts, price regulation is likely applied to induce marginal cost pricing. We will document for our data that on-street prices in the Netherlands are approximately equal to garage prices, so we will assume away any cruising externalities.[11]

Local government policies aim to deal with a number of negative externalities related to parking. It is relevant here to distinguish between negative externalities of the *parking site* (as car parked, as well as garages, are considered to be ugly) and any negative externalities related to *car travel* (e.g., congestion, pollution).

Many districts are in historic centers (built before 1930), where construction of residential, and particularly nonresidential, buildings is strongly regulated to protect historic amenities which create substantial benefits, as they attract tourists and increase house prices (Leichenko et al. 2001). For this reason, in Dutch shopping districts over the last 30 years, with few exceptions, the construction of parking sites has been heavily regulated, and in practice only *underground* parking garages have been allowed. This type of regulation must have strongly increased the private cost of parking provision (although land prices in many shopping centers are sufficiently high to justify underground parking garages even in the absence of regulation). So, this type of regulation shifts the private supply curve upward, but this has furthermore no consequences for our estimation strategy.

The other negative externality related to parking is that negative externalities of car use are not priced. These negative externalities can be (partially) internalized using restrictions on parking using maximum norms regarding the number of parking places. Given appropriate pricing of on-street parking, maximum requirements may *improve* welfare when traffic congestion is not internalized (Shoup 2005; Arnott and Rowse, 2009). Minimum requirements may improve welfare when street parking is underpriced (as it reduces cruising), but this is less applicable in the Netherlands.[12]

In the spirit of Arnott and Rowse (2009), the use of maximum requirements may be interpreted as a welfare-improving (but second-best) policy when pricing of traffic congestion is not feasible. We focus on nonresidential parking only, as we assume them to be the only contributors to traffic congestion and we assume that parking demand and traffic congestion are one-to-one related to each other.

Traffic congestion induces a difference between the private cost curve of parking and the social cost curve of parking. In equilibrium, the market number of parking spaces exceeds then the socially optimal number of parking spaces (conditional on the residential parking permits policy), so a standard deadweight loss (the triangle) arises

[11] This is in line with Van Ommeren et al. (2012), who show that the average on-street cruising time for shopping activities is less than one minute.

[12] Maximum requirements refer to the upper limit of the amount of parking space supplied imposed by the (local) government, while minimum requirements refer to the lower limit of the amount of parking space supplied.

due to the traffic congestion externality. Therefore, the government may restrict the number of parking places to the socially optimal number of parking spaces.

Note that this policy is welfare improving, but prices exceed the marginal cost of parking provision, causing private suppliers to make additional profits. When these profits are passed onto the local government (or passed to inhabitants as a lump sum), the socially optimal equilibrium offers a higher welfare to the population of residents and nonresidents.[13] This is usually the case because most parking supply (all street parking and about half the garages places) are owned by the local government. So, most additional revenues due to maximum parking requirements go to the local government. In addition, governments extract profits from private operators by granting building concessions. In the welfare analysis, we will assume that local governments determine the socially optimal number of parking places, which means there are no welfare losses due to overprovision of parking. So we aim to estimate the social, not the private, cost curve.

2.2.2 Calculation of the welfare loss

Our welfare analysis will be based on the crucial assumption that the total number of parking places in each shopping district is optimally chosen by the government (see section 2.2.1), but there is a welfare loss because too much parking is allocated to residents through parking permits. Furthermore we will assume that the willingness to pay by shoppers exceeds the willingness to pay of current residents with a residential parking permit.[14] If this assumption does not hold for all residents in the short run (for example, just after a shopping center is extended), it is likely to hold in the long run when residents with cars will relocate to other residential locations where there are fewer shops.[15] We emphasize that our welfare calculations do not include any welfare loss for residents parking, which means that we underestimate the welfare loss.

To derive the long-term welfare loss, it would be ideal to have information about the demand function for parking by residents as well as nonresidents (shoppers). We lack this information, so we proceed by making assumptions about the shape of the demand function, so we are able to give the range of welfare loss due to residential parking permits. The welfare loss depends then on the number of residential parking permits per district. In the Netherlands, when paid parking is introduced, residents are entitled to at least one permit.[16]

---

[13] For example the largest Dutch parking operator is largely owned by the pension-fund for civil servants.

[14] In principle, one would like to take into account that some residents may do their shopping with their car so they are also nonresidents. Because the fraction of time spent on shopping is small compared to the overall parking time by residents near their house, this issue can be ignored.

[15] In the long run, except when residential parking permit policies subsidize residents, shopping districts will predominantly contain households who have a low demand for residential parking.

[16] In smaller cities, the number of permits is equal to the number of cars owned. However, if the parking occupancy rate is close to 1, which is more common in residential areas of large cities built before 1930, then it is common to restrict the number of parking permits to avoid cruising (e.g., the number of permits is restricted to maximally one or two per household).

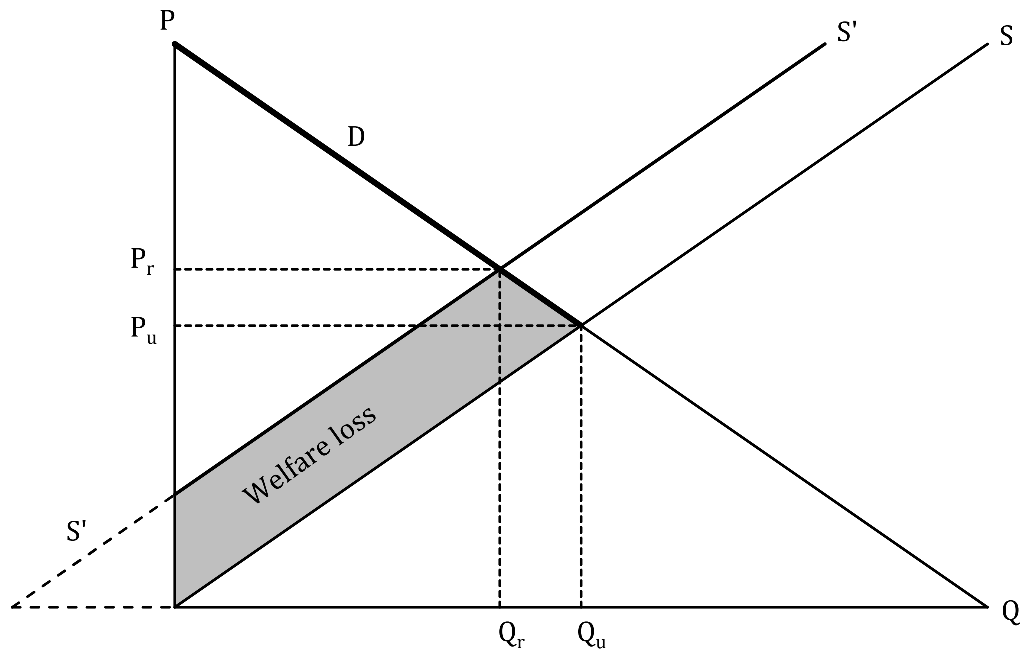


Figure 2.1. Welfare loss of residential parking permits.
Note: the nonresidents are the high-demand consumers (bold line).

The number of residential parking permits provided is usually close to the number of street places. We will assume there are R street parking places occupied by residents at times when shoppers aim to park. In addition, we assume that Q_r garage parking places are used by nonresidents who visit the shops. The remaining M street parking places are assumed to be used some part of the day by residents with permits, but the deadweight loss of these M permits is assumed to be negligible. In this way, we obtain (extremely) conservative estimates of the welfare loss. Later on, we will make assumptions on the numerical values of R, Q_r and M.

We will assume furthermore that the combined willingness to pay of the permit holders is equal to the combined supply costs of the parking places. This is a reasonable approximation, because willingness to pay by the residents with a permit as well as the supply costs of the *first* R street places will be low relative to the equilibrium price.[17]

Given these simplifying assumptions, the welfare loss due to residential parking permits can be derived assuming first the absence of the parking permit policy, and then allow the inverse parking supply curve to shift to the left by R units. This shift is indicated

[17] When residents do not receive parking permits, residential parking close to shopping districts will be less attractive to residents with a strong preference for cars. So, it seems reasonable to assume that the residents' willingness to pay for street parking is low, given the presence of a parking permit. The provision of parking permits reduces the cost of parking for households, preventing efficient household sorting across residence locations (see, similarly, Kim, 2012), so the presence of car-loving residents in shopping districts is likely the result of parking permit policies.

in Figure 2.1 as a shift in the supply function from S to S'. P_r and P_u denote the parking prices in the regulated and unregulated equilibrium.

This shift in supply affects the nonresidents, who are assumed to be the high-demand consumers, indicated by the bold demand curve in Figure 2.1. In this figure the welfare loss is indicated by the shaded area between the supply curve S and the shifted supply curve S'. Given linear nonresidents' demand and supply functions, the total welfare loss per day per shopping district is equal to (see Appendix A2.2 for details):

$$\text{Welfare loss} = \frac{1}{2} sR \cdot (Q_r + Q_u), \qquad (2.1)$$

where Q_r denotes the number of nonresidents in the regulated optimum, Q_u denotes the number of parking places provided to nonresidents in the absence of the provision of parking permits, s denotes the marginal effect of parking supply on parking prices (per day) and R denotes the number of residents' cars parked at times when shoppers aim to park. Q_u is endogenously determined and depends on the price elasticity of demand, the number of nonresidents and the number of residents cars parked.

Given the nonresidents' price elasticity of demand, we can calculate the welfare loss.[18] Because most nonresidents (excluding commuters) park for a short duration, it is usually thought that the demand for parking is rather inelastic. A price elasticity of demand of −0.3 is sometimes suggested, see Litman (2012).[19] We will use this figure in the welfare analysis, along with the extreme cases of perfectly elastic and perfectly inelastic demand.

2.3 Empirical Results

2.3.1 Institutional Context

In Dutch city centers, only a small percentage of residences have a private parking place. Despite the small number of private parking places, most households own a car. So, the large majority of residents rely on on-street car parking. In districts with residential permits, residents may apply for parking permits at a price which is only a tiny fraction of the price paid by nonresidents. This permit allows them to park for free in the area close to the residence but does not offer any other advantages. The permit is predominantly used for residence parking and seldom for other purposes. Application of a permit requires one to have a registered address in the district for which the permit is issued and requires car ownership. Revenue generated from parking permit fees is usually earmarked to cover the administrative costs of providing parking permits. Other parking revenues are either not earmarked or used for transport-related municipality

[18] In the Netherlands, parking demand is likely more elastic than in other countries, because the majority of shoppers do not travel by car, but travel by bicycle or public transport (Mingardo and Van Meerkerk, 2012).

[19] The relevant parking demand sensitivity here is the one that captures changes both at the extensive (the decision to park) as well as the intensive margin (the duration of parking).

expenses.[20] Residential parking policies are ubiquitous: virtually everywhere in the Netherlands residents in paid-parking districts can receive on-street parking permits. In contrast to many other cities in the world (e.g. London, Paris), permit-only parking areas are uncommon, so on-street parking places are in principle available to both residents and nonresidents.

In the US, when street parking prices are below of-street parking prices, it is common to have street parking time limits (Arnott and Rowse, 2013). In contrast, in the Netherlands, there are usually no parking time limits. The proportion of parking places occupied by residents with permits is unknown for most areas, but is generally high. For example, in Amsterdam, on average, between 69 to 80 percent of parking places are occupied by residents with permits (Gemeente Amsterdam, 2005). Local governments aim to avoid cruising for parking by nonresidents through the setting of street prices (particularly in large municipalities) and avoid cruising for parking by residents in the evening by limiting the number of residential permits (usually by putting constraints to the number of permits per household).

In the Netherlands, mixed shopping districts are the norm, so there are both shops and residents in almost each street within a shopping district. Most shops are located downtown, usually within historic city centers (about 80 percent), or within suburban residential districts (about 15 percent). The remaining 5 percent are out-of-town shopping malls. In these shopping districts, the shoppers' willingness to pay for parking *per unit of time* is almost always an order of magnitude higher than the residents' willingness to pay. For example, in Amsterdam, the residents' willingness to pay for parking is maximally € 9 per *day* (but usually much less), whereas for nonresidents who park it is at least € 5 per *hour* (Van Ommeren et al., 2011). The main reason for this difference is that the willingness to pay per unit of time is a decreasing function of parking duration and nonresidents typically park for a much shorter duration than residents. For example, the average parking duration for nonresidents is about one hour in Almere, a city of about 200,000 inhabitants in the Netherlands, see Kobus et al. (2013), whereas many residents park all day.

2.3.2. Data and descriptives

We use a dataset about parking in 308 of the largest shopping districts of the Netherlands for the year 2007 (Parkeermonitor, 2007-2008). The data include only large shopping districts. On average, a shopping district contains about 31,000 square meters of floor area, containing about 200 shops on average. The total floor area in our dataset comprises 34 percent of *all* floor area in the whole country (about 28 million square meters).

[20] For example, it has been proposed to use revenues to finance a traffic safety plan, see Gemeente Amsterdam (2011).

Table 2.1: Descriptives

						Garage parking only				
	Obs.	Mean	SD	Min	Max	Obs.	Mean	SD	Min	Max
Hour street price	290	0.69	0.83	0	4.6					
Hour garage price	161	0.93	0.93	0	5.2	18	0.57	0.89	0	2
Hour price difference	143	0.09	0.75	−3.7	2.1					
Hour parking price	308	0.80	0.95	0	5.2	18	0.57	0.89	0	2
Day street price	276	3.84	6.10	0	41.4					
Day garage price	159	7.00	7.66	0	47.5	18	7.39	10.51	0	36
Day price difference	138	-0.98	5.57	−14	18.4					
Day parking price	292	5.13	7.04	0	47.5	18	7.39	10.51	0	36
Street parking places	308	1172	1018	0	8000					
Garage parking places	308	501	1000	0	7561	18	829	1757	52	7561
Parking places	308	1673	1675	30	11167					
Garage parking share	308	0.22	0.29	0	1					
Floor area (in 1000 m^2)	308	30.6	31.0	4.1	238.2	18	27.5	27.7	5.7	98.6
Parking/100 m^2 fl. area	308	6.44	4.03	0.30	24.59	18	2.16	2.32	0.39	9.65
Downtown	308	0.78	0.42	0	1	18	0.50	0.51	0	1
Suburban	308	0.19	0.39	0	1	18	0.39	0.50	0	1

		Garage capacity present					On-street parking only			
	Obs.	Mean	SD	Min	Max	Obs.	Mean	SD	Min	Max
Hour street price	143	1.06	0.90	0	4.6	147	0.33	0.58	0	2.1
Hour garage price	161	0.93	0.93	0	5.2					
Hour price difference	143	0.09	0.75	−3.7	2.1					
Hour parking price	161	1.23	1.02	0	5.2	147	0.33	0.58	0	2.1
Day street price	139	5.79	7.07	0	41.4	137	1.86	4.08	0	18.9
Day garage price	159	7.00	7.67	0	47.5					
Day price difference	139	-0.98	5.57	−14	18.4					
Day parking price	155	8.02	7.81	0	47.5	137	1.86	4.08	0	18.9
Street parking places	161	1373	1281	0	8000	147	952	535	30	3279
Garage parking places	161	958	1216	24	7561					
Parking places	161	2331	2052	52	11167					
Garage parking share	161	0.42	0.29	0.04	1					
Floor area (in 1000 m^2)	161	42.5	37.6	5.4	238.2	147	17.6	12.3	4.1	82.7
Parking /100 m^2 fl. area	161	6.40	4.02	0.39	23.84	147	6.48	4.05	0.30	24.59
Downtown	161	0.77	0.42	0	1	147	0.79	0.41	0	1
Suburban	161	0.19	0.39	0	1	147	0.18	0.39	0	1

Note: price difference = street price – garage street price. Parking price = max (street price, garage price)

Parking refers to all garage and street parking places up to one hundred meters from the shopping district boundary that are available to the public.[21] We ignore parking places owned by residents for two reasons: first, the number of privately-owned parking places is small (for example, in Amsterdam about 5 to 10 percent of residents in shopping districts possesses a privately owned parking place, see Van Ommeren et al., 2011). Second, these parking places are unavailable to shoppers.

On average, there are about 1,700 parking places per district: 1,200 on-street and 500 in garages.[22] Garage parking is present in about half of the districts, whereas street parking is almost always (94 percent of the shopping districts) present. Descriptives are

[21] The consultancy firm which collected the data defines shopping districts by a minimum number of shops or minimum floor area. Although the boundaries of these shopping districts are subjectively chosen, in most cases it is perfectly feasible to define shopping district boundaries rather precisely. This is particularly easy when the shopping area is largely pedestrianized.

[22] In our data, we are not able to distinguish between street parking and outdoor car parks, so street parking includes outdoor car parks.

reported in Table 2.1, including descriptives about three subsamples (only garage parking; garage parking present; only street parking). Table 2.1 shows that the average garage parking share, defined as the ratio of garage capacity to total capacity, is equal to 0.22 (in districts with garage parking, the average is 0.42, so also then street parking outnumbers garage parking). The average number of parking places per 100 square meters of shopping area is slightly more than six. This value is roughly the same when garage parking is present, indicating that the relationship between number of parking places and floor area is not fundamentally dependent on the presence of garage parking. We have information about parking prices per hour (for the first hour) and per day. In about half of the districts, prices are zero (but in only 20 percent of districts with garage parking).

The average street price is € 0.69 per *hour*, slightly below the average garage price of € 0.93. Given paid parking, the average street price is € 1.50 per hour, in line with other sources, see Van Dijken (2002). When garage and street parking are both present in the same district the average street price is € 1.06 per hour, which slightly *exceeds* the average garage price of € 0.93 per hour. To measure supply costs, we will ignore any existing difference between these prices, consistent with the assumption that the street and garage parking are perfect substitutes. We will use the maximum of street and garage prices per district, which will be referred to as the 'parking price'. The average hour parking price is € 0.81 (see Table 2.1). Using the maximum per district is rather arbitrary, but using other measures, such as the average per district, generates almost identical results.

The average parking price *per day* is € 5.13, about seven times higher than the price for the first hour (implying that parking for longer than seven hours occurs at a discount). The data allow us to distinguish between different shopping districts locations within cities: downtown (e.g., at least 400 shops in the largest inner cities), suburban and out-of-town shopping malls (containing few, but large shops). As emphasized in the introduction, in our data, downtown shopping is the dominant form of shopping, as about 80 percent of all districts are downtown (the share of downtown shopping floor space is even slightly higher).

In addition to parking prices and quantities data from Parkeermonitor, we use data about median annual rent for shop space (per square meter) *per district* to proxy land prices within cities. The shop rent is plausibly the best indicator for land prices in our context of nonresidential parking, because the main opportunity cost of a car park is to forego the benefits of a building that contains shops. These data are obtained from transaction data provided by PropertyNL (see also Van Ommeren and Wentink, 2012). We also use data about municipality population as well as population density per municipality obtained from Statistics Netherlands (2008).

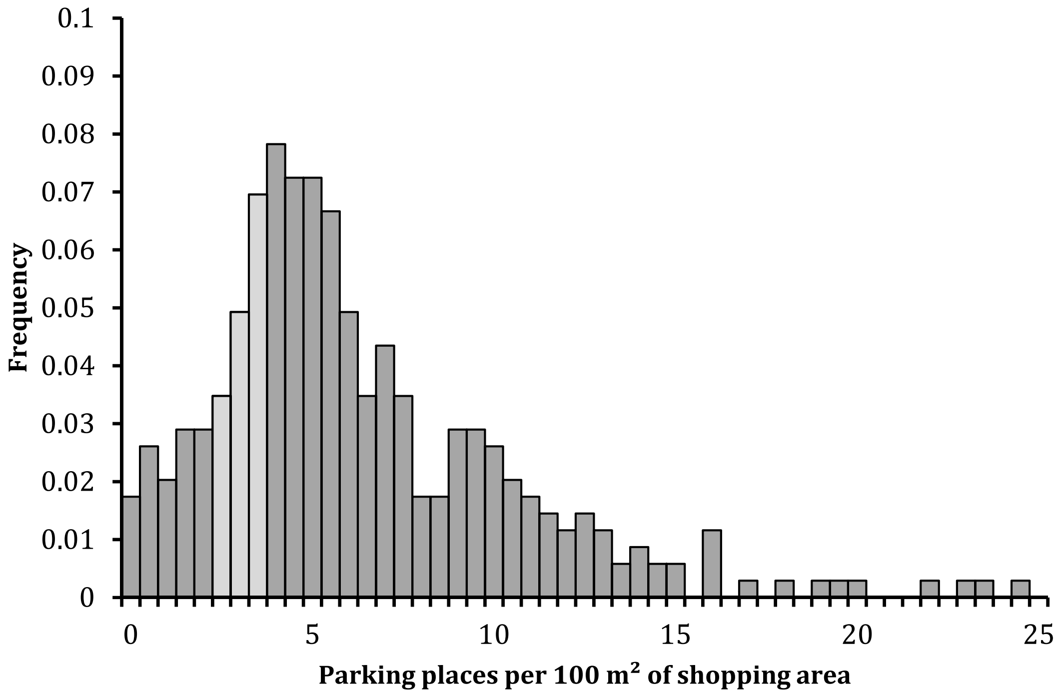


Figure 2.2. Number of parking places per 100 square meter of shopping area

Note: Highlighted bars indicate observations within advised parking requirements range of CROW.

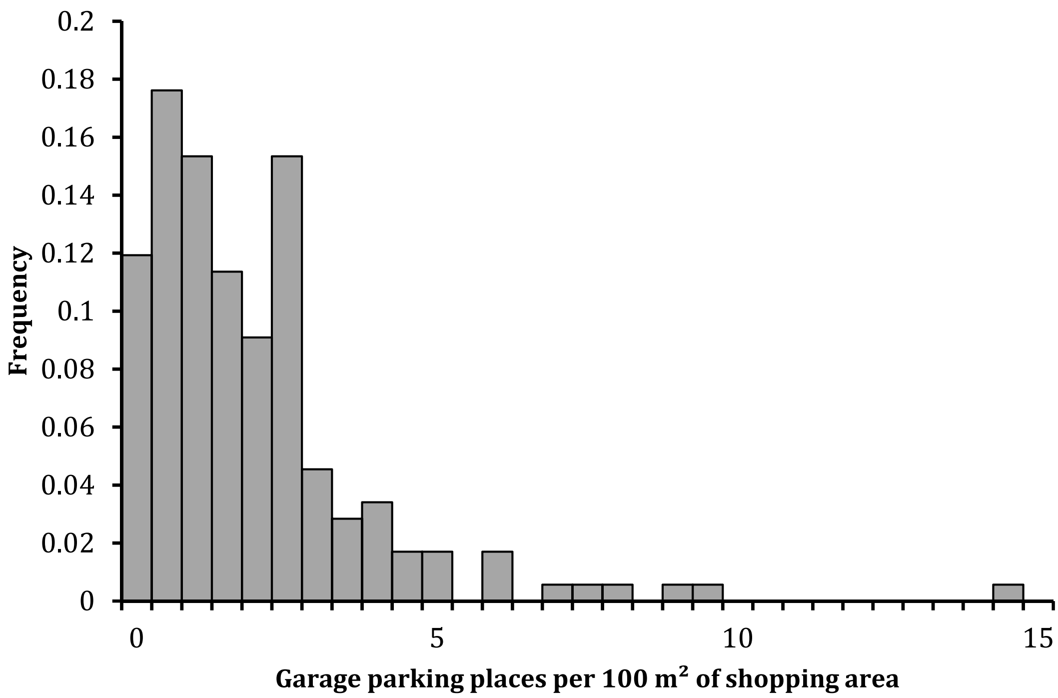


Figure 2.3. Number of garage parking places per 100 square meter of shopping area

Note: Areas with garage parking only. See furthermore Figure 2.2.

The Dutch nongovernmental organization CROW recommends shops to provide between 2.5 and 4 parking places per hundred square meter floor space (CROW, 2008). Note that it is not clear to what extent the use of price of parking is included in these minimum and maximum requirements. Although this organization has no legal power, most Dutch municipalities follow its recommendations, so these requirements allow us to do some consistency checks on the data. The parking places in shopping districts we focus on are also used by residents, so the total parking supply must usually exceed the maximum requirement for shopping (Figure 2.2). When garage parking is present, shoppers still make use of street parking, *garage* supply must be usually less than the minimum requirement for shopping, see Figure 2.3. We see that both figures suggest that our data are consistent with these statements.

2.3.3 Empirical Approach

We estimate the *inverse* supply function for nonresidential parking, so we estimate the price of a parking place as a function of the number of parking places. We will use a cross-section of observations. Hence, we will identify the long-run supply function. We estimate the inverse parking supply function rather than the supply function, because only for the inverse function we are able to find valid instruments to deal with endogeneity, as discussed later on. We assume a linear specification, so:

$$p_{im} = \alpha \ + \beta q_{im} + \gamma x_{im} + \delta x_m + \varepsilon_{im}, \qquad (2.2)$$

where p_{im} denotes the parking price of shopping district i in municipality m, q_{im} denotes the parking quantity, x_{im} denotes district-specific control variables, x_m denotes a municipality-specific control variable and ε_{im} is an error term. Furthermore, α, β, γ and δ are the coefficients to be estimated. We also estimate log-log models where both the dependent and explanatory variables are in logarithms.

One important issue is that the price of parking may vary between districts, because of between-district variation in land prices. Because land prices are unknown, we proxy land prices in several ways. In a basic specification, we use municipality population, municipality population density and within-city shopping district location.

In addition, in a more elaborate specification, we estimate models where we include *municipality fixed effects,* δ_m, as well as median rents for shop space per district as a proxy for land prices.[23] So, we estimate:

$$p_{im} = \alpha \ + \beta q_{im} + \gamma x_{im} + \delta_m + \varepsilon_{im}. \qquad (2.3)$$

[23] We do not control for median rents in the specification without municipality fixed effects, because we frequently miss information about rents in smaller municipalities with one shopping district. These observations essentially dropout given municipality fixed effects.

To identify the inverse supply function of parking, we have to take into account that q_{im} also depends on demand, so q_{im} is endogenous as it is correlated to ε_{im}. We deal with this issue using an instrumental-variables approach. To identify the inverse parking supply function, we use *floor shopping area* z_{im} as an instrument (so in the first step of the IV, we run a regression of q_{im} on z_{im} while controlling for the other explanatory variables in (2.2) and (2.3) respectively). Hence, we argue that the floor shopping area captures the *shoppers' demand for parking*, but does not directly affect the cost of parking, and therefore the inverse parking supply function.[24] This instrument seems plausible, particularly given the range of controls for land prices. We emphasize that the instrument relies on the more fundamental assumption that parking supply costs do not determine the size of the floor shopping area. This assumption seems reasonable, as parking costs are small compared to overall expenses by shops. This is particularly reasonable in the Dutch context where only a minority of shoppers travel by car (e.g., Mingardo and Van Meerkerk, 2012). We also emphasize that this instrument shifts the demand curve and therefore identifies the *social* parking supply curve when regulation is present. So, for example, the instrument is valid given the presence of maximum requirements as long as these requirements are optimal from a welfare perspective.

One issue we have to deal with is that in many districts, parking is free to nonresidents (in our dataset that turns out to be about 50 percent, in particular when garage parking is absent). Parking may be free because there is excess parking supply, so the marginal costs are zero. Another reason is that these zero prices do not reflect marginal parking costs, either because the local government directly subsidizes parking (by buying land and converting into street or garage parking), or because the shop owners pay for parking (Hasker and Inci, 2014).[25] The third reason is that the (suppliers') transaction costs of charging for parking are not negligible. In the Netherlands, electronic paid-parking machines are virtually everywhere introduced. Van Dijken (2002) reports that these transaction costs are about € 350 per place per year, suggesting that it is not cost-effective for suppliers to charge parking when the cost of provision of parking (excluding charging costs) are rather low (e.g. less than € 1 per day). The fourth reason is that the local government enforces maximum parking duration restrictions. These restrictions are extremely common in the US, and can be justified as a second-best policy where policymakers do not have the power to raise the street prices to garage prices (Arnott and Rowse, 2013). However, these restrictions are relatively rare in the Netherlands, and if they apply then they only apply to a few streets within a large shopping district. The

---

[24] Note that larger shopping districts (in terms of shopping floor area) are almost always larger in terms of streets, so the number of street places is directly related to the size of shopping floor area. Consequently, floor area is invalid as an instrument to estimate parking supply functions, whereas perfectly valid for *inverse* parking supply functions.

[25] Hasker and Inci (2014) show, rather surprisingly, that under some circumstances (which likely do not hold in the shopping districts we analyze) that this is efficient. We ignore this issue here.

main exception is smaller municipalities with one main shopping district. Unfortunately, we cannot distinguish between these four reasons.

The above considerations suggest that it may not be wise to remove these zero-price observations from the estimation procedure, because it is likely that zero prices are observed when the supply costs are low, so removing zero-price observations may create a selection bias. We deal therefore with this issue in three different ways.

First, for observations with parking prices below € 2 per day, we do not use information about the exact level of the price, but in the estimation procedure we assume that the marginal cost per day is below € 2 (approximately the level of the transaction costs per day of paying for parking).[26] So, we may then estimate Tobit models using a standard maximum-likelihood procedure, where we have left-censored observations with day prices *below* € 2.

Second, we deal with this issue by estimating Tobit models on a subsample of observations where garage parking is present. In this case, zero prices are observed in only 20 percent of the cases. Of course, selecting observations where garage parking is present creates another, and arguably a similar, endogeneity issue which is not addressed. However, the interpretation of the results is now clearer, as the results refer to districts where garage parking is present. These are probably the districts we are most interested in.

Third, we estimate models including municipality fixed effects (and control for within-municipality differences in rents for shop space). This essentially excludes observations for which there is only one observation per municipality from the estimation procedure. The zero-price observations are predominantly in smaller municipalities, in which there is only one dominant shopping district, so for which we only have one observation. For the subset of observations with at least two observations per municipality**,** the share of observations with zero prices drops to only 20 percent. For this subset, we estimate Tobit models and linear models after excluding zero-price observations.

2.3.4 Main results

The use of floor shopping area as an instrument is key to our estimation procedure. We have tested the validity of the instrument in several ways. First, we use an F-test to determine the strength of the instrument. In all specifications, the F-tests were positive, so the instrument is strong. Second, we have estimated models where we do not use the floor shopping area as an instrument, but its two main components: the floor area dedicated to daily shopping (e.g., a supermarket) and the floor area dedicated to non-daily shopping (e.g., clothing). When we use these two instruments, we find almost identical results.

Third, more informally, we have tested whether the size of the floor area increases the *garage parking share*. One expects that floor area has a positive effect on this share,

[26] For hourly observations, we assume that the marginal cost per hour is below € 0.30.

because an increase in demand for shopping area and therefore for land makes it more beneficial to substitute land for capital (high land prices is normally the main reason that garage parking is supplied). This expectation is confirmed by a two-limit Tobit analysis (with thresholds equal to 0 and 1 and the same explanatory variables as used in the inverse supply function).[27]

The main results are reported in Table 2.2, with additional analyses in Tables 2.3 and 2.4. All specifications show that an increase in parking capacity results in a strong increase in costs of parking.[28] We are particularly interested in the marginal effects of parking capacity, conditional that the price asked exceeds the threshold (when the price below the threshold, the relationship between prices and costs is less likely one-to-one). These marginal effects are equal to the reported coefficients of the Tobit model.

To interpret our results, we find it useful to focus on increases in capacity of 500 parking places. We have chosen 500 parking places, which is the mean number of *garage* parking places. So our experiment is that we want to know what happens to (marginal) parking costs when the number of garage parking places is increased from 0 to 500 as a result of increases in residential parking demand due to parking permit policies. We emphasize that 500 is not a large increase compared with total parking supply per district, which is 1,700 on average, as street parking usually dominates garage parking.

According to specification (1) of Table 2.2, which assumes a linear specification and uses the IV Tobit approach, the marginal effect is about $3.4 \cdot 10^{-3}$, so to increase the supply by 500 places implies an increase in the daily price of about € 1.70. Calculated at the mean, this suggests an inverse price elasticity of supply close to one, so the supply of parking is far from perfectly elastic, suggesting that policies that increase demand (e.g., residential parking permit policies) are quite detrimental for welfare.

Furthermore, these results imply that in larger cities the supply costs are higher. In a large city with 1 million inhabitants (close to the size of Amsterdam), the supply costs per day are about € 16.4 higher than in the smallest municipalities, ceteris paribus. When we control for shopping-district location, which is our preferred specification, we find slightly higher point estimates for the effect of number of parking places, see specification (2) of Table 2.2. When we limit our analysis to districts where garage parking is present, we find slightly lower estimates (see specifications (3) and (4) of Table 2.2). Given a log-linear specification (see (5) and (6) of Table 2.2), the effects of parking capacity are very similar: the inverse price elasticity of supply is also about one and even less when we focus on districts that include garage parking.

[27] One may use the garage parking share as an alternative indicator for the cost of parking using shopping floor area as an instrument for the number of parking places. We find a positive effect of the number of parking places on this share (the full results are in Appendix A2.4, Table A2.1): the share increases by about 0.10 when the number of parking places increases by thousand. This result seems reasonable suggesting that floor area is an appropriate instrument when estimating cost functions.

[28] This is, however, only true for downtown shopping districts, the dominant form of shopping in the Netherlands. This effect is absent for suburban and out-of-town shopping districts.

Table 2.2: Inverse parking supply

Price	IV Tobit				IV Tobit (log-log)			
			Garage present				Garage present	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Parking places	3.168***	3.395***	2.785***	2.843***	0.995***	1.196***	0.880***	0.945***
(/1000)	(0.284)	(0.321)	(0.320)	(0.392)	(0.132)	(0.183)	(0.156)	(0.249)
Municipality	14.4***	12.1***	11.1***	11.1***	0.448***	0.324***	0.325***	0.316***
population	(2.69)	(3.27)	(3.48)	(4.41)	(0.082)	(0.121)	(0.098)	(0.160)
Municipality	0.771	0.636	0.386	0.352	0.142	0.114	0.050	0.043
population density	(0.408)	(0.413)	(0.476)	(0.483)	(0.089)	(0.092)	(0.105)	(0.106)
Shopping district type	no	yes	no	yes	no	yes	no	yes
Log likelihood	-2739	-2712	-1496	-1487	-471	-450	-237	-227
No of observations	275	275	138	138	275	275	138	138
Obs. below threshold	141	141	36	36	141	141	36	36
F-test (weak instruments)	754.05	669.77	399.20	284.26	245.24	140.19	161.04	71.74

Note: municipality population in millions. Municipality population density in thousand persons per square kilometer. The censoring threshold is € 2 or ln € 2 in the log-log specification. * Significant at 10 percent level, ** Significant at 5 percent level, *** Significant at 1 percent level.

Table 2.3: Inverse parking supply functions, alternative specifications

Price	IV linear				IV Tobit (log-log)			
			Garage present				Garage present	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Parking places (/1000)	2.119***	2.627***	2.321***	2.730***	2.856***	2.548***	2.721***	2.639***
	(0.366)	(0.670)	(0.454)	(0.834)	(0.319)	(0.587)	(0.346)	(0.583)
Shop space rent (median)	0.030	0.020	0.039	0.029	0.046*	0.041	0.043	0.038
	(0.027)	(0.028)	(0.033)	(0.035)	(0.023)	(0.023)	(0.025)	(0.025)
Shopping district type	no	yes	no	yes	no	yes	no	yes
Municipality fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
No of observations	48	48	39	39	76	76	48	48
No. of municipality f.e.	19	19	19	19	21	21	19	19
F-test (weak instruments)	217.27	65.29	161.54	47.89	344.10	103.23	181.44	62.57
Obs. with zero prices	no	no	no	no	yes	yes	yes	yes

Note: results for municipalities with at least two (observations about) shopping districts. For other notes, see Table 2.2.

Table 2.4: Inverse parking supply: downtown only

Price	IV Tobit		IV Tobit (Log-log)	
		Garage present		Garage present
	(1)	(2)	(3)	(4)
Parking places (/1000)	4.172***	3.358***	1.689***	1.402***
	(0.428)	(0.526)	(0.233)	(0.333)
Municipality population	-7.09	-0.279	-0.133	-0.083
	(6.66)	(8.29)	(0.171)	(0.238)
Municipality pop. density	0.817*	0.386	0.094	0.017
	(0.493)	(0.575)	(0.096)	(0.115)
Log likelihood	-2145	-1193	-317	-169
No of observations	219	110	219	110
Obs. below threshold	120	28	120	28
F-test (weak instruments)	398.40	152.28	139.71	52,56

Note: results for municipalities with at least two (observations about) shopping districts. For other notes, see Table 2.2.

We have also estimated a range of specifications for models with municipality fixed effects and with the median rent for shop space (see Table 2.3). Again we find that the supply function is upward sloping, although slightly less steep than before. For the (preferred) specification (2), we now find that the effect is about $2.6 \cdot 10^{-3}$ (compared to $3.4 \cdot 10^{-3}$ in Table 2.2). Furthermore, we have examined the model for downtown shopping centers only (see Table 2.4). It appears that the supply costs increase more rapidly with parking capacity in these districts. Hence, this suggests that our results apply to downtown shopping districts and less in out-of-town shopping districts.

2.3.5 Sensitivity analysis

We have re-examined these results in many ways. The most important ones will be discussed here, and are reported in Appendix A2.4, but we would like to emphasize that other, non-reported, specifications generate very similar results. So, our results are extremely robust to specification and data selection.

First of all, we have re-estimated models using different censoring thresholds. This is relevant, because the level of the threshold can be argued to be quite arbitrary. We find that the results are almost identical if we change the level of the threshold (see Table A2.2). For example, a € 4 or € 10 threshold does not substantially alter the supply curve.

Second, we have re-estimated the model for different categories of municipality size. Again, the results are quite robust (see Table A2.3). For example, if we limit the analysis to municipalities with at least 100,000 inhabitants, the slope of the supply curve is somewhat decreased.

Third, we have re-estimated the model using observations for hour prices (see Table A2.4). To compare the results, it is now more convenient to focus on the log-log specification. It appears that the inverse parking supply elasticity is somewhat reduced, especially when garage parking is present (the reduction in this elasticity is only about 0.2), so the results are not extremely sensitive to the choice of the price measure. Nevertheless, it suggests that parking supply is somewhat less sensitive than reported before.

Fourth, we have estimated models without using any instrumental-variable techniques (see Table A2.5). This approach may generate consistent estimates of the supply function but only when the supply function is identical for each shopping district (conditional on control variables), otherwise the supply estimates are usually downward biased. In line with this idea, it appears that the coefficients are substantially lower, although we still find a (statistically significant) positive effect of parking quantity on parking costs in all specifications, except for one (specification (8)).

Fifth, we have assumed the government intervention to be socially optimal (e.g., they may include maximum parking requirements). So we have assumed that underground parking regulation is welfare improving and conditional on this regulation that quantity requirements are optimal. However, this may not always be the case.

For example, let us suppose that some local governments impose minimum garage parking requirements beyond the optimal market equilibrium (e.g., to guarantee sufficient supply for residents with parking permits). We don't know in which districts minimum garage parking requirements are applied. However, the distribution of the garage parking places in Figure 3 provides some suggestive evidence for the existence of minimum parking requirements in some districts. The remarkably high frequency of shopping districts just above (the minimum requirement of) 2.5 (garage) parking place per 100 square meter suggests that there is some degree of (maybe distortionary) government regulation in these districts. Excluding these districts does not change the empirical results.

2.4 Welfare analyses

2.4.1 Main analysis

The welfare losses due to residential parking permit policy depend on the number of cars parked when nonresidents aim to park (R). On average, each shopping district contains about 1,200 street parking places and the number of parking permits is roughly the same.[29] However, approximately half of residents with a residential parking permit park their car during the day during weekdays shopping hours (but a much higher share Saturdays), see e.g. Trajan (2009), so we assume R to be only 500. The number of nonresidents is equal to the number of garage parking places, so Q_r is equal to 500.

Let us assume now that nonresidents' parking demand is perfectly price elastic. When removing the residential parking policy, parking prices do not fall, but the demanded quantity for street parking by nonresidents increases (by 500 parking places). Given (1), the welfare loss per parking permit equals € 1.06 per day, so € 388 per year. When parking demand by nonresidents is perfectly price inelastic, the demanded quantity does not change, and the welfare loss per permit equals € 258 per year.[30] Given a moderate price elasticity of −0.3, the implied annual welfare loss is € 275 per permit. This is a substantial welfare loss compared to the mean yearly cost of a parking place, which is about € 1930.

Given the assumption that the number of on-street parking places is equal to the number of households with a car, and that in these shopping districts, only half of the households own a car (which is a conservative estimate), the welfare loss is about € 140 per household living in these districts, or € 70 per capita. Nationwide, the welfare loss will be € 100 to 140 million per year according to our conservative estimate (assuming an annual loss of € 258 to 388 per parking place, 1200 on-street parking places per shopping district and 308 shopping districts).

We emphasize that the above estimate is likely an extremely conservative estimate. For example, in the plausible case that the number of residential parking permits (and demand for parking by nonresidents) is larger than presumed, then the annual welfare

---

[29] During the day, when shops are open, cruising by residential is usually negligible. In contrast, the occupancy rate is essentially one in the evening/night, so cruising for street parking by *residents* in the *evening* is common. Using information about house prices, the average cruising cost for residents are estimated to about € 1 per day in Amsterdam, see Van Ommeren et al. (2011).

[30] In case of a perfectly elastic price, the welfare loss is equal to $0.5 \times 3.4 \cdot 10^{-3} \times 500(500 + 1000) =$ € 1275 per shopping center per day. Given an average number of 1200 permits (as the number of parking permits is roughly equal to the number of on-street parking places) per shopping district, the welfare loss per parking permit is € 1.06 per day, or € 388 per year. When the demand is fully price inelastic, the welfare loss per district is equal to $0.5 \times 3.4 \cdot 10^{-3} \times 500(500 + 500) =$ € 850 per day, implying a loss of € 258 per parking permit per year.

loss per residential parking permit is much higher, because the welfare loss increases more than proportionally in the number of parking permits. So, for example if the number of parking permits is twice as high as assumed, then the welfare loss per parking permit is *at least* twice high.

2.4.2 Sensitivity analysis of welfare analysis

In the welfare analysis we have calculated the welfare loss by varying the price elasticity of demand. In this section we will examine the robustness of our result, by also varying the share of residents who park their car on-street during the day and who receive a parking permit (see Appendix A2.1 for mathematical details). We keep the number of nonresidents fixed at 500, while we vary the price elasticity as well as the share of residents who park their car on-street during the day as a proportion of street capacity denoted by α (so $\alpha = R/$total street capacity). Table 2.5 shows the yearly welfare losses per parking place.

Table 2.5 shows that the welfare losses are almost proportional to the share of residents who park their car during the day. This result is intuitive, because the higher the share, the more additional parking places have to be supplied for nonresidents and the higher the equilibrium parking price. When nonresidents are more price sensitive (the price elasticity is higher in absolute value), the welfare loss is higher, but the effect of the price elasticity on welfare loss is limited. Even when only 10 percent of the residents park their car during the day, the annual welfare loss is € 63 per parking place. In streets where 70 percent of the residents park their car, the annual welfare loss can be as high as € 534 per parking place.

The welfare loss is due to a loss of consumer and producer surplus. Much of this welfare loss is borne by nonresidents, who experience a reduction of their consumer surplus. The loss of consumer surplus relative to the total welfare loss is equal to $(P_r - P_u)/(sR)$ (see Appendix A2.3 for details) and usually close to one. For example, given a demand elasticity of -0.3, the loss of consumer surplus accounts for 80 to 90 percent of the total welfare loss (see Table 2.5). This relative loss is less when nonresidents are more price sensitive, but higher when nonresidents are less price sensitive. In addition to the loss in consumer surplus, there is a small loss in the surplus of producers, i.e. the commercial and public parking suppliers.

Finally, the results in our welfare analysis strongly depend on the slope of the supply function. The slope of the supply function was estimated to be $3.4 \cdot 10^{-3}$ in the main analysis (see Table 2.2). The results of alternative models (see Table 2.3), suggest that the marginal supply costs are around $2.5 \cdot 10^{-3}$. Given this more conservative estimate, the welfare effects diminish accordingly by about 30 percent.

Table 2.5: Welfare losses and equilibrium price

	Demand elasticity (ε)					
Share of residents who park (α)	−0.1	−0.3	−0.6	−1.0	Relative loss of CS (ε = −0.3)	Equilibrium price
0.1	63	64	65	65	0.81	2.11
0.2	126	129	133	136	0.83	2.52
0.3	190	196	204	211	0.85	2.92
0.4	254	264	276	288	0.87	3.33
0.5	318	332	350	368	0.88	3.74
0.6	383	402	425	450	0.89	4.15
0.7	448	471	501	534	0.90	4.56

2.5 Conclusion

In the current paper, we aim to provide insight into the welfare losses of policies that provide on-street parking permits to residents almost free of charge. We focus on shopping districts, which are usually downtown, where there is also demand for parking by nonresidents, in particular shoppers. We derive the welfare loss by estimating (inverse) parking supply functions. Our empirical results indicate that downtown parking supply is far from perfectly elastic with an inverse price elasticity of supply of about one. This suggests that the ubiquitous provision of residential parking permits substantially increases the costs of parking supply. Rough welfare calculations indicate that the provision of on-street parking permits induces an annual welfare loss of about € 275 per parking permit, which is about 15 percent of the parking supply costs. 80 to 90 percent of this loss is due to a loss of nonresidents' consumer surplus.

A parking permits policy provides advantages to local residents that are denied to nonresidents. It is well known that residents have strong incentives to prevent *local* policies that are welfare improving. In the spirit of Kunreuther and Kleindorfer (1986), we suggest that providing residents the option to sell their residential parking permit might be a politically acceptable solution which is welfare improving. To create a market for residential parking permits has a number of attractive properties: the price of the permits will reflect the residents' willingness to pay for parking, households who choose residence locations will internalize the social costs of street parking and local governments may reduce (or increase) the number of parking permits by buying (selling) the permits at market values. This idea is similar in spirit to the idea by Shoup (2004) who proposes to give residents the right to commercially exploit street parking and who may keep local parking revenue.

Appendix 2.A: Derivation of demand function and welfare loss

A2.1: The demand function in the unregulated equilibrium

We assume there is a number of nonresidents Q, which use garage parking. R denotes the number of residents who park their car. The demand and inverse supply functions are linear. Due to the presence of street parking, there are no fixed supply costs. The nonresidents are the high-demand consumers, so in the unregulated equilibrium there is only nonresidents parking and $S = sQ$. In the regulated equilibrium $S' = s(Q + R)$. The number of nonresidents Q_r equals 500. Given a point elasticity $\varepsilon = \frac{\partial Q}{\partial P}\frac{P_r}{Q_r}$ (defined for the regulated equilibrium), the slope of the demand function is $\frac{\partial P}{\partial Q} = \frac{1}{|\varepsilon|}\frac{s(Q_r+R)}{Q_r}$ and the intercept is: $C = s(Q_r + R) + Q_r\left(\frac{1}{|\varepsilon|}\cdot\frac{s(Q_r+R)}{Q_r}\right) = s(Q_r + R)\left(1 + \frac{1}{|\varepsilon|}\right)$, so the demand function for parking can be written as $D = -\frac{s(Q_r+\mathrm{R})}{Q_r|\varepsilon|}Q + s(Q_r + \mathrm{R})\left(1 + \frac{1}{|\varepsilon|}\right)$. The number of nonresidents Q_u in the unregulated equilibrium can then be obtained by solving $D = S$. This yields: $Q_u = Q_r\frac{Q_r(|\varepsilon|+1)}{Q_r(|\varepsilon|+1)+R}$.

A2.2: Derivation of the total welfare loss

The total welfare loss due to the shift in supply from S to S' is the reduction of the area between the demand and supply curve in Figure 1. Hence:

$$
\begin{aligned}
\text{Welfare loss} &= \int_0^{Q_u}\big(D(Q) - S(Q)\big)dQ - \int_0^{Q_r}\big(D(Q) - S'(Q)\big)dQ \\
&= \int_0^{Q_u} D(Q)\,dQ - \int_o^{Q_r} D(Q)dQ - \int_0^{Q_u} S(Q)dQ + \int_0^{Q_r} S'(Q)\,dQ \\
&= \int_{Q_r}^{Q_u} D(Q)\,dQ - \int_{Q_r}^{Q_u} S(Q)dQ + \int_0^{Q_r}(S'(Q) - S(Q))dQ \\
&= \frac{1}{2}sR(Q_u - Q_r) + sRQ_r = \frac{1}{2}sR(Q_u + Q_r),
\end{aligned}
$$

as $D(Q_u) - S(Q_u) = 0$ and $D(Q_r) - S(Q_r) = \frac{-s(Q_r+R)}{Q_r|\varepsilon|}Q_r + s(Q_r + R)\left(1 + \frac{1}{|\varepsilon|}\right) - sQ_r = sR$. So $\int_{Q_r}^{Q_u}(D(Q) - S(Q))dQ = \frac{1}{2}(sR + 0)(Q_u - Q_r)$.

A2.3: Calculation of the loss of consumer surplus

The loss of consumer surplus is equal to:

$$
\begin{aligned}
\Delta\, CS &= \int_0^{Q_u}(D(Q) - P_u)\,dQ - \int_0^{Q_r}(D(Q) - P_r)\,dQ \\
&= (P_r - P_u)Q_r + \frac{1}{2}\,(P_r - P_u)(Q_u - Q_r) = \frac{1}{2}(P_r - P_u)(Q_u + Q_r).
\end{aligned}
$$

The relative loss of consumer surplus is then:

$$\frac{\Delta CS}{Welfare\ loss} = \frac{\frac{1}{2}(P_r - P_u)(Q_u + Q_r)}{\frac{1}{2}sR(Q_u + Q_r)} = \frac{(P_r - P_u)}{sR}.$$

A2.4: Various complementary analysis

Table A2.1: Garage parking share

Garage parking share	Two-limit Tobit			IV Two-limit Tobit	
	(1)	(2)	(3)	(4)	(5)
Parking places (/1000)	0.101***	0.069***	0.050**	0.108***	0.094***
	(0.019)	(0.018)	(0.019)	(0.021)	(0.024)
Municipality population		-0.117	0.157	-0.121	0.144
		(0.202)	(0.238)	(0.200)	(0.239)
Municipality population density		0.153***	0.163***	0.139***	0.144***
		(0.031)	(0.031)	(0.031)	(0.031)
Shopping district type	no	no	yes	no	yes
Constant	-0.147	-0.303	0.310	-0.340	-0.320
	(0.053)	(0.059)	(0.182)	(0.061)	(0.178)
Log likelihood	-232	-211	-209	-2732	-2721
No of observations	308	308	308	308	308
No of obs., no garage parking	147	147	147	147	147
No of obs., no street parking	18	18	18	18	18
F-test (weak instruments)				707.03	582.26

For notes, see Table 2.2.

Table A2.2: Inverse parking supply functions using different thresholds

Day price	€4 threshold				€10 threshold			
			Garage present				Garage present	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Parking places	2.985***	3.228***	2.704***	2.789***	2.786***	2.869***	2.821***	2.941***
(/1000)	(0.279)	(0.321)	(0.313)	(0.385)	(0.309)	(0.372)	(0.387)	(0.504)
Municipality	13.7***	11.1***	10.9***	10.4**	15.5***	13.6***	13.5***	11.5**
population	(2.63)	(3.21)	(3.38)	(4.31)	(3.04)	(3.89)	(4.17)	(5.60)
Municipality	0.978**	0.813**	0.481	0.429	0.455	0.388	0.382	0.338
population density	(0.409)	(0.413)	(0.467)	(0.475)	(0.490)	(0.484)	(0.613)	(0.612)
Shopping district type	no	yes	no	yes	no	yes	no	yes
Log likelihood	-2663	-2638	-1467	-1458	-2458	-2438	-1319	-1313
No of observations	275	275	138	138	275	275	138	138
Obs. below threshold	162	162	45	45	219	219	95	95
F-test (weak instr.)	754.05	669.77	399.20	284.26	754.05	669.77	399.20	284.26

Note: regression on parking price. The censoring threshold is € 4 in specification 1-4 and € 10 in specifications 5-8. For other notes, see Table 2.2.

Table A2.3: Inverse parking supply functions, for minimum city size

Day price		
	(1)	(2)
Parking places (/1000)	2.727***	2.465***
	(0.538)	(0.460)
Shop space rent (median)	0.027	0.019
	(0.027)	(0.024)
Shopping district type	yes	yes
Municipality fixed effects	yes	yes
Log likelihood	-419	-495
No of observations	42	50
No. of obs. below threshold	10	12
Minimum city size	100,000	50,000
F-test (weak instruments)	130.42	144.96

Note: IV Tobit estimates. For other notes, see Table 2.2.

Table A2.4: Inverse parking supply functions (hour price)

Hour price	IV Tobit				IV Tobit Log-log			
			Garage present				Garage present	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Parking places	0.381***	0.425***	0.312***	0.310***	0.746***	0.987***	0.570***	0.584***
(/1000)	(0.041)	(0.047)	(0.044)	(0.053)	(0.098)	(0.149)	(0.093)	(0.138)
Municipality	0.795**	0.492	0.368	0.584	0.345***	0.196	0.258***	0.294***
population	(0.381)	(0.451)	(0.449)	(0.557)	(0.069)	(0.105)	(0.074)	(0.109)
Municipality	0.246***	0.237***	0.220***	0.232***	0.153**	0.125	0.099	0.102
population density	(0.059)	(0.060)	(0.067)	(0.068)	(0.075)	(0.080)	(0.087)	(0.088)
Shopping district type	no	yes	no	yes	no	yes	no	yes
Log likelihood	-3163	-2804	-1536	-1530	-615	-596	-340	-333
No of observations	308	308	161	161	308	308	161	161
Obs. below threshold	147	147	42	42	147	147	42	42
F-test (weak instr.)	707.03	582.26	401.60	271.26	215.80	116.86	138.06	62.57

Note: regression on parking price. The censoring threshold is 0.35 in the linear analyses and log (0.35) in the log-log analyses. For other notes, see Table 2.2.

Table A2.5: Inverse parking supply functions (no instrumenting)

Day price	IV Tobit				IV Tobit Log-log			
			Garage present				Garage present	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Parking places	2.565***	2.504***	2.044***	1.740***	0.630***	0.525***	0.427***	0.148
(/1000)	(0.244)	(0.272)	(0.272)	(0.313)	(0.091)	(0.104)	(0.108)	(0.128)
Municipality	14.5***	15.4***	12.3***	17.1***	0.493***	0.623***	0.401***	0.689***
population	(2.72)	(3.31)	(3.43)	(4.19)	(0.080)	(0.105)	(0.091)	(0.119)
Municipality	1.037**	1.092**	0.497	0.632	0.191	0.211	0.063	0.090
population density	(0.411)	(0.413)	(0.471)	(0.469)	(0.086)	(0.084)	(0.098)	(0.093)
Shopping district type	no	yes	no	yes	no	yes	no	yes
Log likelihood	-508	-506	-361	-358	-264	-258	-162	-154
No of observations	275	275	138	138	275	275	138	138
Obs. below threshold	141	141	36	36	141	141	36	36

Note: municipality population in millions. Population density in thousand persons per square meter. The censoring threshold is € 2 in the linear analyses and log (€ 2) in the log-log analyses. For other notes, see Table 2.2.

3. Car ownership and residential parking subsidies: Evidence from Amsterdam[31]

3.1 Introduction

During the second half of the 20th century, car ownership levels have increased considerably in many countries around the world. Differences in car ownership levels between countries are still substantial as a result of differences in household income, gasoline and car taxation as well as public transport provision (Dargay et al., 2007; Dargay and Gately, 1999; Giuliano and Dargay, 2006). Despite their success, cars are also associated with urban sprawl and negative external effects such as pollution and congestion (Glaeser and Kahn, 2004).

There is large spatial variation in car ownership within countries and cities. It has been extensively documented that car ownership levels in city centers are much lower than in suburban and rural areas, due to a combination of shorter travel distances, higher population densities, and better access to public transport, which makes car ownership less beneficial, (see, for example Button et al., 1980; Clark, 2007; Cullinane, 2002; Cullinane and Cullinane, 2003; Giuliano and Dargay, 2006; Handy et al., 2005; Ingram and Liu, 1999).

It is, however, largely unknown to what extent ownership levels are affected by residential parking policy (Guo, 2013). This is an important question because it is well known that around the world the price of residential parking is strongly reduced by policies. In most European cities, parking is subsidized through the provision of residential permits for parking on street, whereas in many US cities, parking supply is strongly increased through minimum parking requirements, resulting in cheap parking (Shoup, 1999; Van Ommeren et al., 2011).

The welfare consequences of these parking policies are likely minimal in locations where provision of parking is cheap. The opposite is true in city centers that have been evolved before the introduction of the car, such as the historic centers of most European cities. In these centers, on-street as well as off-street parking is extremely scarce and, not surprisingly, prices for both types of parking tend to be high.

We will focus on the consequences of parking subsidies offered to residents in the center of Amsterdam, which was developed before 1800. Parking costs are high here: street parking costs € 5 per hour, residential parking costs about € 3,600 per year and a two-car garage costs about € 70,000 (Cition, 2014; Van Ommeren et al., 2011). The demand for parking is distorted by the provision of residential parking permits which allow residents to park on street in the district where they live at a nominal fee of maximally € 400 annually. Note that the residents still have to find a parking space, so

[31] This chapter is based on joint work with Jos van Ommeren and Hans Koster. It has been published as De Groote, J., Van Ommeren, J., Koster, H. (2016). Car ownership and residential parking subsidies: Evidence from Amsterdam. Economics of Transportation, 6, 25-37.

they may still incur additional search and walking costs. The (implicit) subsidy associated with parking permits, about € 3,200 per year, will then increase car ownership above the optimal level from a welfare perspective if all externalities due to car ownership and usage are internalized.

In Amsterdam parking policy varies by district. In many parking districts the number of parking permits would far exceed the number of on-street parking spaces in case of unconstrained provision, inducing residential cruising for parking, particularly in the evening when residents come home from work (Van Ommeren et al., 2011). Households receive maximally one or two permits depending on the district they live in. In a number of one-permit parking districts, households also have to wait several years in order to obtain a parking permit. In the city center, the average waiting time is one year. Households that are on the waiting list for a parking permit are required to own a car and therefore pay the full (non-subsidized) price of parking. Consequently, the length of the waiting list determines the (implicit) subsidy received by households.

To the best of our knowledge, this is the first empirical paper that aims to estimate the effect of residential parking subsidies on welfare through increases in household car ownership. In the theoretical economics literature that analyzes parking, car ownership is usually assumed to be given (e.g., Arnott and Rowse, 1999). In this literature, the focus is on the welfare effect of too low on-street prices, so parking for nonresidents is subsidized (see Arnott and Inci, 2006; Arnott and Rowse, 2009, 2013; Shoup, 2006). This reflects the US institutional setting, where on-street parking prices in many cities are far below commercial parking prices.

In contrast, we focus on an institutional environment, common in most European cities, where on-street and off-street prices are approximately equal, but where parking for residents is subsidized through the provision of residential parking permits. We estimate the effect of parking subsidies on welfare for the city center of Amsterdam by focusing on the effect of waiting lists for parking permits on car ownership. Waiting lists provide useful variation in the parking price for residents, because households have to live in the district and own a car to be on the waiting lists. This means they incur parking costs equal to the full market price while they are on the waiting list. The length of the waiting lists is not uniform over the city but varies by district (up to four years). The estimated effect of waiting-list duration allows us to derive the price elasticity of car demand. Previous studies indicate that the price elasticity of car ownership usually ranges between −0.1 and −0.5 (Whelan et al., 2000; Dargay, 2002). These rather inelastic demand elasticities for car ownership incorrectly suggest that the provision of parking permits in Amsterdam may only have a small effect, implying that the welfare effects of parking permit provision would be limited. However, we emphasize that these studies do not refer to demand elasticities in city centers. It is plausible that the price elasticities in city centers will be higher, which would be consistent with the observation that car ownership tends to be lower in city centers.

In this paper, we use a cross-sectional identification strategy, which has the advantage that we can identify long-run effects of parking subsidies. The use of cross-sectional data, however, also has disadvantages if one is interested to measure a causal effect of parking policies on car ownership. In particular, it is plausible that spatial differences in car ownership levels are also due to household sorting based on household characteristics, in particular household income and size, as well as location characteristics such as population density, which are known to vary over space (Potoglou and Kanaroglou, 2008). Hence, in order to identify a causal effect, we control for a large range of household and location characteristics. Car ownership may also vary due to differences in unobserved household and location characteristics. To mitigate the problem of these unobserved characteristics, we employ a spatial boundary-discontinuity design (BDD), as introduced by Black (1999). The analysis hinges on the assumption that unobserved characteristics can be regarded as variables that vary continuously over space, while parking policy is district-specific and therefore varies discretely over space. Hence, our key identifying assumption to identify a causal effect of policy on car ownership is that household sorting at the boundary is continuous. The identification strategy is useful to determine the effect of waiting-list duration on car ownership, but it is unable to capture the causal effects of paid parking on car ownership, because households residing in the paid-parking districts may park their cars outside the permit area in a free-parking district and walk to their homes and incur low additional costs. This is much less likely for households residing in the waiting-list districts near the city center because they are not allowed to park their cars in surrounding paid-parking districts without waiting lists.

Our main finding is that car ownership is rather strongly reduced due to waiting lists for parking permits. Every year of waiting-list duration decreases car ownership by about 2 percentage points, which implies a price elasticity of car demand of −0.8. The (implicit) subsidy of a parking permit (with an average waiting duration of one year) induces an annual deadweight loss of about € 270 per permit, which is close to earlier findings by Van Ommeren et al. (2014). However, we measure residential parking demand, while the latter paper focusses on parking supply near shopping centers and ignores further indirect welfare implications of residential parking, like the loss of product variety in shops because of less convenient visitor parking, as suggested by Molenda and Sieg (2013).

Another important insight is that providing parking permits is an income-regressive policy. Households with an annual income of € 100,000 are five times more likely to receive the subsidy provided by a parking permit than households with a minimum income.

The paper continues as follows. Section 3.2 introduces the model setup, Section 3.3 discusses the institutional context, Section 3.4 provides an overview of the data, Section 3.5 shows the results and Section 3.6 calculates the welfare effects. Section 3.7 concludes.

3.2 Institutional context: Amsterdam

3.2.1 Car ownership: stylized facts

In the Netherlands, there are about 0.6 cars per capita for the population older than 18 years, which is comparable to other European countries.[32] Car ownership in Amsterdam, which is the largest city of the Netherlands with about 800,000 inhabitants, is only 0.37 per capita. This is in line with the stylized fact that car ownership is lower in larger cities. In Table 3.1, it can be shown that car ownership has strongly increased in the last few decades in Amsterdam (by about 5 percentage points, or 13 percent over the last 20 years), but in the rest of the Netherlands the growth in car ownership has been at least twice as high.[33] Notably, in contrast to the rest of Amsterdam, car ownership has remained stable in the city center over the last decades. At the end of the 1980s, car ownership was still higher in the center than in some other neighborhoods (East and West), but nowadays, ownership is the lowest in the city center.

There is a range of explanations for the relative decline of car ownership in the center. As (gross) income is a very good predictor for car ownership, one possible explanation is that neighborhoods have experienced different levels of income growth. However, household income differences between neighborhoods nowadays are extremely small (see Table A3.1 in Appendix 3.A). Since 2005, increases in income have been quite uniform within Amsterdam (see Bureau Onderzoek en Statistiek, 2014). Before 2005, incomes have increased more rapidly in the center (see Bureau Onderzoek en Statistiek, 2007), so car ownership would have increased more strongly in the city center if income would be the only factor that determines car ownership. Another explanation is that the income elasticity of car demand is lower in the center. However, somewhat surprisingly, within-country studies suggest that the income elasticity is in fact higher in urban areas than in rural areas (Dargay, 2002). As shown in Appendix 3.A, it seems that the income elasticity of car demand is indeed slightly higher in the city center. This implies that a uniform income increase may in fact reduce the differences in car ownership between the city center and the suburbs.

3.2.2 Parking policy

A more plausible explanation for the relative decline of car ownership in the center is the (almost) fixed supply of parking in the historic city center. In the center of Amsterdam, constructing parking garages is extremely expensive, so few residents own private parking spaces and commercial off-street parking is limited (Van Ommeren et al., 2011). Consequently, due to the strong increases in household income witnessed over the last 50 years, demand for residential street parking has strongly increased.

[32] Slightly confusing, in the literature, car ownership is measured either per household, capita, or adult capita, so for persons older than 18 years. In this section we provide data per adult capita. In the data analyzed later on we use car ownership per household.

[33] A similar development is observable in the other European countries. In London, car ownership per capita has even decreased from 0.43 to 0.39, while in the UK it has increased from 0.54 to 0.59 over the last 15 years (London datastore, 2014, and UK government, 2013).

Table 3.1: Car ownership in Amsterdam (per adult capita)

Area	1986-1991	1994-1997	1998-2000	2001-2004	2005-2008
Center	0.31	0.32	0.32	0.31	0.31
West	0.27	0.27	0.28	0.29	0.31
East	0.28	0.30	0.32	0.34	0.34
South	0.35	0.38	0.41	0.42	0.43
Amsterdam	0.32	0.33	0.35	0.36	0.37
Netherlands		0.47	0.51	0.55	0.57

Note: Car ownership is measured as number of cars per capita older than 18 years. Sources: Gemeente Amsterdam (2011) and CBS Statline.

From the beginning of the seventies, Amsterdam has struggled with a parking-intrusion problem, so residents were unable to park in front of their homes because of strong parking demand. To address this increased demand for parking, paid on-street parking for nonresidents was introduced combined with a restrictive residential parking-permit policy. This has led to the introduction of paid-parking districts in 1992 with fairly high visitor parking fees (up to € 5 per hour or € 40 per day in 2015) (Gemeente Amsterdam, 2000). Residential car owners were offered the opportunity to apply for a parking permit, which is only valid in the neighborhood where residents live and which cannot be traded among households.

Permits for residents generally cost between € 100 and € 400 per year. This is only a fraction of the on-street tariff (about 2.5 percent) and also considerably less than the price in the commercial off-street parking market, which is around € 3,600 per year for a full subscription in the center (and between € 1,200 and € 2,400 for a nighttime subscription (see Q-Park, 2014)). A parking permit therefore subsidizes car owners by about € 3,200 per year, which is about half the cost of owning a car net of parking expenses (Nibud, 2015).

The substantial subsidy has created a strong demand for permits that far exceeds the stock of street parking in many paid-parking districts. Given excess demand for parking permits, the number of parking permits has been limited to one per household or two per household, depending on the district in which the household resides.

In the city center, despite the one-permit-per-household restriction, there is still excess demand for parking permits, which has led the local government to introduce waiting lists for permits. Waiting lists nowadays vary from only a few months for neighborhoods further from the center to about four years in the city center. Households on waiting lists are obliged to live in the district where they are on the waiting list and own a car, implying that these households pay the market price for parking of about € 3,600 per year while they are on the waiting list. This institutional feature is important for our interpretation of the results, because it means that we are able to put a monetary price on the cost of waiting one year longer for a permit.

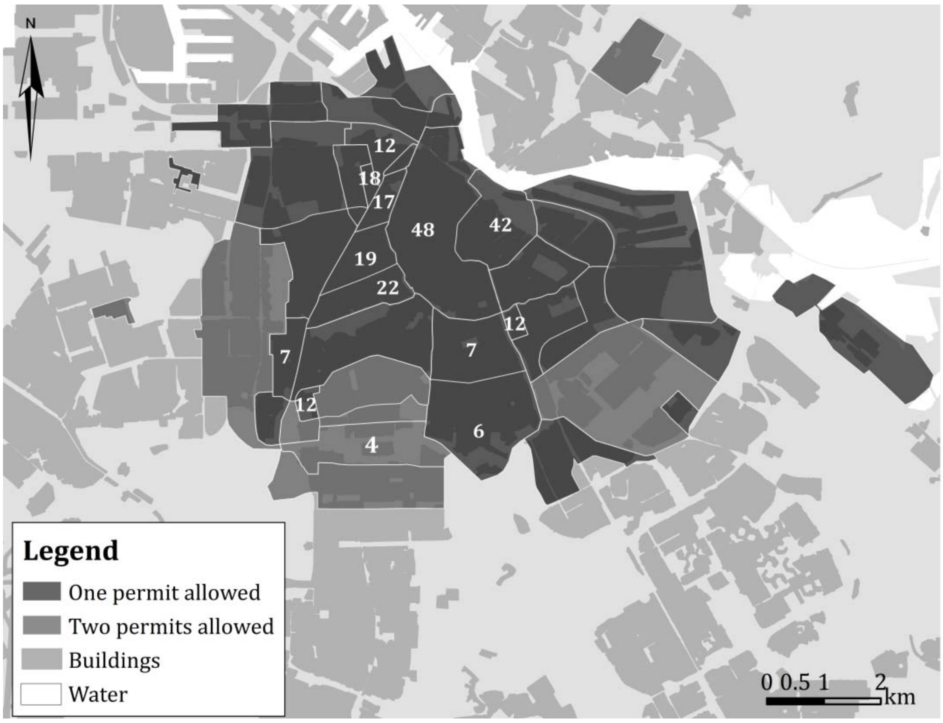


Figure 3.1: Parking Districts In Amsterdam

Note: Numbers refer to waiting-list duration in months in 2010. Source: Cition.

Figure 3.1 shows the different parking regimes in Amsterdam. The dark-colored areas refer to the paid-parking districts where only one permit is allowed (the 'one-permit districts') and the lighter areas are the paid-parking districts where two parking permits are allowed ('two-permits districts'). The numbers indicate the waiting-list duration in months in 2010. There are 13 waiting-list districts with varying waiting-list durations. We have accurate information for the waiting-list duration for the year 2010. For 2000, we have a good proxy for the actual waiting-list duration because we know the subscription length of the first person on the waiting list (Gemeente Amsterdam, 2000). In the analysis, where we analyze car ownership between 2004 in 2012, we use the average of the waiting-list duration for the years 2000 and 2010.

3.3 Econometric framework and identification

We aim to estimate the impact of waiting-list duration on car ownership. Our identification strategy uses cross-sectional variation and exploits spatial variation in car ownership, which has the advantage that in principle long-run effects are identified. We estimate:

$$C_{ijt} = \beta D_j + \gamma_1 P_{1j} + \gamma_2 P_{2j} + \delta_t + \varepsilon_{ijt}, \tag{3.1}$$

where C_{ijt} is the number of cars owned by household *i* in district *j* in year *t*. In the analysis, we will estimate linear models, because these models are more efficient, easier to interpret and because it is more straightforward to include fixed effects. Nonetheless, we will also estimate a multinomial probit model in the sensitivity analysis (see Table 3.7). We focus on the effect of waiting-list duration D_j. With the exception of one area, waiting lists only occur in one-permit districts, so we control for locating either in a one-permit district P_1 or a two-permits district P_2, where the reference is a free parking district. We also control for year fixed effects δ_t.

The main disadvantage of this specification is that it ignores that most spatial differences in car ownership are likely not due to parking policy, but due to household sorting. For example, households that have a stronger preference for cars may locate outside the city center (Glaeser et al., 2008). Therefore, in the next specification, we control for household characteristics H_{ij}, such as household income and household size, and locational factors L_j, such as population density, distance to the city center and distance to the parking district boundary. This leads to:

$$C_{ijt} = \beta D_j + \gamma_1 P_{1j} + \gamma_2 P_{2j} + \boldsymbol{H}_{ij}\delta + \boldsymbol{L}_j\eta + \delta_t + \varepsilon_{ijt}. \tag{3.2}$$

A major concern here is that it is impossible to control for all household and location factors that are correlated with D_j, because many factors are unobserved to the econometrician. This may bias the results. In order to disentangle the effect of waiting-list duration from other unobserved factors, such as the accessibility of public transport, the presence of shops and sorting of households, we adopt a *boundary-discontinuity design* (BDD) (see Bayer et al., 2007; Black, 1999).

We include boundary fixed effects to control for unobserved location characteristics and household sorting. This specification is then given by:

$$C_{ijt} = \beta D_j + \gamma_1 P_{1j} + \gamma_2 P_{2j} + \boldsymbol{H}_{ij}\delta + \theta_{ib} + \delta_t + \varepsilon_{ijt}, \tag{3.3}$$

where θ_{ib} denotes the boundary fixed effects; i.e., a number of dummy variables that are equal to one if parking-district boundary b is the closest parking-district boundary to household i. In this specification, it is not useful to control for location factors L_j, as we control for spatial heterogeneity by including the boundary fixed effects. We will show in the sensitivity analysis that the results are reasonably robust to the inclusion of location factors.

The key identifying assumption is that unobserved household and location characteristics are absorbed by the boundary fixed effects θ_{ib}. To make this assumption more plausible, one would like to select households that are within a very close vicinity of the boundary (e.g. 25 meters), but this has the disadvantage that the boundary sample becomes extremely small implying large standard errors. In order to obtain a sufficient number of observations, we select observations within a threshold distance d_T (which varies from 50 to 200 meters in the empirical analysis, in line with Black, 1999 and Bayer et al., 2007). To further improve on identification we will only include observations in one-permit districts, to avoid the possibility that households in waiting lists just park their cars in an adjacent free parking district with minimal additional time costs of travelling. Hence, the effect of waiting-list duration is estimated based on:

$$C_{ijt} = \beta D_j + \boldsymbol{H}_{ij}\delta + \theta_{ib} + \delta_t + \varepsilon_{ij}, \quad \text{if } d_{ib} < \mathrm{d}_T \text{ and } P_1 = 1, \tag{3.4}$$

where d_T is the pre-defined threshold distance and d_{ib} refers to the distance to the nearest district boundary.

Again, the identifying assumption is that unobservable household characteristics are (reasonably) continuous at the boundary or are uncorrelated to D_j. To make this assumption more plausible, we will also estimate models on subsamples of households who live in waiting lists districts and focus on rental housing only. Because the lion's share of rental housing in the city center of Amsterdam is public housing, for which also extensive waiting lists exist, sorting seems to be less of a problem then.

We further note that this identification strategy is unable to capture the causal effects of residing in one-permit districts P_{1j} or two-permits districts P_{2j}, because households residing in one-permit areas may park their car outside the permit areas. Hence, the effect of residing in permit districts should be continuous over space and cannot properly identified using a BDD. This is not the case for households in waiting-list districts, who live closer to the city center and therefore do not live close to free-parking districts.

Finally, it seems reasonable to argue that, *conditional on car ownership*, waiting lists do not have any additional effect on kilometers driven. Consequently, a reduction in car ownership implies a reduction in car kilometers and the effects of waiting time on car ownership and car kilometers must be comparable. We will therefore repeat the above analysis using car kilometers rather than car ownership as the dependent variable in the sensitivity analysis.

3.4 Data and descriptives

We employ two similar (cross-sectional) datasets with detailed information about household car ownership for the metropolitan area of Amsterdam (the municipality of Amsterdam and surrounding municipalities). For the years 2004 to 2007, the data was collected by *WDM*, and from 2008 to 2012 by its successor *Bisnode*. Car ownership is systematically lower in the WDM dataset. In our analysis, we will combine both datasets and include year dummies, which should control for any systematic difference between these datasets.

The data distinguish between zero, one or at least two cars per household.[34] The

[34] Because having three cars is extremely rare in the Netherlands, the measurement error generated by not observing the exact number of cars is negligible.

Table 3.2: Descriptives

	Metropolitan area	Amsterdam municipality	One-permit districts	Waiting-list districts
Number of cars *(car ownership)*	0.735	0.641	0.512	0.520
Car kilometers per year	10,105	9,139	7,921	8,034
Car kilometers per year per car	14,330	14,785	15,885	15,904
Waiting-list duration *(in years)*	0.252	0.331	0.691	1.138
Waiting list district	0.221	0.291	0.608	1.000
One-permit district *(excl. waiting-list districts)*	0.143	0.188	0.393	0.000
Two-permits district *(excl. one-permit districts)*	0.092	0.121	0.000	0.000
Free parking district *(excl. permit districts)*	0.544	0.400	0.000	0.000
Distance to district boundary *(km)*	1.270	0.713	0.219	0.237
Distance to city center *(km)*	5.041	4.037	2.440	2.322
Distance to nearest railway station *(km)*	2.107	1.811	1.438	1.403
Population density *(per km^2)*	9,775	11,217	16,313	16,984
Monthly household income *(€)*	2,944	2,856	2,880	2,956
Household size	2.33	2.28	2.10	2.07
Age *(average of adults)*	44.6	43.5	40.9	41.4
Number of observations	37,501	28,504	13,660	8,299

Note: In the columns, the metropolitan area includes the Amsterdam municipality, the municipality includes one-permit districts and one-permit districts include waiting list districts.

location of the household is available at the 6-digit zip-code level (PC6). On average,slightly less than twenty properties on the same side of a street share the same 6-digit zip code, so the location is precisely determined (its size is about equal to a census block in the US). There is also information about many other household characteristics, such as income, size, etc. The combined dataset contains over 37,000 observations, of which over 28,000 are within the municipal borders of Amsterdam. Table 3.2 reports descriptive statistics of the variables of interest.[35]

In the first column, the descriptives are shown for the whole metropolitan area. The average distance to the city center is about 5 km.[36] The last three columns provide descriptives for three subsamples of households closer to the city center: the Amsterdam municipality, one-permit districts and waiting-list districts. Households in the latter two districts live at 2.4 and 2.3 km respectively from the city center.

The first row of Table 3.2 clearly shows that the number of cars per household is strongly decreasing in distance to city center: for example, car ownership is 0.52 in one-permit and waiting-list districts, about 20 percent less than in the Amsterdam municipality where it is about 0.64. The next rows show that the number of kilometers driven per year also decreases with distance to city center, and that this is due to the reduction in car ownership, as the distance travelled per car is slightly higher in the city center.

[35] The survey seems reasonably representative. Car ownership is 0.74 per household, and therefore about 0.38 per adult, which is almost identical to the 0.37 reported in Table 3.1.
[36] The city center is here defined as the Dam Square.

Table 3.3: Car ownership per district

District	No. of cars	2 or more cars	1 car	No cars
Waiting list	0.520	0.070	0.380	0.550
One-permit without waiting list	0.500	0.055	0.390	0.555
Two-permits	0.694	0.103	0.488	0.409
Free parking	0.780	0.137	0.506	0.357
Average	0.641	0.098	0.445	0.457

The descriptives indicate that there is some spatial heterogeneity in household characteristics within the Amsterdam metropolitan area. For example, average household size in waiting lists districts is about 10 percent below the metropolitan average.[37] As discussed earlier, household income shows no spatial pattern.

The district characteristics distinguish between four mutually-exclusive parking district categories: waiting-list districts, one-permit districts without a waiting list, two-permits districts and parking districts that have no paid parking and therefore no residential permits.[38] Even at the scale of the metropolitan area, a substantial proportion of households lives in areas with paid parking and therefore parking permits: 22 percent of households resides in a waiting-list district, 14 percent in a one-permit district without waiting lists, and 9 percent in a two-permits district.

The average waiting-list duration is slightly more than one year for households living in a waiting-list district. Waiting lists for residential permits will mainly affect households that aim to increase the car ownership (from zero to one car) and will register on the waiting list. This may either refer to *incumbent* households (who have lived for a certain period within a waiting-list district) who aim to increase car ownership for example because of changes in the household characteristics (income, children) or to *new* households (that move into the waiting-list district). Note that incumbent households that have moved into the waiting-list district before there was a (substantial) waiting list and aimed to increase car ownership were facing lower waiting costs. Consequently, the effect of waiting-time duration will be an underestimate of the long-run effect. Given data on the duration of residence from Statistics Netherlands, it appears that about 12 percent of the households was living in the city center before 1992, when paid parking was introduced. Again, because waiting lists may not have been important at that time, our estimates of the effect of waiting lists on car ownership will be underestimates.

The descriptives indicate that waiting-list districts are very similar to other one-permit districts with respect to location and household characteristics. It will therefore make sense to only focus on one-permit and waiting-list districts in the estimation later on. Note that only about one quarter of households within the municipality of Amsterdam

[37] One explanation is the presence of a large share of public rental housing throughout the city (about 60 percent of all houses in the municipality).
[38] This is not completely accurate. As Figure 3.1 shows, there is a two-permit district with waiting lists. However, this is a business districts with very few households, so we ignore it in the analysis.

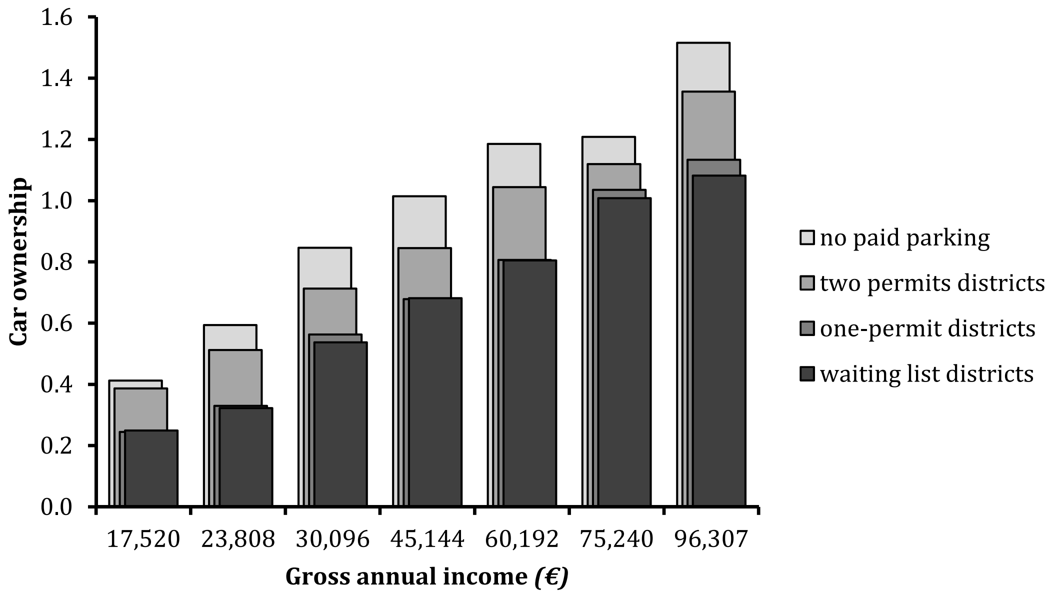


Figure 3.2: Average per-household car ownership and income

Note: The different categories are mutually exclusive.

own their house. To control for unobserved household characteristics, we employ a BDD where we include boundary fixed effects. In our data, the *average* distance for observations in one-permit and waiting-list districts is only slightly above 200 meters.

Table 3.3 reports car ownership levels again for the municipality of Amsterdam by tabulating the number of cars per household for four mutually-exclusive parking districts. It shows that even in the free-parking district (and therefore no permit provision), the share of households with two or more cars is only 14 percent. Hence, it seems that most households decide on whether or not to have one car. This is particularly true in waiting-list districts and other one-permit districts, where the share of households that have more than two cars is about 5 to 7 percent and where the majority of households decide to have no car.

The provision of parking permits implies a substantial (implicit) subsidy (of about € 3,200 per year) to households with cars. To receive the subsidy the household must relocate to districts that offer these subsidies. It is well known that car ownership strongly increases with household income. Importantly, the positive relationship between car ownership and income holds regardless of the parking district where the households are located (see Figure 3.2).

We distinguish between seven income levels. Gross annual income of the poorest group is about € 18,000 (approximately the minimum wage for a full-time job in the Netherlands) and of the highest-income group is almost € 100,000 (about three times average income). In waiting-list and other one-permit districts, where the implied subsidy is the highest, car ownership of the highest-income group is about four to five times higher than of the poorest group. This indicates that, conditional on residence location, high-income households disproportionately benefit from residential parking-permits schemes. This distributional effect of residential parking subsidies is by no means unique: public-transport subsidies also tend to benefit the higher-income groups disproportionally (see e.g. Frankena, 1973). What is unique, however, is that the subsidy is very substantial, as it is equal to about 18 percent of the poorest group gross annual income, and is income regressive.

3.5 Empirical results

3.5.1 Baseline results

We report the baseline results of the effect of waiting-list duration on car ownership in Table 3.4. Columns (1) to (3) report results based on equations (1) to (3) using 28,504 observations for households living in the municipality of Amsterdam. We start with an OLS regression without controls, except for the type of parking district, then we add household and location controls (distance to the city center, distance to the parking district boundary, distance to the railway station, population density). Finally, we add boundary fixed effects. In the latter specification, we do not control for location controls.[39]

In column (1) the coefficient with respect to the length of the waiting list is negative. The effect of waiting-list duration on car ownership is equal to −0.016, so one year increase in the waiting list leads to a decrease in car ownership of 1.6 percentage points. The effect becomes statistically insignificant if we include household and location characteristics in column (2) and boundary fixed effects in column (3). In these specifications, the effect of locating in a one-permit district is strongly negative, which is only *suggestive* evidence that one-permit restrictions strongly reduce car ownership because households that live close to a district with free parking may park in the latter district. Hence, we cannot exclude the possibility that the effect is at least partially explained by sorting on household unobservables. If this is the case, we may expect a continuous rather than discrete change of car ownership over space.

Figure 3.3 depicts the car ownership coefficients when the one-permit district variable in column (3) is replaced by multiple dummy variables. It appears that car ownership decreases rather strongly around the one-permit boundary, but *without a noticeable discrete jump* at the boundary. Hence, this effect might not only be explained by parking policies, but also be explained by household sorting along the parking district boundaries.

In the next specifications, we therefore only focus on one-permit districts. This allows us to more accurately estimate the effect of waiting-list duration between districts with and without waiting lists for parking permits. In column (4) of Table 3.4 we select observations within 100 meters of the nearest parking-district boundary. Although the selected sample refers to only 12.5 percent of the observations in the full sample, the

[39] In column (2) the estimated effects of the location controls are available upon request. If we also control for location characteristics in (3), the results are virtually unchanged.

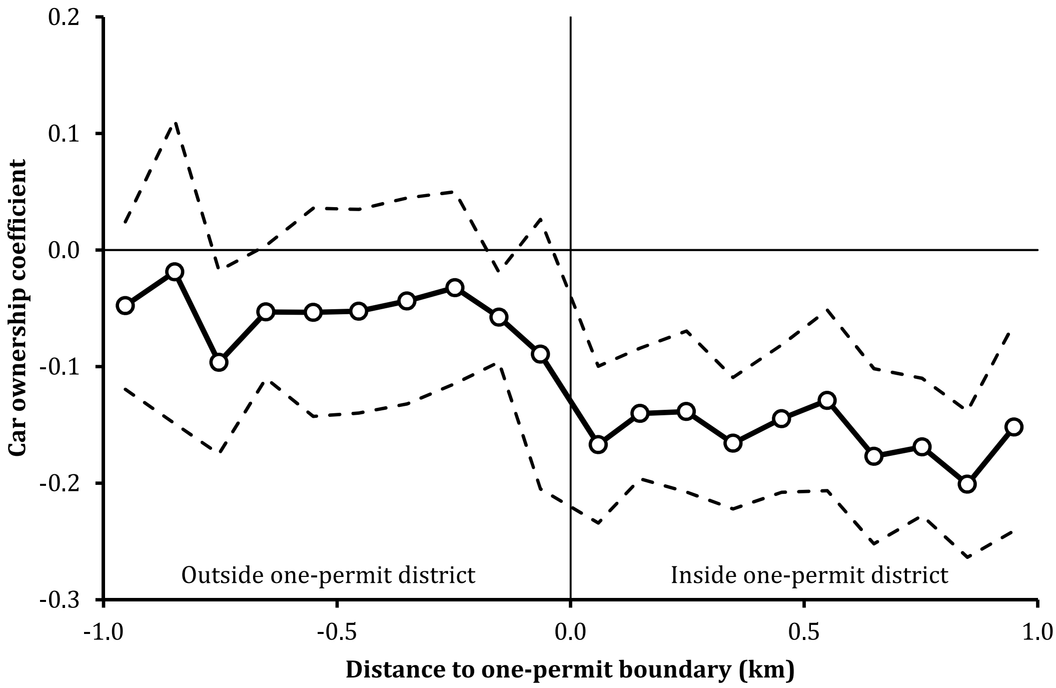


Figure 3.3: Car ownership coefficient around one-permit boundaries
Note: The car ownership coefficient is estimated as in column (3) when the one-permit district variable is replaced by multiple dummy variables. The dotted lines indicate the 95-percent confidence interval.

standard error of the waiting-list effect does not increase substantially, implying that the main disadvantage of selecting samples close to the boundary – a strong decrease in efficiency of the estimates – hardly applies here. We now find that the negative effect of waiting-list duration is much more substantial (and statistically significant at conventional significance levels). As discussed above, the boundary-discontinuity set-up is more likely to lead to consistent estimates and is therefore preferred over the OLS estimates. The results appear somewhat sensitive to the choice in area size, but we come back to this issue in the sensitivity analysis.

Column (5) reports the results where we only focus on households in waiting-list districts, so the effect is identified based on districts with a positive waiting-list duration. The point estimate of waiting-list duration remains unchanged compared to the reported effect in column (4).[40] In column (6) we focus on locations near boundaries of districts with a large (over a year) difference in waiting-list duration. Similar to Bayer et al. (2007), we then identify the coefficient on differences that are economically meaningful. More importantly, the larger differences are less likely to be subject to measurement error. For the areas with long waiting lists, we know that these areas also had long waiting lists in 2000. For other areas, due to some changes in district boundaries, it is more difficult to determine the average waiting-list duration across the sample period. We again find that

[40] Note furthermore that the standard error of the effect is reduced, which may be explained by the fact that households who live in districts with a positive waiting-list duration are more similar to each other.

Table 3.4: Baseline results: the effect of waiting list duration on car ownership
(dependent variable: number of cars)

	(1) OLS	(2) OLS	(3) BDD	(4) BDD	(5) BDD	(6) BDD
Waiting-list duration	−0.016**	0.003	−0.003	−0.022**	−0.022***	−0.034***
	(0.008)	(0.006)	(0.007)	(0.009)	(0.006)	(0.004)
One-permit district	−0.254***	−0.121***	−0.111***			
	(0.021)	(0.014)	(0.022)			
Two-permits district	−0.042***	−0.029***	−0.038***			
	(0.006)	(0.008)	(0.009)			
Income *(log)*		0.445***	0.447***	0.456***	0.437***	0.422***
		(0.009)	(0.010)	(0.026)	(0.031)	(0.049)
Household size *(log)*		0.216***	0.218***	0.219***	0.214***	0.205***
		(0.008)	(0.008)	(0.024)	(0.041)	(0.051)
Single household		−0.086***	−0.085***	−0.028	−0.012	−0.026
		(0.020)	(0.020)	(0.044)	(0.070)	(0.137)
Couple		0.027**	0.027	−0.015	0.025	−0.003
		(0.011)	(0.011)	(0.037)	(0.048)	(0.168)
Family		−0.055***	−0.054	0.001	0.048	0.016
		(0.018)	(0.018)	(0.039)	(0.058)	(0.187)
Secondary school		0.014	0.007	0.040**	0.039	0.114**
		(0.024)	(0.026)	(0.019)	(0.024)	(0.043)
Vocational education		0.032***	0.029***	0.034	0.004	0.092*
		(0.009)	(0.009)	(0.024)	(0.028)	(0.049)
Age		0.016***	0.017***	0.009**	0.012**	0.009
		(0.002)	(0.002)	(0.004)	(0.005)	(0.008)
Age^2 (/1000)		−0.142***	−0.149***	−0.058	−0.090	−0.033
		(0.022)	(0.024)	(0.044)	(0.062)	(0.086)
Location characteristics	No	Yes	No	No	No	No
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Boundary fixed effects	No	No	Yes	Yes	Yes	Yes
One-permit districts	No	No	No	Yes	Yes	Yes
Waiting-lists districts	No	No	No	No	Yes	No
Min. waiting-list duration difference *(in months)*	∞	∞	∞	∞	∞	12
Max. distance to boundary *(in m)*	∞	∞	∞	100	100	100
Number of observations	28,504	28,504	28,504	3,565	1,988	468
R^2	0.046	0.245	0.247	0.232	0.255	0.272

Note: Standard errors are in parenthesis and clustered at the parking-district level. Note that in specification (2), we also control for distance to the district boundary, distance to the city center, distance to the nearest railway station and population density. The reference household is a multi-person household with university degree education level. The asterisks indicate significance levels. *** p<0.01, ** p<0.05, * p<0.1.

the effect of waiting-list duration is negative and the point estimate of −0.034 is somewhat stronger compared to the previous estimates, which suggests that measurement error is less of a problem here, as this would lead to a bias towards zero. However, in the analysis, we will use the more conservative estimate of −0.022 of columns (4) and (5).

It is useful to express these results in terms of price elasticities of demand. According to our preferred specifications, waiting lists reduce car ownership by about 2 percentage points per year. As the average car ownership level in the waiting-list district is 0.50, this corresponds to a 4 percent decrease in car ownership, which implies that the price elasticity of demand is about -0.8.[41] The demand for cars appears considerably more elastic than the average values reported in the literature. Arguably, our finding of a more price elastic demand in the center of Amsterdam is plausible because of the availability of close substitutes for the car, in particular public transport and the bicycle, which is likely to increase this elasticity.

We find that the estimated effect of the logarithm of income on car ownership is robust with respect to specification and is between 0.42 and 0.46. The implied *income* elasticity of car ownership is then about 0.7 (obtained by dividing the estimated effect of the logarithm of income by the average car ownership in our data, which is 0.64).[42] In Appendix 3.A we show that cars are a generally a normal good and can only be considered as a luxury good for low-income households. In general, car demand of households residing in one-permit districts is slightly more income elastic.

3.5.2 Sensitivity analysis

The results above indicate that the effect of waiting-list duration on car ownership is generally negative once we select samples closer to the parking boundary, with point estimates between 0.003 and -0.034, while our preferred estimates are -0.022. In this subsection, we will perform a range of robustness checks.

First, we examine whether our results are sensitive with respect to excluding important control variables and to focus on rental housing only. If excluding important observable household and location characteristics will not lead to substantially different results, this might indicate that unobservable household characteristics are also not very important in explaining the effect of waiting lists on car ownership. Therefore, to investigate the sensitivity of our results with respect to important controls, we exclude all household characteristics in columns (1)-(3) in Table 3.5. It is shown that the effect of waiting-list duration becomes somewhat stronger (up to twice as large). However, because unobservable household characteristics are likely strongly correlated to observable household characteristics it will be unlikely that the effect of waiting lists on car ownership can be fully explained by sorting. In the second set of specifications in Table 3.5 (columns (4)-(6)) we include the location characteristics. The effect of waiting-list duration appears stronger than in the baseline specification. Hence, controlling for, arguably the most important (unobserved) amenities amplifies the effect, so our initial estimates may be underestimates.

One might still be worried that sorting is the main explanation for the negative effect of waiting lists on car ownership. We therefore also estimate specifications where we only focus on households occupying *rental housing*. There are two fundamental reasons

[41] As calculated in the welfare analysis section, a year on the waiting list increases car user costs by about 5 percent, so the elasticity is $\varepsilon \approx -0.04/0.05 \approx -0.8$.

[42] This elasticity is close to the elasticity of 0.61 found by Clark (2007) for the UK.

Table 3.5: Sensitivity analysis: household and location characteristics
(dependent variable: number of cars)

	Exclude all household characteristics			*Include location characteristics*			*Only rental housing*		
	(1) BDD	(2) BDD	(3) BDD	(4) BDD	(5) BDD	(6) BDD	(7)	(8)	(9)
Waiting-list duration	−0.048 ***	−0.040 ***	−0.060 ***	−0.033 **	−0.057 ***	−0.072 ***	−0.038 ***	−0.060 ***	−0.045 ***
	(0.008)	(0.016)	(0.007)	(0.016)	(0.016)	(0.017)	(0.013)	(0.011)	(0.018)
Waiting-list duration × sh. of public housing							0.003	0.012	-0.019
							(0.015)	(0.029)	(0.016)
Household char.	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Location char.	No	No	No	Yes	Yes	Yes	No	No	No
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Boundary fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
One-permit districts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Waiting-lists districts	No	Yes	No	No	Yes	No	No	Yes	No
Min. waiting-list duration diff. *(in months)*	∞	∞	12	∞	∞	12	∞	∞	12
Max. distance to boundary *(in m)*	100	100	100	100	100	100	100	100	100
Number of observations	3,565	1,988	468	3,565	1,988	468	2,655	1,466	339
R^2	0.043	0.071	0.074	0.234	0.259	0.285	0.167	0.194	0.239

Note: Standard errors are in parenthesis and clustered at the parking-district level. The reference household is a multi-person household with university degree education level. The asterisks indicate significance levels. *** p<0.01, ** p<0.05, * p<0.1.

to only focus on these households. First, the majority of the Amsterdam rental housing market is public housing (and rent-controlled), which is allocated based on public housing waiting lists, with waiting durations of minimally 15 years in the city center. The allocation process of public housing makes it rather difficult for households to sort exactly across the parking district boundary. Hence, by focusing on rental housing, the potential econometric problem of sorting based on unobserved household characteristics is mitigated. Note, however, that public houses are occupied by low-income households, which may be less sensitive to waiting lists for parking permits. Second, private rental houses are occupied by households for whom the expected residence time is substantially lower than for owners. For these renting households, the implied benefits associated with waiting are small or even zero, in particular when the parking permit waiting duration exceeds the expected residents' duration. It is then more likely that waiting list duration will have a more pronounced effect on car ownership. In our data, it is unknown whether a rental house is a public house, but we have access to the share of public housing in the 6-digit zip-code area (which contains on average 12 houses). For the majority of observations, the share is either zero or one, so the share is a reasonable indicator of public housing without too much measurement error.

For households that live in rental housing, we estimate the same models as above, however we interact the waiting-list duration with the share of public housing in the 6-digit zip-code area. It appears that car ownership of rental households is more sensitive to waiting-list duration, with negative effects of about −0.04. This confirms the hypothesis that because residents' durations are lower for rental housing, the effect is

Table 3.6: Sensitivity analysis: distance to the boundary
(dependent variable: number of cars)

	Within 200 meters of a boundary			*Within 50 meters of boundary*		
	(1)	(2)	(3)	(4)	(5)	(6)
	BDD	BDD	BDD	BDD	BDD	BDD
Waiting-list duration	−0.004	−0.015**	−0.019***	−0.047**	−0.034	−0.058***
	(0.009)	(0.006)	(0.005)	(0.019)	(0.022)	(0.019)
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Boundary fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
One-permit districts only	Yes	Yes	Yes	Yes	Yes	Yes
Waiting-lists districts only	No	Yes	No	No	Yes	No
Min waiting-list duration diff. *(in months)*	∞	∞	12	∞	∞	12
Max distance to boundary *(in m)*	200	200	200	50	50	50
Number of observations	7,650	4,317	972	1,321	741	164
R^2	0.222	0.242	0.248	0.245	0.298	0.384

Note: Standard errors are in parenthesis and clustered at the parking-district level. Note that in specification (2), we also control for distance to the district boundary, distance to the city center, distance to the nearest railway station and population density. The reference household is a multi-person household with university degree education level. The asterisks indicate significance levels. *** p<0.01, ** p<0.05, * p<0.1.

more pronounced. We also observe that the interaction term with public housing is essentially zero. As sorting along the boundary is much more difficult for households that are eligible for public housing, this provides evidence that sorting on unobservable household characteristics along the boundary is unlikely to be a main explanation of the results.

In Table 3.6 we check robustness of the results with respect to the distance to the boundary threshold, as the assumption on the boundary threshold is somewhat arbitrary. Columns (1) to (3) show results when we select observations within 200 meters of a parking district boundary. The results show that the effect of waiting-list duration has a tendency to become smaller when the chosen area is larger and is not statistically significantly different from zero in column (1). However, when we focus on observations only within 50 meters of a parking district boundary, the effects become stronger. All specifications listed in columns (4)-(6) show that the point estimates are larger in magnitude than the baseline specifications. However, because of the low number of observations, the results are much less precise. Nevertheless, it is reassuring that if we focus on observations closer to parking district boundaries the results become stronger.

In columns (1) to (3) in Table 3.7 we let the waiting-list duration effect vary for households with a below-average income and above-average income. It is shown that above-average income households tend to react stronger to longer waiting-list durations by reducing car ownership.[43] The main explanation for this finding is likely that car ownership levels for these households are much higher than for below-average income

[43] We have also estimated these regressions for seven income groups leading to similar results.

Table 3.7: Sensitivity analysis: income-specific effects, car kilometers and multinomial probit: marginal effects

	Income-specific effects			*Multinomial probit (average effect)*			*Car kilometers*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7) BDD	(8) BDD	(9) BDD
Waiting-list duration				−0.029***	−0.041*	−0.029	−392.9**	59.0	−473.1**
				(0.011)	(0.024)	(0.073)	(187.1)	(86.1)	(182.9)
Waiting-list duration × income below average	−0.011	−0.006	−0.025***						
	(0.012)	(0.009)	(0.008)						
Waiting-list duration × income above average	−0.046***	−0.050***	−0.051***						
	(0.007)	(0.014)	(0.009)						
Household char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location characteristics	No	No	No	Yes	Yes	Yes	No	No	No
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Boundary fixed effects	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
One-permit districts	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Waiting-lists districts	No	Yes	No	No	Yes	No	No	Yes	No
Min waiting-list duration diff. *(in months)*	∞	∞	12	∞	∞	12	∞	∞	12
Max distance to boundary *(in m)*	100	100	100	100	100	100	100	100	100
Number of observations	3,565	1,988	468	3,565	1,988	468	3,565	1,988	468
R^2	0.232	0.257	0.273				0.220	0.240	0.257
Log-likelihood				-2,495	-1,365	-290			
Panel B: Implied price elasticities									
Income below average	−0.51	−0.46	−1.44***						
Income above average	−1.09***	−1.14***	−1.16***						

Note: Standard errors are in parenthesis. For columns (1)-(3) and (7)-(9), we report clustered standard errors at the parking-district level. For columns (4)-(6) we report bootstrapped standard errors clustered at the parking-district level (500 replications). The asterisks indicate significance levels. *** p<0.01, ** p<0.05, * p<0.1.

households (0.81 versus 0.39 in the city center). Hence, households are more sensitive to the duration of waiting when their incomes increase. In Panel B, we provide the implied price elasticities. It appears that the implied price elasticity for above-average income is robust over different specifications and slightly more negative than −1, while it is not very robust for below-average income households.

Columns (4)-(6) in Table 3.7 report the results of a multinomial probit model, which distinguishes between three categories: zero cars, one car and (at least) two cars. We provide three specifications and report the *average total marginal effect* of waiting-list duration on car ownership, for ease of comparability with the baseline estimates. Let us define β_1 as the marginal effect of an additional year of waiting on the change in probability of owning one car and β_2 on the change in probability of owning two cars. Hence:

$$\begin{aligned} \beta_1 &= \mathcal{P}\big(\bar{D}_j + 1, C = 1\big) - \mathcal{P}\big(\bar{D}_j, C = 1\big), \\ \beta_2 &= \mathcal{P}\big(\bar{D}_j + 1, C = 2\big) - \mathcal{P}\big(\bar{D}_j, C = 2\big), \end{aligned} \tag{3.5}$$

where $\mathcal{P}(\,\cdot\,)$ denotes the probability. So the overall change in car ownership is then:

$$\mathbb{E}\big(C_{ij}\big|\bar{D}_j + 1, P_1, P_2, H_{ij}, \delta_t\big) - \mathbb{E}\big(C_{ij}\big|\bar{D}_j, P_1, P_2, H_{ij}, \delta_t\big) = \hat{\beta}_1 + 2\hat{\beta}_2 \tag{3.6}$$

We evaluate this marginal effect at the mean values of the sample. To calculate the standard errors of (3.6), we use bootstrapped standard errors, clustered at the parking district level. Because the models do not converge once we include parking district boundary fixed effects, we report results without fixed effects. We do, however, include location controls. The results should therefore be interpreted with some caution. In column (4) of Table 3.7 the average marginal effect of an increase in waiting list duration of one year on car ownership is −2.9 percentage points, which is very similar to the baseline specification. Column (5) shows that the effect is somewhat stronger once we focus on areas with some waiting lists. However the estimated effect is somewhat imprecise and therefore not statistically significantly different from the corresponding estimate of the baseline specification. The average marginal effect becomes very imprecise once we focus on boundaries with waiting list differences of over a year (column (6)), which is mainly due to the low number of observations. In general, our results seem to be robust to the choice between multinomial probit and linear models.

Until now, we have focused on car ownership. As a sensitivity check, it is useful to examine the effect of waiting lists on (annual) car kilometers. Thus, we will repeat our baseline analysis (as reported in columns (4)-(6) in Table 3.4) with annual car kilometers as a dependent variable. We emphasize that our measure is a noisy variable, because it is measured in five broad classes, rather than being a continuous variable. Furthermore, car kilometers are self-reported by households, and therefore likely subject to strong measurement error. Columns (7)-(9) in Table 3.7 report the results. The reported effect in column (7) indicates that one year of waiting for a permit reduces annual car distance by about 393 kilometers (almost 4 percent of the average distance travelled in the city center). Hence, estimates based on car ownership and car kilometers suggest similar effects of waiting lists. The car distance results are however not robust to specification as we find a statistically insignificant (and even positive) estimate in column (8) where we select households in waiting-lists districts. On the other hand, in column (9), where we select households in neighborhoods with large differences in waiting-list duration, an increase in the waiting list of a year leads to a decrease of 473 car kilometers.

3.6 Parking policy and welfare

The provision of residential parking permits yields a deadweight loss if the price of the permit is less than the marginal costs of parking (the costs of providing and maintaining parking space). We have estimated the effect of waiting lists on car ownership, which is useful because waiting lists imply that households incur parking costs equal to the market price while they are on the waiting list. We first focus on the welfare effect of a residential permit in one-permit districts where there is no waiting list. We assume that the marginal costs of parking are equal to the street market price, as paid by nonresidents as well as households that do not own a permit. So, we derive the deadweight loss under the assumption that all externalities due to car ownership and driving the car are internalized through optimal street parking prices. This includes the possibility that parking prices are used as a second-best solution to reduce traffic congestion, as suggested by Glazer and Niskanen (1992) and Verhoef et al. (1995).

We focus on prices of owning a car P, and number of cars Q. We emphasize that the price of owning a car includes the price of parking a car. The deadweight loss of the residential parking permit policy depends on the price for permit holders P_P, the price for no-permit holders P_{NP}, car ownership levels given parking permits Q_P, and car ownership levels without these permits Q_{NP}. In the current market equilibrium observed for Amsterdam, (nearly) every car owner possesses a parking permit, so $P = P_P$ and $Q = Q_P$.

We write the deadweight loss of the parking permits policy ΔW, as the integrated difference between the inverse supply and demand function:

$$\Delta W = \int_{Q_{NP}}^{Q_P} \big(S(Q) - P(Q)\big)\mathrm{d}Q. \tag{3.7}$$

We assume a constant-elasticity inverse demand curve $D(Q)$. This function can be written as $D(Q) = P_P(Q/Q_P)^{1/\varepsilon}$, where ε is the price elasticity of car demand, which has been estimated above. We assume that the cost of owning a car net of parking cost is exogenous and equal to P_0.

In order to derive the welfare effects of parking permits, we also need information on the car supply function $S(Q)$. We do not have information about the latter, so we derive the welfare loss based on different assumptions with respect to the car supply function Given the assumption that parking supply is fully elastic, $S(Q) = P_{NP}$ equation (3.7) can be rewritten as:

$$\Delta W = \int_{Q_{NP}}^{Q_P} P_{NP}\, dQ - \int_{Q_{NP}}^{Q_P} P_P \left(\frac{Q}{Q_P}\right)^{\frac{1}{\varepsilon}} \mathrm{d}Q. \tag{3.8}$$

Parking supply is unlikely to be fully elastic. For example, a recent study by Van Ommeren et al. (2014) for the Netherlands suggests that this elasticity is around one. Given a unit elasticity, the car supply function can be written as: $S(Q) = P_0 + (P_{NP} - P_0)(Q/Q_{NP})$. Equation (3.7) can then be written as:

$$\Delta W = \int_{Q_{NP}}^{Q_P} P_0 + (P_{NP} - P_0)\left(\frac{Q}{Q_{NP}}\right)\mathrm{d}Q - \int_{Q_{NP}}^{Q_P} P_P \left(\frac{Q}{Q_P}\right)^{\frac{1}{\varepsilon}} \mathrm{d}Q. \tag{3.9}$$

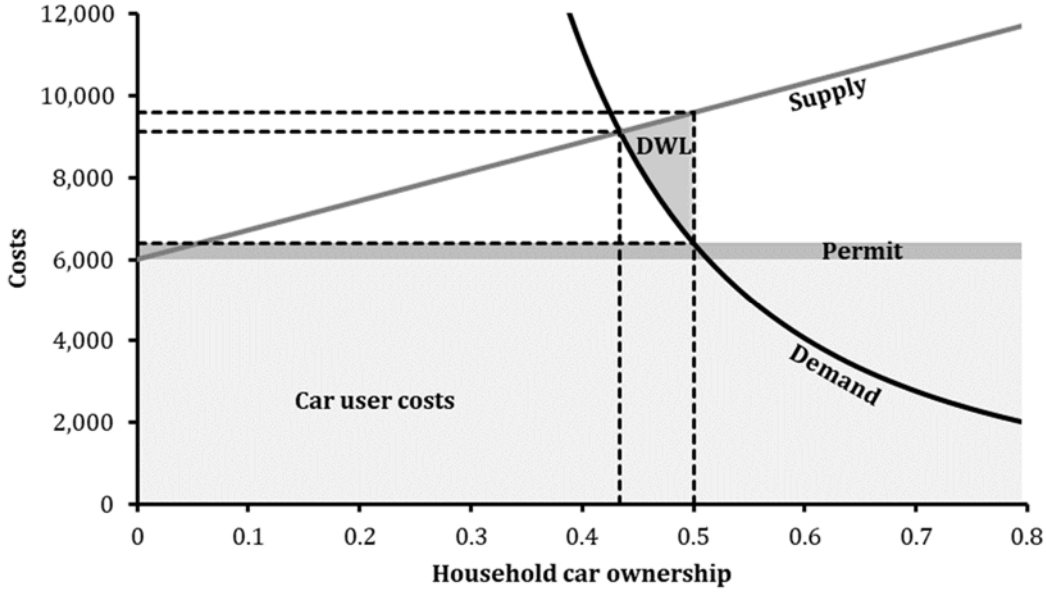


Figure 3.4: Deadweight loss (DWL) of parking permits

Figure 3.4 shows the deadweight loss in case of unitary elastic supply. We assume that the annual price of owning a car excluding parking costs, denoted by P_0, is equal to € 6,000 (Nibud, 2015). The price of a parking permit is (maximally) € 400, so P_P equals € 6,400. The market price of parking a car is about € 3,600 per year so P_{NP} equals € 9,600. Consequently, a parking permit implies an annual subsidy of approximately € 3,200.

We will now estimate the welfare effects in case of positive waiting-list durations We are interested in the economic value of the permit to the household given that the household has to wait a number of years in order to get the permit. One complication is that the value of a permit for a household who waits for a parking permit depends on the expected time that the parking permit will be used and the discount rate at which the future will be discounted. The average elapsed residence duration is 7.9 years in the city center (see Bureau Onderzoek en Statistiek, 2013). This implies that the total duration is two times longer. This is in line with the fact that the average resident has a 7 percent chance to move to another city each year, implying the average (median) residence time is about 15 (10) years (see Denktank Markt en Overheid, 2011). Given a discount rate of 4 percent, the net present value of the additional car user costs is about 5 percent per year of waiting-list duration.

Table 3.8 reports the deadweight losses for a parking permit for which one does not have to wait given different assumptions on the price elasticity of demand and the supply elasticity. Our most conservative estimate of the deadweight loss is € 330, based on a unit elastic supply and a price elasticity of demand of −0.65. However, the annual deadweight loss may be as high as € 600 given a situation with a fully elastic supply and a price elasticity of demand of −1.00. One straightforward exercise is to calculate the social gain

Table 3.8: Welfare effects per permit per year

	Price elasticity	
	−0.65	− 1.00
Unit elastic supply	−€ 330	−€ 440
Fully elastic supply	−€ 400	−€ 600

of charging a fee for providing parking permits. In Amsterdam, by charging € 400 for the parking permit (the maximum tariff nowadays) rather than providing the permit almost for free, it appears that the welfare loss is reduced by almost 20 percent.

The presence of a waiting list reduces the deadweight losses of parking permits, as a waiting list increases the price of parking towards the market price, which reduces the deadweight loss. Only an 'infinite' waiting list yields no deadweight loss, as residents are then forced to continuously pay the market price for parking. Figure 3.5 shows the relative (lower bound) welfare gains of the length of the waiting-list (given an unit elastic supply and a price elasticity of demand of −0.65). For example, a four-year waiting list (the maximum length in Amsterdam during the study period) reduces the annual welfare loss per permit to about € 140. The average waiting list is slightly more than one year, so the average deadweight loss in the waiting-list area is about € 270. Given 13,000 parking permits in this area (Gemeente Amsterdam, 2000), the annual deadweight loss of parking permits is € 3.5 million in this area alone. We have seen in Table 3.7 that the price elasticity tends to be higher for households with higher household incomes, which implies that especially high-income households contribute to this welfare loss.

It is interesting to compare this estimate to the welfare loss of parking permit provision estimated by Van Ommeren et al. (2014). In this study, parking *supply* elasticities have been estimated in 275 main shopping areas in the Netherlands. These shopping areas are almost always mixed in the sense that they contain many shops as well as housing. Their estimates imply that through the provision of residential parking permits, nonresidents have to pay higher prices for parking as nonresidents are forced to use commercial off-street parking, which is more costly. Given demand elasticities for parking by nonresidents – which are not estimated but are assumed – it appears that their estimates of the welfare losses of parking provision are almost identical to the losses indicated in the current study.

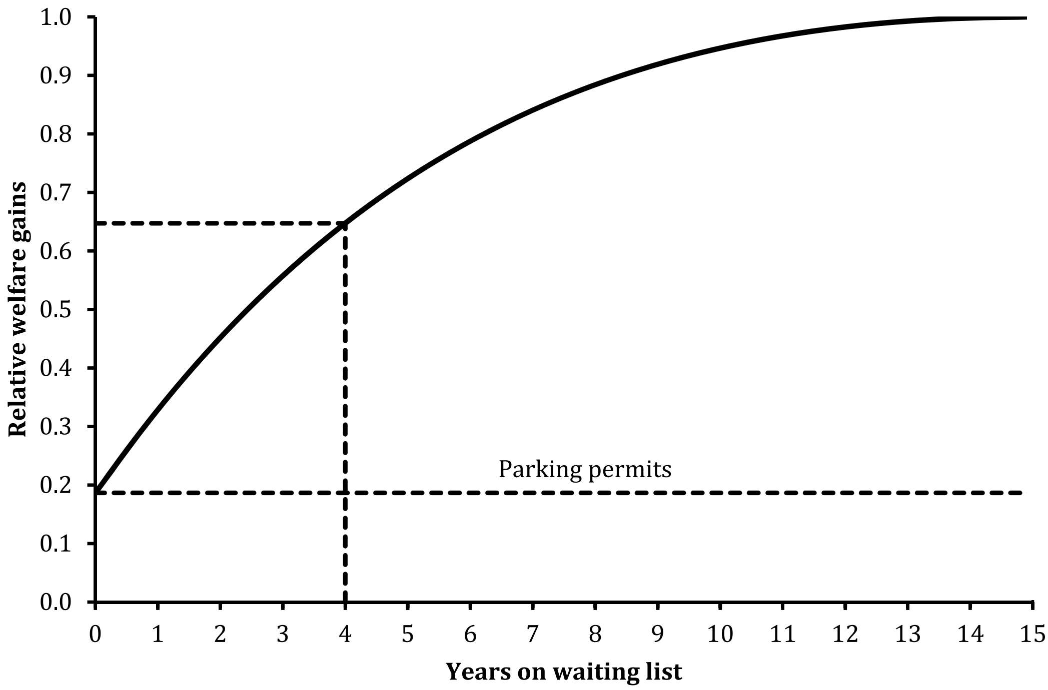


Figure 3.1: Relative welfare gains of parking permits and waiting lists

3.7 Conclusion

Very little is known about the effect of parking policy on car ownership, which is a relevant issue because in many cities around the world residential parking is strongly subsidized, so levels of car ownership are likely above welfare-optimal levels. It is plausible that the welfare loss of these subsidies is particularly substantial in city centers where the cost of parking is high and where car demand price elasticities may also be higher.

In the current paper, we aim to estimate the welfare implications of these residential parking subsidies through changes in car ownership. In particular, we analyze the welfare effects of a policy that provides parking permits to residents in Amsterdam. We focus on waiting-list districts, where households may receive maximally one permit after a waiting period that varies between districts (up to four years). In order to be registered on a waiting-list, households are obliged to own a car forcing them to pay the full price of parking while waiting. Our identification strategy exploits spatial variation in the waiting time for parking permits.

We demonstrate that car ownership is lower within parking districts with longer waiting durations. Households react to the (implicit) price increase of waiting longer by reducing car ownership: every year of waiting-list duration decreases car ownership by about 2 percentage points, which implies an (implicit) price elasticity of car demand of about -0.8. The sensitivity checks indicate that this is likely an underestimate, as the results tend to get stronger the more we try to control for household sorting.

Longer waiting lists for parking permits increase the residential parking price to a level that is closer to the full market price, so longer waiting lists reduce the deadweight loss induced by providing parking permits. Our results indicate that a parking permit scheme strongly decreases welfare. A parking permit, with an average waiting duration of one year, induces an annual welfare loss of € 270, or about € 3.5 million in the city center alone. Such a high welfare loss is plausible given that the implied annual subsidy is about € 3,200 per parking permit.

According to our estimates, increasing the fee for residential parking permits strongly reduces the welfare loss. For example, a fee of only € 400 per year (about 12 percent of the market price of parking) reduces the deadweight loss by almost 20 percent. Alternatively, by limiting the provision of parking permits that distort the market and thereby creating waiting lists, local governments may substantially reduce the deadweight loss. For example, a waiting duration of four years reduces the deadweight loss by about 65 percent although the welfare loss is still at least € 140 per permit.

We further show that the subsidy of residential parking associated with the provision of parking permits is mainly beneficial to high-income households, as car demand is very income elastic. This implies that a residential parking subsidy policy is not only distortionary, it is also income-regressive and the welfare loss induced is mainly due to overconsumption of cars by high-income households.

Appendix 3.A: Income and car ownership

We investigate here whether income elasticity of car demand is specific to the location of the household. We report here district-specific income effects on car ownership and the implied income elasticities which is estimated using the specification in column (3) of Table 3.4 combined with information about mean car ownership which is reported in Table A3.1. It appears that there is little variation between districts in the value of the income elasticities, with the one-permit districts having the highest income elasticities.

We have repeated the above analysis, where we allow the income elasticities to depend on household income. Figure A3.1 shows that income elasticities *strongly decrease* with household income and it appears that income elasticity is the same for each parking district for income levels above € 30,000, while income elasticities for households with an income below € 30,000 tend to be substantially higher when they reside in one-permit districts.

Table A3.1: Income effect per parking district

	Income *(log)*		Mean income	Mean car ownership	Income elasticity
Waiting-list district	0.412	(0.015)	2,956	0.520	0.792
One-permit without waiting	0.409	(0.015)	2,762	0.500	0.818
Two-permits district	0.451	(0.038)	2,932	0.694	0.649
Free-parking district	0.471	(0.012)	2,805	0.780	0.604

Note: Standard errors are in parentheses.

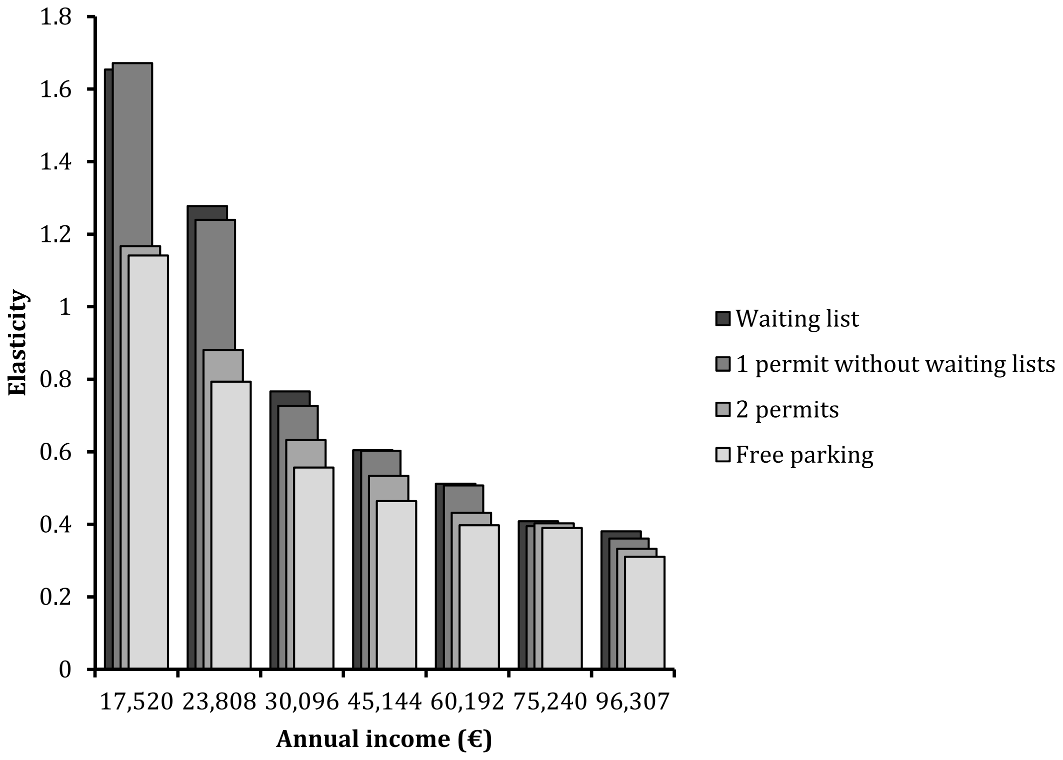


Figure A3.1: Income elasticity of car ownership

4. The impact of parking policy on house prices[44]

4.1. Introduction

Parking policies typically aim to reduce demand for street parking in order to reduce cruising for parking. We know very little of the effect of these policies on residents (Bakis et al., 2017). Information on this effect is particularly relevant when residents have a strong influence on local parking policy either as voters or informally through lobbying. For example, the political economy literature indicates that it will be difficult for local governments to introduce welfare-improving parking policies if residents are not in favor of these policies (see Marcucci et al., 2005; De Borger and Proost, 2012; Russo, 2013; Button, 2006 in the context of road pricing).

In this paper we estimate the effect of the introduction of paid parking on house prices for Amsterdam and Utrecht, two major cities in the Netherlands. In both cities, paid parking and residential parking permits are introduced at the same time. These permits allow residents to park locally for an unlimited time for a fraction of the price compared to nonresidents (Van Ommeren et al., 2011). For example, in Amsterdam the price of an annual parking permit is about € 100 and maximally € 400, which compares favorably to the nonresidential parking tariffs of € 5 per hour (or € 40 per day). Parking permits are license plate-specific and non-tradable, and allow residents to park in the same streets where also nonresidents are allowed to park.

Car ownership has strongly increased during the second half of the 20th century (Dargay and Gately, 1999; Whelan, 2007). The increase in demand for residential parking has led to excess demand for parking, which has resulted in wasteful cruising (Van Ommeren et al., 2012). This is particularly so in historic city centers with urban structures designed before the introduction of cars, where off-street parking is limited. Policymakers around the world have reacted with different kinds of policies in order to deal with parking scarcity (Topp, 1991; Kodransky and Hermann, 2011).

One important policy, advocated by economists, is the introduction of paid parking. In almost all European countries (the main exception is Greece) we have seen a strong rise in paid parking over the last 30 years. This strong rise is firmly supported by theory that indicates that paid parking is the preferred tool to regulate the on-street parking market (Arnott et al., 1991; Arnott and Rowse, 1999; Anderson and De Palma, 2004; Arnott and Inci, 2006). In contrast to alternative parking policies which restrict parking through quantitative restrictions (such as minimum parking requirements, parking time limits, see Manville, 2013), paid parking improves welfare when reducing cruising for parking, because it generates government revenue (Arnott, 2006; Arnott and Rowse, 2009).

[44] This chapter is based on joint work with Jos van Ommeren and Hans Koster. It has been published as De Groote, J., Van Ommeren, J. and Koster, H. (2018). The impact of parking policy on house prices. Journal of Transport Economics and Policy 52(3), 267-282.

Paid parking is typically introduced in areas with excess parking demand, so where severe cruising for parking is observed by local authorities. In the Netherlands, on-street prices in paid-parking areas are set roughly equal to commercial off-street parking prices (in contrast to cities in many other countries including the US). Moreover, the number of parking permits is constrained such that residential parking demand does not exceed parking supply (Van Ommeren et al., 2012).[45] Hence, paid parking strongly reduces parking demand by nonresidents resulting in minimal levels of cruising after the introduction of paid parking.

Residents benefit from the introduction of paid parking, because it reduces cruising costs, but they also have to pay higher prices for parking. A priori, it is not clear which effect dominates, so in general it is unknown whether they favor paid parking. In the Netherlands, the use of residential parking permits implies that the parking price paid by residents is much lower than for nonresidents. Nevertheless, residents still face an increase in the price for parking for a number of reasons. First, they have to pay for the permit. Second, and potentially more important, friends and family who visit residents have to pay the full price for parking, leading to a potential reduction in social contacts. Third, the number of permits per household is restricted (usually one per household). When the demand for cars by the household exceeds the number of permits, then the household faces the nonresidential price for parking for the marginal car, which has increased. This suggests that only when there is a *substantial* benefit to residents from the introduction of paid parking through a large reduction in cruising, then they will favor the introduction of paid parking.

The introduction of paid parking will be reflected in housing prices when it strongly affects residents. For example, Bakis et al. (2017) investigated the effect of paid parking on house prices in Istanbul when residents do not receive parking permits and are therefore faced with the same price increase for parking as nonresidents. They find substantial decreases in house prices (about 10 percent) after the introduction of paid parking. In the context of Amsterdam and Utrecht, where residents vote for the introduction of paid parking and receive parking permits when paid parking is introduced, the reduction in house prices induced by paid parking must be substantially less.[46]

We estimate the effect of the introduction of paid parking and residential parking permits between 1985 and 2014 on housing prices for Amsterdam and Utrecht by using a hedonic house price analysis. In these cities, as well as other cities in the Netherlands, paid parking was still restricted to city centers until the beginning of the 1990s. Since the

[45] In Amsterdam and Utrecht, parking permits are restricted to one per household in the city center but in some suburbs two parking permits are provided per household. Because off-street parking is scarce, households seldom have more cars than permits. For example in Amsterdam, only 6 percent of households with one permit has more than one car (De Groote et al., 2016).

[46] For example, the price effect of a parking permit of € 100 per year in Amsterdam amounts to an € 2,000 annualized value given a 5-percent discount rate, which is less than one percent of the average house price.

1990s, municipalities are allowed to extract revenues from parking. This gave both municipalities an incentive to increase parking tariffs and to introduce paid parking throughout the city (Van Dijken, 2002).

Importantly, in both cities, local residents play an important role in the decision whether paid parking is introduced. In Utrecht, residential parking is locally introduced after a (non-binding) referendum (Verkeersnet, 2013). In Amsterdam, it is the *local* council that decides on the introduction of paid parking, after which the municipal government is allowed to set the price of street parking.[47]

In the city centers of Amsterdam and Utrecht, parking prices were strongly increased in the early-1990s and mid-1990s respectively. This led to increased demand for parking in surrounding areas, which induced residence in these areas to vote in favor of paid parking. In our identification strategy, we exploit the strong expansion of paid parking over time in different areas.[48]

We do not find any evidence of an effect of parking policy on housing prices. We note that standard errors are quite small, so that the lack of the statistically significant price effects is not related to a lack of precision. This implies that it seems that residents are on average indifferent to the introduction of paid parking. We will argue that this suggests that paid parking was introduced at the right moment from the residents' point of view. This interpretation is in line with a political economy argument that residents will vote for paid parking if it is beneficial to them.

The structure of this paper is as follows: section 4.2 explains the econometric framework and section 4.3 describes the data. Section 4.4 reports the results, followed by the sensitivity analysis in section 4.5. Section 4.6 concludes.

4.2 Econometric framework

We aim to estimate the effect of parking policy on house prices. Houses are considered to be bundles of attributes, such as floor space, maintenance and location, including whether or not there is paid parking. Using a hedonic price function, we estimate the implied price for paid parking in a paid-parking area (Brown and Rosen, 1982; Palmquist, 1984; and Rosen, 1974). In Amsterdam and Utrecht, the large majority of houses are apartments. We focus on the price effects for apartments because of their higher floor-to-area ratio, so apartments are more likely to be prone to an undersupply of parking. This also reduces

[47] It is plausible that residents that own private off-street parking spaces are less likely to vote in favor of paid parking, because they do not benefit directly from reductions in cruising time. In both cities, private ownership of parking is low (about 6 percent of households in owner-occupied housing and less in public housing). This makes it plausible that paid parking is introduced when residents with privately-owned parking are not in favor.

[48] Waiting lists for parking permits are common in the city centers, but paid parking was introduced in these areas before 1985 and are excluded in our empirical analysis where we focus on the introduction of paid parking after 1985.

variation in unobserved house and street characteristics between the city center and other areas, which should yield more accurate results.

One statistical issue is that paid parking is more likely to occur in districts closer to the city center, so the introduction of paid parking is not random over space. To address this issue, we exploit temporal variation in paid-parking area designation by including zip-code fixed effects, so compare price changes between treated and non-treated areas. In the Netherlands, zip-code areas encompass about half a street (on average 15 households), which is comparable to a census block in the United States. These fixed effects essentially control for all unobserved time-invariant spatial attributes, implying that we identify the effects of parking policy on house prices over time (Van Ommeren and Wentink, 2012).

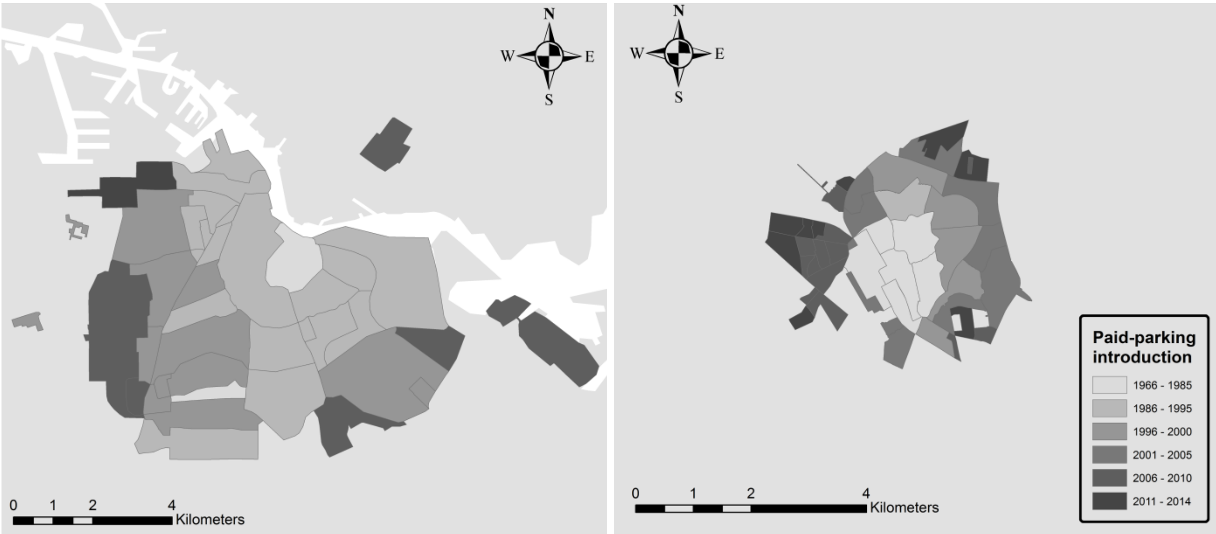
Furthermore, we only include areas where paid parking was introduced after 1985, implying that we exploit differences in the timing of the implementation in paid parking.[49] The induced price change may not necessarily be instantaneous. Prices may change in anticipation of the parking policy change, or may slowly adjust to the parking policy change after implementation. In both cases, one tends to underestimate the effect of the introduction of paid parking in our setup. To mitigate this issue, we exclude observations within one year before and after the introduction of paid parking.

More specifically, let y_{ijt} be the logarithm of the price of apartment i in district j in year t. We control for housing attributes h_{it}, include year fixed effects θ_t, and control for the possibility that prices have developed differently within the city center and in the suburbs by including a distance-year interaction effect $(d_i \times \tau_t)$, where d_i refers to the distance to the city center and τ_t refers to year. The preferred specification to be estimated is:

$$\begin{aligned} y_{ijt} = \alpha p_{jt} + \beta\left(p_{jt} \times o_{it}\right) + \gamma o_{it} + \delta c_{it} + \zeta h_{it} + \eta_i + \theta_t + (d_i \times \tau_t) \\ + (b_i \times \tau_t) + \varepsilon_{ijt}, \end{aligned} \tag{4.1}$$

where p_{jt} is a dummy indicating whether district j has paid parking at time t, o_{it} indicates whether the apartment has a privately-owned parking space, c_{it} is a vector of private parking characteristics such as having a garage, η_i are zip-code fixed effects, and ε_{ijt} is an independently and identically distributed error term. Hence, α measures the impact of a paid-parking policy, while β measures the price effects for households that own a private parking space. The latter may be important because these households most likely benefit from reductions in cruising time. γ, δ, ζ, η_i and θ_t are other parameters to be estimated.

[49] Hence, we exclude areas where paid parking was never introduced and areas where paid parking was introduced before the period investigated.



Amsterdam *Utrecht*

Figure 4.1: Paid-parking districts in Amsterdam and Utrecht.

As apartments with private parking may have been constructed in different times and the price developments of apartments from different times may have been different, we also include a construction decade-year interaction effect ($b_i \times \tau_t$).

4.3 Data

We use housing transaction data from 1985 to 2014 from the Dutch Brokers Association (NVM), which includes over 2.5 million observations of owner-occupied houses all across the Netherlands and provides us with detailed information about housing transactions. The dataset includes house prices and house characteristics, like surface area, construction year and location. We use the most detailed 6-digit zip code (roughly comparable to a US census block) to identify the location of the houses. In order to reduce heterogeneity between houses over time, we only use the 5-digit zip code areas that existed before the year 2000, so newly-built neighborhoods with possibly different supply of parking facilities are excluded. This leaves us with 123,260 observations for Amsterdam and Utrecht.

We have obtained information on parking districts from both municipalities and verified for each district the year of implementation. For Amsterdam we have 40 parking districts of which the average size is 139 hectares. For Utrecht we have 33 parking districts that are on average 27 hectares. Figure 4.1 shows the paid-parking districts including when paid parking was introduced. It can be clearly seen that paid parking was first introduced in the city center and later in areas around the center.

Table 4.1 reports the main descriptives for the full dataset, but also for the subsets of paid-parking areas, free-parking areas and the transition areas, where paid parking was introduced during the study period (1985-2014). The average house price is on average € 214,000. Houses are small in Amsterdam and Utrecht (82 m^2 versus the Dutch average of 117 m^2).

Table 4.1: Descriptives: Amsterdam and Utrecht

	Full Dataset	*Paid parking*	*No paid parking*	*Paid parking >1985*
House price *(€)*	213,555	253,095	131,908	232,885
Floor space *(m^2)*	81.7	81.9	81.3	82.0
Number of rooms	3.07	3.02	3.16	3.07
Constructed before 1945	0.589	0.723	0.313	0.731
Outdoor parking	0.021	0.016	0.032	0.017
Garage parking	0.048	0.047	0.052	0.042
Year	2005	2006	2001	2005
Number of observations	123,260	83,044	40,216	90,313

In Table 4.1 we also observe that paid-parking areas are usually close to the center, as the average house price is much higher than in areas without paid parking (€ 253,000 versus € 132,000). Areas where paid parking is implemented during the study period are comparable to the areas where paid parking has already been introduced.

Private parking space is rare. In the dataset only about 5 percent of the houses has a garage. Outdoor parking, which is privately-owned parking space without the additional protection that a garage offers, is even less common. In the dataset only about 2 percent of the houses has privately-owned outdoor parking space. It is more common in the areas without paid parking than in the paid-parking areas.

An important assumption in models that rely on temporal variation is that pre-trends are similar. We have tested this first between paid-parking areas and non-paid-parking areas, see Figure 4.2. The black line represents the average house price in the areas with paid parking, while the gray line represents the average house price in the areas without paid parking. The gray areas show the confidence intervals.

During the study period, house prices have consistently been higher in the paid-parking areas and seem to have similar price trends. Due to the wide confidence interval it is hard to compare the trends before the large-scale introduction of paid parking in the mid-1990s, whereas in the late-1990s house prices have increased more rapidly in the areas with paid parking. This, however, does not necessarily mean there is a causal effect of paid parking on house prices. There may be other confounding factors, like different house price trends between the city center and the fringes. We will take this into account in the statistical analysis.

In order to get a more meaningful comparison between the paid-parking and non-paid-parking areas, we only analyze the areas where paid parking was introduced after 1985. This ignores the city centers and the fringes, and should therefore reduce the effect of different price trends in different areas to some extent. Figure 4.3 shows the average house prices within this constricted sample. The pattern is similar to the pattern in Figure 4.2.

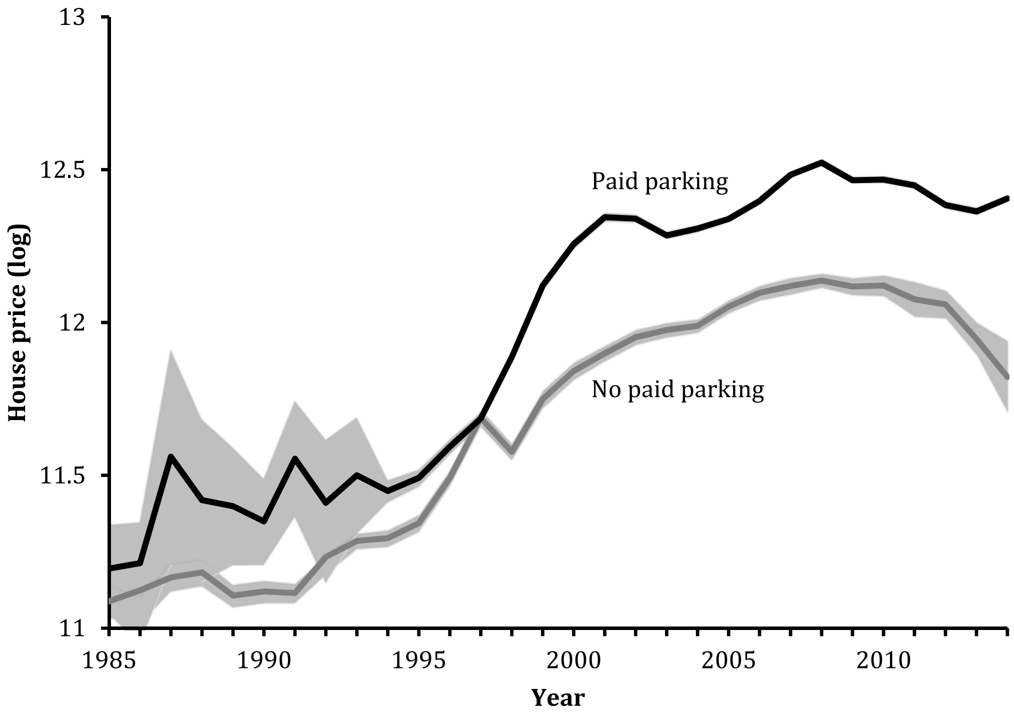


Figure 4.2: House prices in areas with paid parking and areas without paid parking

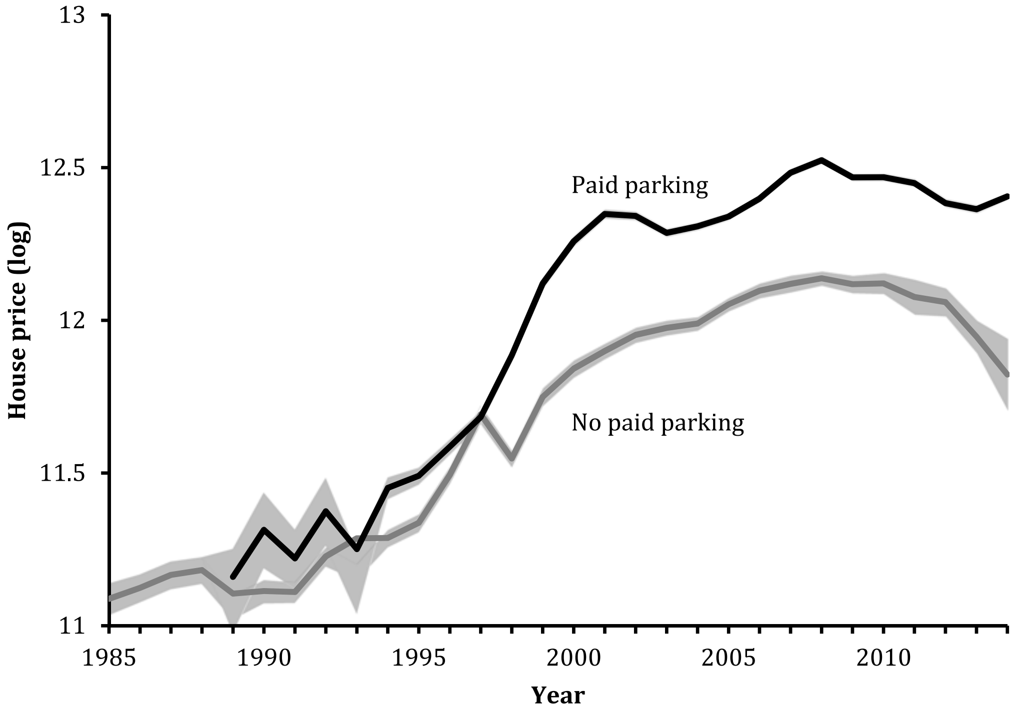


Figure 4.3: House prices in areas where paid parking was introduced after 1985

4.4 Results

As we have information on the location and timing of paid parking, we can estimate the direct effect of paid parking on house prices and on the value of privately-owned parking spaces. We cluster the standard errors at the parking district level. The results are reported in Table 4.2.

Column (1) relies on the full dataset including apartments in the cities of Amsterdam and Utrecht. We find that the introduction of paid parking seems to have had a positive effect on house prices: prices are 4 percent higher in paid-parking areas. Properties with garage parking space are 6 percent more expensive, while having an outdoor private parking space implies a price increase of 3 percent. We find that private parking outdoor spaces are almost twice as expensive in paid-parking areas, which probably reflects the fact that land has become more expensive in and close to city centers. In any case, this coefficient is unlikely to reflect a causal effect of parking policies.

To address the issue that paid-parking areas may have had different temporal trends from free parking areas, we only include observations in parking districts in which paid parking is introduced after 1985. This reduces the number of observations by about 25 percent and implies that we identify the effect of parking policies based on differences in the timing of implementation. Column (2) suggests that the direct effect of paid parking on house prices disappears. Also, the indirect effect via a change in the price of private parking spaces is far from being statistically significant. Private parking space is more valuable if we only focus on areas where paid parking was introduced during the study period. Private parking space increases house prices by 6 (outside parking) to 9 percent (garage parking). Interestingly, these estimations are similar or lower than those found for US cities, which indicate that private parking space is worth between 9 and 17 percent of the price of a house (Manville, 2013; Gabbe and Pierce, 2017), with several studies finding 12 percent (Jia and Wachs, 1999; Litman, 1995). This difference might be a result of lower levels of cruising in the Netherlands, which makes private parking less valuable, but it may also be a result of other differences between the Netherlands and the US. For example, the value of private parking space may depend on car ownership levels.

The coefficients of the other control variables, however, have not changed. Their signs are as expected, with positive coefficients for size and central heating. The only unexpected result is the negative coefficient for garden. This coefficient, however, applies to a poorly maintained garden. As maintenance is valued highly, a well-maintained garden increases the value of a house.

Table 4.2: House price: Amsterdam and Utrecht
(dependent variable: the log of house price)

	(1)	(2)	(3)	(4)
	Full Sample	*Paid parking >1985*	*Amsterdam*	*Utrecht*
Paid parking	0.039***	−0.011	0.009	0.003
	(0.013)	(0.013)	(0.019)	(0.011)
Paid parking × private parking	0.026**	−0.016	−0.026	−0.004
	(0.011)	(0.016)	(0.018)	(0.018)
Outdoor parking	0.029***	0.064***	0.073***	0.086***
	(0.008)	(0.016)	(0.019)	(0.019)
Garage parking	0.060***	0.093***	0.103***	0.087***
	(0.009)	(0.017)	(0.021)	(0.021)
Log size	0.770***	0.774***	0.853***	0.839***
	(0.041)	(0.062)	(0.021)	(0.043)
Log size × distance to city center	−0.005	−0.004	−0.024	−0.185***
	(0.027)	(0.045)	(0.023)	(0.044)
Log size × distance to city center^2	-0.003	0.002	0.001	-0.003
	(0.003)	(0.007)	(0.004)	(0.010)
Garden	−0.033***	−0.031***	−0.029***	−0.014
	(0.006)	(0.006)	(0.006)	(0.018)
Garden maintenance	0.098***	0.102***	0.099***	0.113***
(0 = bad, 1 = good)	(0.006)	(0.004)	(0.005)	(0.006)
Central heating	0.062***	0.064***	0.068***	0.050***
	(0.006)	(0.006)	(0.007)	(0.005)
Insulation (5)	yes	yes	yes	yes
Construction year (7)	yes	yes	yes	yes
Construction year × year (7×30)	yes	yes	yes	yes
Distance to city center × year (30)	yes	yes	yes	yes
Zip-code fixed effects (8789)	yes	yes	yes	yes
Year fixed effects (30)	yes	yes	yes	yes
Number of observations	123,260	90,313	78,938	11,375
R^2	0.951	0.951	0.954	0.941

Notes: In columns (2)-(4) we only include districts in which paid parking is introduced during the study period. Standard errors are in parentheses and clustered at the parking-district level. *** p<0.01, ** p<0.5, * p<0.10.

In columns (3) and (4) in Table 4.2 we make a distinction between Amsterdam and Utrecht respectively, as cities may have very different unobserved traits that may be correlated to changes in parking policies. However, it is confirmed that parking policies do not affect house prices in neither Amsterdam nor Utrecht. Given the 95-percent confidence interval the direct price effect in Amsterdam is maximally 4.6 percent (0.009 + 1.96 × 0.019), while the negative indirect effect on parking spaces is maximally 6.2 percent (−0.026 −1.96 × 0.019). For Utrecht the maximum effects are even smaller, despite the fact that we only have a little more than 11,000 observations.

Our results imply that the house price effects of paid parking policies are unlikely substantial and most likely absent. This result strongly differs from those obtained for Istanbul, where residents did not receive residential parking permits and where residents were not able to vote about introduction of paid parking (Bakis et al. , 2017). The absence of such a negative (or positive) effect implies that the main benefit of paid parking to residents, that is less cruising, is offset by additional costs (for example permit costs, visitors that have to pay, not be able to park a second car). Such a finding is in line with political economy arguments such as Russo (2013), who show that residents resist measures that are detrimental to them.

To make this argument more explicit in the context of our paper, let us now make the assumption that residential cruising costs will increase over time in the absence of change in policy. This assumption is in line with studies which show that car demand, and therefore parking demand, increases because of increases in income (Dargay and Gately, 1999; Whelan, 2007). Furthermore, let us assume that politicians favor the introduction of paid parking to reduce parking demand, but the implementation depends on the residents will have to vote in favor of its introduction. Arguably, when cruising costs are still low, paid parking will not be implemented, because the reductions in cruising costs will be small when paid parking is introduced. However, it will be implemented when residents are indifferent between paid and free parking, resulting in the absence of any effect of paid parking. A negative effect of paid parking would imply the absence of substantial residential cruising, indicating that paid parking was introduced too early from the residents' standpoint, whereas a positive effect would imply severe cruising for parking prior to the introduction of paid parking, indicating that paid parking was introduced too late from the residents' perspective.

4.5 Sensitivity analysis

We will now perform a battery of sensitivity analyses, which are reported in Table 4.3. In columns (1) to (3), we focus on Amsterdam and in the columns (4) to (6) we pay attention to Utrecht.

In column (1) we include not only apartments, but all other housing types (terraced, semi-detached and detached properties). As most houses are apartments, this increases the number of observations by only about 5 percent and leaves the results unaffected. In column (2) we try to further aim to address the issue of unobserved trends that are correlated to the introduction of paid parking by including a squared interaction term of distance to the city center and transaction year. Again we do not find any effect. In column (3) we make a distinction between the effect of paid parking on the value of private outside and garage parking spaces. Both coefficients are statistically insignificant, but interestingly, only the garage parking coefficient is negative for both Amsterdam and Utrecht (column (6)). Hence, paid parking may have had some negative effects on the value of garage parking. But again, the standard errors are too large to make precise statements. We repeat the same set of specifications for Utrecht in columns (4)-(6), confirming the absence of a statistically significant effect of parking policy on house prices.

Table 4.3: House price: Amsterdam and Utrecht: sensitivity analysis
(dependent variable: the log of house price)

	(1)	(2)	(3)	(4)	(5)	(6)
		Amsterdam			*Utrecht*	
Paid parking	0.010	0.019	0.009	-0.001	-0.001	-0.003
	(0.017)	(0.022)	(0.019)	(0.009)	(0.012)	(0.012)
Paid parking × private parking	-0.018	-0.014		-0.016	-0.004	
	(0.015)	(0.020)		(0.012)	(0.018)	
Paid parking × outdoor parking			-0.0002			0.024
			(0.011)			(0.019)
Paid parking × garage parking			-0.051			-0.027
			(0.029)			(0.033)
Outdoor parking	0.067***	0.062***	0.053***	0.055***	0.085***	0.064***
	(0.017)	(0.021)	(0.012)	(0.021)	(0.019)	(0.023)
Garage parking	0.093***	0.091***	0.126***	0.060***	0.086***	0.104***
	(0.017)	(0.022)	(0.029)	(0.013)	(0.021)	(0.024)
Insulation (5)	yes	yes	yes	yes	yes	yes
Construction year (7)	yes	yes	yes	yes	yes	yes
Construction year × year (7x30)	yes	yes	yes	yes	yes	yes
Distance to city center × year (30)	yes	yes	yes	yes	yes	yes
Distance to city center^2 × year (30)	no	yes	no	no	yes	no
Zip-code fixed effects (6619)	yes	yes	yes	yes	yes	yes
Year fixed effects (30)	yes	yes	yes	yes	yes	yes
Number of observations	82,789	78,938	78,938	23,908	11,375	11,375
R^2	0.953	0.954	0.954	0.949	0.941	0.941

Notes: We only include districts in which paid parking is introduced during the study period. Standard errors are in parentheses and clustered at the parking-district level. *** p<0.01, ** p<0.5, * p<0.10.

Throughout the analysis we assume that the value of parking space relative to the house has remained constant over time. We have tested if the value of private parking has changed over time in the Netherlands. Figure A4.1 in Appendix 4.A shows that the garage coefficient has remained roughly constant over time and that there is no difference between cities with and without paid parking. For a more detailed discussion on the relative value of parking space over time we refer to Appendix 4.A.

4.6 Conclusion

In our analysis we have estimated changes in house prices as a result of changes in parking policy; that is the introduction of paid parking and introduction of residential parking permits in two large Dutch cities for a period of about 30 years. The most important result from the analysis is that there is no statistically significant effect of parking policy on house prices. We neither find a direct effect, nor an effect via the willingness to pay for a private parking space. This strongly suggests that paid parking has been introduced at about the moment where residents are indifferent about the introduction of paid parking. This finding is in line with political economy arguments (Russo, 2013), who show that residents resist measures that are detrimental to them.

The influence of the introduction of paid parking on house prices of residences with private parking space is less clear, but most likely there is no effect. Some findings suggest that the economic value of privately-owned parking is reduced when paid parking is introduced.

Can we say anything about the welfare effects of the introduction of paid parking? The absence of any negative effect on local residents strongly signal a *positive* welfare effect of this policy, as the introduction of paid parking for nonresidents likely has improved the efficiency of this market. However, for a more elaborate welfare analysis, one should also consider the welfare effects on visitors and commercial activities such as retail. We leave this for further research.

Appendix 4.A: Private parking space in the Netherlands

It may be insightful to see if the implementation of paid parking is correlated with changes in the relative value of private parking spaces. Based on reported parking revenues, we can distinguish between municipalities with and without paid parking. In 2009, about 36 percent of the Dutch municipalities had paid parking. As paid parking is more common in the larger municipalities, 64 percent of the observations, or about 1.5 million observations, is within a city with paid parking. We can derive whether or not the relative value of private parking space has increased (for example, due to increased car ownership) or decreased over time and whether this development has been different between municipalities with and without paid parking. The analysis suggests that garage parking space is rather consistently more valuable in municipalities without paid parking, but that the difference is only about one percent of the total house price.

The main analysis assumes that the relative value of parking space has remained constant over time. The relative value of parking space may, however, have changed over time unrelated to parking policy. Therefore we have also estimated a model using data on the whole of the Netherlands. We distinguish between cities with and without paid parking, so we can compare the development of the relative value of parking space between cities with and without paid parking. We have estimated this model separately for every year, so we can track the coefficients related to private parking spaces over time. In short, the model looks as follows:

$$y_{ijt} = \beta_t c_{it} + \gamma_t h_{it} + \eta_{it} + \varepsilon_{ijt}, \tag{4.2}$$

so the coefficients are year-specific. As we estimate the coefficients per year, we do not need year dummies or year interaction effects. As we estimate the zip-code fixed effects η_{it} per year, we also control for very local differences in house-price developments.

We report the descriptive stats for the full sample in Table A4.1. Average house prices have increased from € 64,000 in 1985 to nearly € 200,000 in 2008. In the dataset 10 percent of the apartments possesses a private garage parking spot and another 6 percent possessed an outdoor parking spot. Apartments with garage parking were generally larger and more expensive. Interestingly, apartments with a garage are generally more expensive than apartments without. This may indicate that garages have a non-negligible influence on house prices, but it may also be due to other characteristics, such as floor space, that are correlated with owning a garage.

We estimate the annual private-parking coefficients municipalities with and without paid parking. Table A4.2 shows the coefficients of the control variables at 5-year intervals. The coefficients of the control variables do change a bit over time, which suggests that apartment characteristics are valued differently over different time periods. Interestingly, the coefficient of floor space has changed considerably over time. The coefficient was relatively low in the mid-1990s, but higher in the late 2000s.

Table A4.1: Descriptives: the Netherlands

	Full dataset	*Apartments*	*Apartments with garage parking*	*Apartments with Outdoor parking*
House price *(€)*	194,881	162,330	232,596	191.342
Floor space *(m^2)*	117.3	86.0	105.1	92.7
Number of rooms	4.35	3.22	3.24	3.05
Apartment	0.27	1.00	1.00	1.00
Constructed before 1945	0.26	0.28	0.05	0.05
Year	2003.2	2004.4	2004.8	2005.1
Number of observations	2,409,379	653,455	66,758	40,995

Table A4.2: Value of a privately-owned parking spot
(dependent variable: the log of house price)

	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014
Outdoor parking	0.005	0.029***	0.053***	0.045***	0.048***
(paid parking)	(0.008)	(0.004)	(0.002)	(0.002)	(0.003)
Outdoor parking	0.022	0.047***	0.047***	0.028***	0.041***
(no paid parking)	(0.015)	(0.009)	(0.005)	(0.004)	(0.004)
Garage parking	0.088***	0.120***	0.097***	0.084***	0.079***
(paid parking)	(0.007)	(0.004)	(0.002)	(0.002)	(0.002)
Garage parking	0.091***	0.109***	0.114***	0.083***	0.091***
(no paid parking)	(0.011)	(0.008)	(0.005)	(0.003)	(0.004)
Floor space *(log)*	0.667***	0.577***	0.611***	0.647***	0.701***
	(0.007)	(0.004)	(0.002)	(0.002)	(0.002)
Garden	0.020	-0.009	-0.016**	-0.035***	-0.036***
	(0.026)	(0.014)	(0.006)	(0.004)	(0.005)
Garden maintenance	0.079***	0.079***	0.095***	0.092***	0.126***
	(0.004)	(0.002)	(0.001)	(0.001)	(0.001)
Central heating	0.050***	0.073***	0.062***	0.045***	0.042***
	(0.005)	(0.002)	(0.001)	(0.001)	(0.002)
Insulation (5)	yes	yes	yes	yes	yes
Construction year (7)	yes	yes	yes	yes	yes
Zip-code × year fixed effects (8789)	yes	yes	yes	yes	yes
Number of observations	24,295	105,575	176,667	194,774	142,754
R^2	0.914	0.844	0.899	0.922	0.919

Notes: Standard errors are in parentheses and clustered at the parking-district level. The asterisks indicate the 10 (*), 5 (**) and 1%(***) significance levels. All specifications include year and zip-code fixed effects and year-distance to city center interaction effects. Apartments constructed before 1945 are the reference categories.

As expected, garage parking is valued higher than outdoor parking. On average, garage parking space increases the value of a house by about 10 percent (see also Figure A4.1, which shows the per-year garage coefficient) while outdoor parking space increase house prices with 4 percent. Interestingly, the relative value does not differ much between cities with and without paid parking (relative value does not differ much between cities with and without the relative value does not differ much between cities with and without paid parking (the per-year private parking space coefficients (not shown) are also very similar in municipalities with and without paid parking).

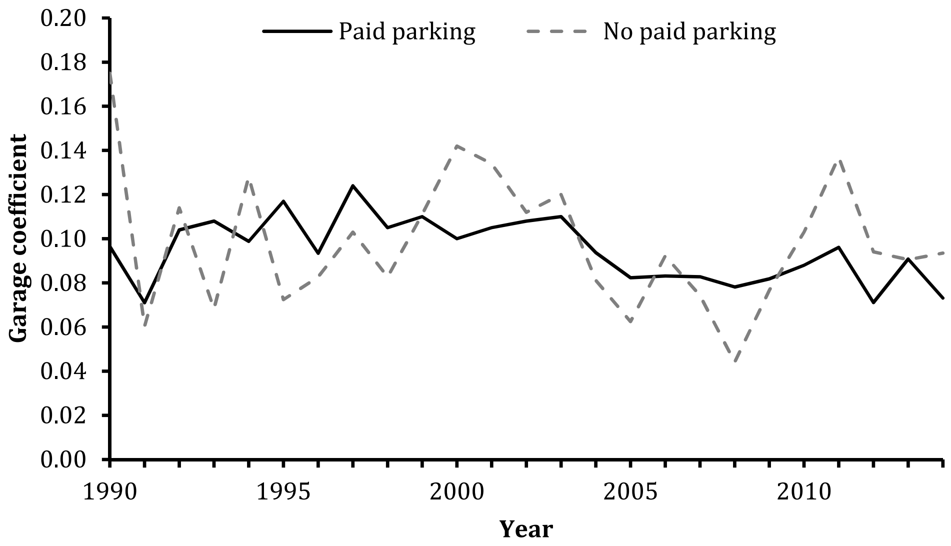


Figure A4.1: Relative value of garage parking space

The year-to-year changes are substantial, but the patterns are very similar. The relative value of garage parking space peaked at around 2000, and has decreased afterwards. Hence, the absence of an effect of parking policies on house prices is unlikely to be explained by time-varying preferences for private parking spaces.

5. The effect of daily parking tariffs and monthly subscription fees on parking demand of hospital employees[50]

5.1. Introduction

Parking space is often underpriced (Arnott and Inci, 2006; Arnott et al., 2015; Arnott and Rowse, 2009, 2013; Gragera and Albalate, 2016; Inci, 2015). Economic theory suggests that, in absence of cruising, parking space should be provided at its resource costs (Calthrop et al., 2000). In Europe, increasingly more cities adopt this policy by introducing paid street parking for nonresidents (Mingardo et al., 2015). On the other hand, residents (who have political power through voting) usually pay less than nonresidents through residential parking permits, which is unlikely welfare-optimal (Van Ommeren et al., 2011).

Similarly, employers usually do not charge the full parking price to their employees, because the provision of free parking space is not taxed as income (Van Ommeren and Wentink, 2012). Willson (1992) and Willson and Shoup (1990) claim that this encourages car use by employees, as their parking demand is elastic (Gillen, 1977; Kelly and Clinch, 2009). This leads to welfare losses, depending on the elasticity of supply (Van Ommeren et al., 2014). These welfare losses are not borne by the employer, but are passed on to society in the form of lower tax revenues. Therefore, policies that induce firms to introduce paid parking would improve social welfare.

To our knowledge, only a few studies have analyzed the costs associated with underpriced employer-provided parking (Van Ommeren and Russo, 2014; Van Ommeren and Wentink, 2012; Willson, 1992; Willson and Shoup, 1990). One potential reason is that parking price changes may be endogenous. For example, price increases may be a result of increased parking demand, which causes the estimations to be biased. In this study, we estimate these losses by using an exogenous price increase, which should avoid this econometric problem.

Another potential reason is that employee-paid parking is rare and has therefore not received much attention in the literature. Interestingly, there is one industry where employee-paid parking is relatively common: hospitals (Van Ommeren and Russo, 2014). We can only speculate why this is the case, but the following two factors most likely contribute. First, many hospitals have grown a lot over the last decades due to an improvement in technology, but relocating to another location is very costly. This provides an incentive to economize on space. Second, hospitals are generally familiar with paid parking for visitors and patients, so introduction of paid parking for workers is relatively straightforward.

[50] This chapter is based on joint work with Jos van Ommeren and Hans Koster. The manuscript has been submitted and is awaiting approval.

In their paper, Van Ommeren and Russo (2014) estimate the welfare losses due to parking overconsumption in a Dutch hospital using different exogenous price changes. In this paper, we employ a similar approach for another Dutch hospital. However, we extend their analysis by making a difference between the extensive margin (subscription fee increases) and the intensive margin (parking tariff increases). Moreover, we investigate the effect of bicycle subsidy on parking demand and focus on shifts in the daily aggregate parking demand distribution as a result of the price increases using quantile regressions.

To be more specific, we study an increase in parking prices for employer-provided parking at the Maastricht University Hospital (UMC+) in the Netherlands, which has over 7,000 employees. This hospital has several parking areas, including parking garages for employees. The motivation to increase parking prices was that the space used for parking was needed to construct a new hospital building. Instead of building new underground parking space, the hospital opted to increase the price of parking to reduce peak-hour parking demand.

The new tariff structure has two important features: an increased peak-hour tariff on busy days and a monthly subscription fee. Both depend on the employees' residence location and fall with employees' commuting distance. Hence, employees who live closest to the hospital experienced the highest tariff increases and the highest subscription fees. We therefore expect the strongest decreases in parking demand for this group, especially as the bicycle is a good substitute for the car at short distances.

Importantly, employees' monthly subscription fees are reimbursed in case an employee does not park at least once during peak hours over the entire month. This implies that for the first day the employee considers parking in a month, the parking price is equal to the sum of the subscription fee and the daily price. This higher price for the first day allows us to distinguish between two different price effects on parking demand. First, the effect on the extensive margin, that is, whether or not an employee parks during a month. Second, there is the effect on the intensive margin, that is, daily parking demand given that an employee parks at least once during the month. The geographic tariff differentiation enables us to accurately estimate both price effects.

A third important aspect of the new parking tariff structure was in the form of a bicycle subsidy. As parking demand is generally higher in winter, bicycle usage was subsidized during this period to further reduce car parking. In this way, the hospital aimed at reducing seasonal variations in parking demand, thereby reducing under- or oversupply of parking.

In the literature, there is not much known about bicycle subsidies and their effect on bicycle usage by commuters. Wardman et al. (2007) find that a modest financial reward strongly increases bicycle usage in Great Britain. The literature is unclear whether the bicycle is a close substitute to the car and whether the substitutability differs for countries where bicycle use is more common, such as the Netherlands. Parkin et al. (2008), Stinson and Bhat (2004) and Wardman et al. (2007) claim that higher car ownership levels reduce bicycle usage, which indicates that car and bicycle are substitutes. However, Hu and Schneider (2015) suggest that the bicycle is more likely a substitute for the bus than for the car.

We find that daily parking demand is reduced by 5 percent when the daily parking tariff is increased by € 1, whereas it is reduced by 2 percent when the monthly subscription fee is increased by € 1. We offer compelling evidence that bicycle subsidies reduce parking demand.

We show that inducing firms to set parking prices closer to the parking resource costs can lead to significant welfare gains. In particular the introduction of higher parking prices is effective to reduce demand during peak hours. Higher parking prices may yield long-run welfare gains of about 8 percent of the resource costs, which is slightly less than the 10 percent found by Van Ommeren and Russo (2014).

The rest of our paper is organized as follows. In section 5.2, we discuss the estimation methodology, followed by a section about the hospital parking policy and the data. In section 5.4, we discuss the results. Section 5.5 is the welfare analysis and section 5.6 concludes.

5.2. Data and descriptives

5.2.1. The hospital and its parking policy

The Maastricht University Hospital has about 7,200 employees. In the period we investigate (September 2014 until December 2016), employees have the opportunity to park their cars at several hospital-owned parking lots. The hospital aimed to reduce parking capacity from 2,100 to 1,650 and therefore changed its parking policy in October 2015. We report some descriptives in Table 5.1. In the old regime, employees had to pay € 0.75 per day. In the new parking regime, daily parking tariffs increase during peak hours, defined from 6:00 till 14:00 on Monday till Thursday, and fall with commuting distance: employees closest to the hospital (within 2 kilometers) have to pay € 3, while employees furthest away (over 7 kilometers) have to pay € 1 for parking during the peak hours. Outside peak hours, the tariff was unchanged. On average, employees pay € 1.31 per day in the current regime.

Furthermore, bicycle use is subsidized in the new regime, which further increases the relative price of car parking. The reward for bicycle use is between € 0.50 and € 1.00, increasing with distance, between early October and the end of March, which we will label as "winter". Cycling seems to be an important transport mode, as the share of bicycling is at least half the demand of car users during winter.[51]

In the new regime, employees also have to buy a monthly subscription, which cost between € 1 and € 5, depending on commuting distance, see Table 5.1. Employees only have to pay for the subscription during a month when they actually make use of the

[51] Reliable bicycling transaction data is only available for the winter period when bicycle parking was subsidized, so these data cannot be used to estimate the effect of the subsidy on bicycle parking demand.

Table 5.1: Parking tariffs (Monday to Thursday)

	Old regime	New regime			
Commuting distance	All hours	Non-peak hours	Peak hours	Subscription	Bicycle subsidy
<2 km	€ 0.75	€ 0.75	€ 3.00	€ 5.00	€ 0.50
2-5 km	€ 0.75	€ 0.75	€ 2.00	€ 3.00	€ 0.75
5-7 km	€ 0.75	€ 0.75	€ 1.50	€ 2.00	€ 1.00
>7 km	€ 0.75	€ 0.75	€ 1.00	€ 1.00	€ 1.00
Average tariff	€ 0.75	€ 0.75	€ 1.31	€ 1.61	€ 0.94

Note: the average tariff refers to the weighted average, using number of workers in a tariff group as weight. Bicycle subsidy refers to winter months only.

hospital parking during that month. So, peak-hour parking tariffs increased by about € 0.56 per day (€ 1.31 – € 0.75) in the new regime. The monthly subscription fee is € 1.61 on average, whereas the average bicycle subsidy is € 0.94.

5.2.2 Data

We have employee parking transaction data from September 2014 to December 2016 (data from September 2015, the month before the tariff increase, is missing), which is over a year before the start of the new regime and over a year after the start of the new regime. For employees we know the commuting distance (and the exact employment period). For 6,600 employees we were able to match parking transaction data to the commuting distance. We exclude employees that were not employed during the entire study period, which leaves us with 4718 employees. We also use daily weather data from the Royal Netherlands Meteorological Institute (KNMI) to capture the effect of variation in weather on parking demand.

We know for every employee whether he or she parked at a particular day and at what time. We also know the exact time of the day when the employees parked their cars. We select only observations from Monday to Thursday, as only for these days we have variation in prices. This leaves us with roughly 4 million daily parking observations (4718 employees × 823 days). We focus on a subset of employees who park at least once on a peak day (Monday to Thursday) during the observation period, which leaves us with almost 1.9 million observations.

5.2.3. Descriptives

The average daily parking demand per employee in our sample is slightly above 0.27. As we exclude the employees who never park, the average parking demand will be even lower. The relatively low demand is a result of the inclusion of observations of all employees, including those who do not work on a certain day.[52] Daily parking demand

[52] In comparison, in the Netherlands, about 60 percent of employees commute to work by car (CBS, 2004). Note that in Dutch hospitals it is quite common to work part-time, as well as in the weekends or at night. So, even employees who work full-time are not present each day of the workweek (as they may work sometimes in the weekends).

Table 5.2: Daily parking demand

	Parking		Parking during peak hours	
Commuting distance	Old regime	New regime	Old regime	New regime
<2 km	0.123	0.074	0.101	0.053
2-5 km	0.160	0.118	0.134	0.097
5-7 km	0.226	0.190	0.193	0.160
>7 km	0.331	0.334	0.288	0.286
Average	0.280	0.269	0.243	0.229
Number of observations	835,086	1,085,140	835,086	1,085,140

during peak hours (between 6:00 and 14:00) is 0.24, so almost 86 percent of all parking transactions are during the peak hours.

A priori, one expects that employees living nearby will react the strongest to increases in parking tariffs, as they have better substitutes for the car. It is therefore relevant to note that about 34 percent of employees live within 7 kilometers from the hospital and 3.5 percent live even within two kilometers. The majority of the commuters (66 percent) live further away than 7 kilometers. One does not expect much effect of the price increase, as it was only € 0.25, including a € 1 subscription fee.

There is a strong association between commuter distance and parking demand. Table 5.2 shows this relationship for the old regime (about 800,000 observations) as well as the new regime (about 1.1 million observations). We also give this information for parking during peak hours. These data show that parking demand is less in the new regime for distances up to 7 kilometers. As one may expect, parking demand rises with commuting distance.

To estimate the effect of the monthly subscription fee on monthly parking demand, we also analyze the number of times an employee parks in a month during peak hours. We have one observation per month per employee, for which we have about 127,000 observations (4718 employees × 27 months).

Table 5.3 shows monthly parking demand, the monthly *extensive margin* (the share of employees who park at least once during the month), and the monthly *intensive margin* (monthly parking demand given that an employee parks at least once during the month). Employees park about four days per month during peak hours on average, which is consistent with the previous table, falls in the new regime.

The extensive margin is 0.62 in the old regime, but only 0.54 in the new regime. The intensive margin is, on average, about six in the old regime and seven in the new regime. Note that this suggests that the intensive margin increases in the new regime, but this is a spurious relationship, because, as we will show, this is entirely due to a selection effect of employees who park at least once.[53] Figure A5.1 in Appendix A5.3 shows the distribution of the monthly parking frequency per employee conditional on parking at least once. In the new regime, infrequent parking (one to ten times per month) becomes less common, whereas frequent parking (over ten times per month) does not change.

[53] In the new regime, the employees with low parking demand are most likely refrain from parking, which implies that the employees who continue to park have a higher demand for parking on average.

Table 5.3: Monthly parking demand during peak hours

	Parking per month		Extensive margin		Intensive margin	
Commuting distance	Old	New	Old	New	Old	New
<2 km	1.62	0.89	0.350	0.172	4.63	5.19
2-5 km	2.18	1.62	0.458	0.298	4.77	5.43
5-7 km	3.13	2.64	0.562	0.441	5.58	6.00
>7 km	4.73	4.76	0.692	0.636	6.84	7.48
Average	3.98	3.81	0.623	0.536	6.38	7.10

The new parking regime has been introduced to reduce *aggregate daily* parking demand, particularly on peak days. Hence we will also analyze the effect of the new regime on the number of parking transactions per day (for the whole hospital) in order to establish whether it induced a reduction in parking demand on days which are typically characterized by high demand (e.g., rainy days on Tuesday) or whether it induced a uniform decrease of parking demand. For this analysis, we exclude holidays (to reduce heterogeneity). This leaves us with 504 days.

Table A5.1 in the Appendix shows the descriptives of aggregated demand. On average, parking demand is about 1250 per day. In the new parking regime, demand is reduced by slightly over 50 parking transactions per day. Such a reduction is also suggested by the cumulative distribution of aggregated daily demand, which can be found in Figure A5.2 in Appendix 5.4.

5.3. Econometric methodology

We aim to estimate the causal effect of *(i)* the introduction of a parking policy change on the probability of parking during peak hours, outside peak hours or not parking on a certain day; *(ii)* a monthly parking subscription fee on the *extensive* margin of peak parking, defined here as parking during the peak at least once during a month (as the subscription fee is per month); *(iii)* the daily tariff on the *intensive* margin of parking, which is the probability that an employee parks on a certain day given that he or she parks at least once per month, and *(iv)* parking prices on the distribution of daily aggregate parking demand, that is, at the level of the hospital (using quantile regressions).

As described earlier, we rely on a panel dataset where every employee-day combination is an observation. We focus on a subsample of employees that were employed during the whole observation period and parked at least once during this period. Hence, our panel dataset is balanced.

We know the exact commuting distance for every employee at the beginning of the study period. Hence, commuting distance is time-invariant.[54] Prices for parking depend on the residence location, but differ only between four commuting-distance intervals (0-2, 2-5, 5-7, >7 km) and change with the new parking regime. We include these intervals and the interaction of these intervals with the new parking regime. In essence, we aim to

[54] Only 3 percent of the employees changed residence in such a way that the parking tariff was influenced, so the induced measurement error is negligible.

exploit variation over time in the parking probability of employees by controlling for day-of-the-week and month fixed effects.[55]

First, we estimate a multinomial logit model in which we distinguish between parking outside the peak hours, parking during the peak hours and not parking. We model the probability π_{ikt} that employee i chooses option $k = 0, 1, 2$ on day t. The reference group is not parking ($k = 0$), so we get the following model:

$$\pi_{itk} = \frac{\exp(\sum_{j=2}^{4} \beta_{j0}\, d_{ij} + \sum_{j=1}^{4} \gamma_{j0} p_t d_{ij} + w_{t0})}{1 + \sum_{K=1}^{2} \exp(\sum_{j=2}^{4} \beta_{jK}\, d_{ij} + \sum_{j=1}^{4} \gamma_{jK} p_t d_{ij} + w_{tK})}. \tag{5.1}$$

In this way, we estimate the probability of parking outside and inside peak hours compared to not parking. In the equation d_{ij} equals one if employee i is within commuting-distance interval j, while p_t is the parking regime indicator, and w_{tK} are day-of-the-week fixed effects. β_{jK} and γ_{jK} are the parameters to be estimated.

Second, we estimate the effect on parking frequency per month using linear regression models. Hence, we estimate the following equation:

$$Q_{im} = \sum_{j=2}^{4} \tilde{\beta}_j\, d_{ij} + \sum_{j=1}^{4} \tilde{\gamma}_j p_m d_{ij} + \widetilde{m}_m + \tilde{u}_{im}, \tag{5.2}$$

where Q_{im} denotes the parking frequency of employee i in month m and u_{im} is the error term. Third, note that $Q_{im} = E_{im} \times I_{im}$, where $E_{im}$is the monthly *extensive margin*, that is, the probability that an employee parks during a month, and I_{im}, the monthly *intensive margin*, that is, the parking probability for employees who park at least once per month. The extensive margin is estimated in the same way as in (5.2), so we replace Q_{im} with E_{im}.

Furthermore, we estimate the effect of paid parking on the intensive margin. As we now make a selection of employees for which holds that $E_{im} = 1$, and do not have balanced panel, we include employee fixed effects σ_i.[56] Hence, we estimate:

[55] We do not have information about which days employees work. We cannot rule out the possibility that employees change their working days as a result of the parking policy change, which then means that working days is an endogenous control.

[56] In this set-up, in order to control for unobserved time-invariant employee heterogeneity, one can estimate models with employee fixed effects. However, because the data is a balanced panel, employee fixed effects will not influence the causal effect of parking policy on parking probability.

$$I_{im} = \sum_{j=2}^{4} \breve{\beta}_j \, d_{ij} + \sum_{j=1}^{4} \breve{\gamma}_j p_m d_{ij} + \breve{m}_m + \breve{\sigma}_i + \breve{u}_{im}, \qquad if \; E_{im} = 1. \tag{5.3}$$

In (5.2) and (5.3), rather than using commuting-distance intervals, we also estimate models using commuting-distance-dependent daily parking tariffs τ_{it} as found in Table 5.1, so we replace $\sum_{j=1}^{4} \gamma_j p_t d_{ij}$ with $\delta\tau_{it}$.

Fourth, we are interested in the effect of the new regime on the distribution of parking demand at the level of the hospital. We analyze the aggregated daily parking demand using quantile regressions (see, for example, Koenker and Bassett, 1978; Koenker and Hallock, 2001; Machado and Mata, 2005). In this set-up we are able to identify the influence of the new parking regime on parking demand in both low- and high-demand settings. Let Q_θ be the θth quantile of the daily parking demand distribution (S) and recall that p_t denotes the parking regime. Furthermore, we include day-of-the-week fixed effects w_t and weather controls X_t. Thus, we estimate the following equation, where $\beta(\theta)$ is a vector of coefficients.

$$Q_\theta(S|p_t) = \tilde{\gamma}_j p_t(\theta) + w_t(\theta) + X_t'\beta(\theta). \tag{5.4}$$

Fifth, we estimate the effect of the bicycle subsidy, which was only given during winter months in the new regime. We introduce the dummy variables s_t and w_t, which are one during summer and winter months in the new parking regime respectively. We then estimate the parking frequency P_{it} of employee i on day t in the following equation:

$$P_{it} = \sum_{j=2}^{4} \hat{\beta}_j \, d_{ij} + \sum_{j=1}^{4} \delta_j s_t d_{ij} + \sum_{j=1}^{4} \vartheta_j w_t d_{ij} + X_t'\omega + \mu_t + \hat{u}_{im}, \tag{5.5}$$

where X_t' are weather controls and μ_t are calendar month fixed effects. $\hat{\beta}_j$, δ_j, ϑ_j and ω are the coefficients to be estimated.

5.4. Main results

5.4.1 Daily parking demand

We estimate the effect of the parking regime on employees' choice to park during peak hours, during off-peak hours or not to park at all, using a multinomial logit model. Table 5.4 reports the marginal effects of the new regime. The estimated coefficients can be found in Table A5.2.

Table 5.4: Daily peak and off-peak demand

Parking frequency	Off-peak hours		Peak hours	
Marginal effects				
New parking regime				
<2 km	−0.001	(0.001)	−0.048***	(0.002)
2-5 km	−0.005***	(0.001)	−0.037***	(0.001)
5-7 km	−0.003***	(0.001)	−0.033***	(0.001)
>7 km	0.005***	(0.0004)	−0.002***	(0.001)
Number of observations	1,920,226			
Log likelihood	−1,301,595			

Note: We use a multinomial logit model on peak days (Monday to Thursday). Standard errors between brackets. Significance levels are indicated by asterisks. * 10%, ** 5%, *** 1% significance level. Month-of-the-year fixed effects were excluded in order to calculate the marginal effects.

The results show that demand for off-peak-hour parking is hardly affected by the introduction of the new parking regime.[57] Hence, the main effect of the new parking policy is an overall reduction in parking demand though a reduction in peak demand. The magnitude of the effect ranges from 0.3 percentage points for the employees living further away than 7 kilometers to almost 5 percentage points for employees living closer than 2 kilometers. Given an average parking demand of 0.27, the effects are substantial.

5.4.2 Monthly parking demand

We now focus on the effect of the new parking regime on employee's monthly parking demand during peak hours, as we have seen that demand for off-peak hours does not play an important role. In Table 5.5 we analyze the total effect, as well as the intensive and extensive margins per commuting distance category.[58] Consistent with the results of Table 5.4, as shown in column (1), demand of employees who live closest to the hospital are affected strongest by the new regime. On average, employees closer than 2 kilometers reduce their demand by 1.1 days per month, whereas demand by the employees outside 7 kilometers reduced by 0.36 days per month.

In column (2) and (3) the dependent variable is a dummy variable indicating whether someone parked at least once a month. We see a decrease in the extensive margin particularly for those with a small commuting distance, which supports the hypothesis that the subscription fee discourages particularly employees with a short distance from parking during a certain month. Using the monetary price increase for the first parking

[57] There is a small but statistically significant *decrease* in off-peak-hour parking demand by employees in the 2-5 and 5-7 kilometer group, whereas there is a small *increase* in the outside-7-kilometer group. Hence, they suggest that for employees who live nearby, peak and off-peak-hour parking demand are complementary, while for those who live further away, peak hour and off-peak-hour parking demand are almost perfect substitutes (as the decrease in peak-hour demand is close to the increase in off-peak-hour demand). In any case, the reduction in peak-hour parking demand is an order of magnitude stronger than the reduction in off-peak-hour parking demand.

[58] We have also estimated the corresponding Poisson models, which gives very similar results.

Table 5.5: Monthly parking demand (during peak hours)

Parking frequency per month	(1)	(2)	(3)	(4)	(5)
	Parking demand	Extensive margin		Intensive margin	
New parking regime					
<2 km	−1.119***	−0.163***		−1.414***	
	(0.233)	(0.031)		(0.484)	
2-5 km	−0.957***	−0.145***		−1.224***	
	(0.106)	(0.015)		(0.172)	
5-7 km	−0.878***	−0.106***		−1.137***	
	(0.126)	(0.016)		(0.142)	
>7 km	−0.364***	−0.041***		−0.491***	
	(0.084)	(0.010)		(0.088)	
Total price increase			−0.028***		
			(0.006)		
Tariff increase					−0.748****
					(0.125)
Month fixed effects (27)	yes	yes	yes	yes	yes
Parking frequency >0	no	no	no	yes	yes
Employee fixed effects (4718)	yes	yes	yes	yes	yes
Number of observations	127,386	127,386	127,386	73,250	73,250
R^2	0.647	0.547	0.547	0.625	0.625

Note: The extensive margin is the probability to park at least once and the intensive margin refer to monthly parking demand given that an employee parks at least once. Standard errors between brackets Significance levels are indicated by asterisks. * 10%, ** 5%, *** 1% significance level.

transaction (the combination of the tariff increase and the subscription fee), we show in column (3) that a € 1 tariff increase reduces the probability that an employee parks during a month by almost 3 percentage points. Given that the extensive margin is about 0.58 on average, this equals a 5 percent decrease. We assume here that the monthly subscription fee, including the tariff increase of the first parking transaction, only affects the extensive margin, whereas the daily increase only affects the intensive margin.

In column (4) we also see a decrease in parking demand at the intensive margin in the new regime. Employees who live closer than 7 kilometers reduce monthly parking demand by over one transaction per month, whereas it is half a transaction for employees outside 7 kilometers. As the average intensive margin in the old regime ranges from 4.6 to 6.8 for these groups in the old regime, the derived price elasticities are around −0.3.[59]

Column (5) shows that a tariff increase of € 1 decreases demand at the intensive margin by 0.75 days per month. As the average intensive margin is about 6, this is a 12 percent decrease. Hence, the effect on the intensive margin is stronger than on the extensive margin.

The results imply that, given that about 60 percent of the employees park at least once during a month, a € 1 daily tariff increase reduces aggregated parking demand by 2,100 (−0.75 × 0.60 × 4700 employees) transactions per month, which is about 105 per day, or

[59] The midpoint price elasticity for employees living within 2 kilometers of the hospital is $\frac{Q_1-Q_0}{Q_1+Q_0}\cdot\frac{P_1+P_0}{P_1-P_0} = \frac{-1.4}{(2\cdot 4.6-1.4)}\cdot\frac{(3+0.75)}{(3-0.75)} \approx -0.30$. Similarly, for employees living further than 7 kilometers away it is −0.26. The employees who live further away are therefore slightly less price-sensitive.

8 percent of the original demand. This result indicates that the target of reducing parking demand by 450 transactions per day is not met at all.

The effect of the subscription fee is less straightforward to measure, due to the aforementioned selection effect. Given that employees who do not park in the new regime parked slightly less than twice per month (1.8 times) on average in the old regime, the effect of a € 1 subscription fee is a reduction of about 240 ($4700 \times 1.8 \times -0.028$) parking transactions per month or 12 parking transactions per day (one percent of the original demand). Note that the average parking tariff increase faced by the employees is about € 0.56, while the average subscription fee including the parking tariff increase is about € 2.17 (€ 1.61 + € 0.56). This means that the average effect at the intensive margin of the new regime is about −60 (0.56×-105) and that at the extensive margin is about −25 (2.17×-12), which is about 5 and 2 percent of the original parking demand respectively.

5.4.3 Aggregate daily parking demand (distribution)

In this section we investigate the effect of the new parking regime on aggregate daily parking demand and specifically on the distribution of the number of parking transactions per day (during peak days) to check if higher parking tariffs affect demand more on relatively calm or busy days. We do this by estimating quantile regressions on different parts of the daily parking-transaction distribution. We control for day of the week and weather conditions. Table 5.6 gives the results of the 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} quantile.

The coefficient of the new parking regime is negative and statistically significant for all quantiles. The results seem to indicate that days with high parking demand (the high quantiles) are affected slightly more by the new parking regime, but due to the large standard errors we cannot reject the hypothesis that the reduction is uniform and about 65 transactions per day. The weather controls show the expected effects: good weather (sunshine) clearly decreases parking demand in all quantiles, whereas bad weather (rain and wind) increase parking demand.

It is also interesting to investigate whether the effect of the new regime depends on weather conditions. Observe that in Table 5.6, parking demand is strongly affected by sunshine. Therefore, we interact sunshine share with the new parking regime. The results are shown in Table 5.7.

It again appears that parking demand has decreased more at the higher end of the parking distribution.[60] Sunshine again reduces parking demand, but the effect is generally weaker in the new regime, as the sunshine share interaction term is usually positive. This means that the difference in parking demand between both regimes is stronger during fully overcast days than during sunny days. As parking demand is lower on sunny days,

[60] Sunshine generally reduces parking demand. For example, on a fully sunny day, total parking demand is reduced by about 100 to 210 cars in all quantiles in the old parking regime.

Table 5.6: Quantile regression daily parking demand

Parking per peak day	10%	25%	50%	75%	90%
New regime	−45.8**	−67.5***	−64.9***	−60.8***	−76.2***
	(21.6)	(24.2)	(11.2)	(9.1)	(13.2)
Sunshine share	−96.4**	−112.5***	−91.5***	−78.4***	−78.8***
	(38.4)	(43.0)	(20.0)	(16.1)	(23.5)
Precipitation	2.13	2.06	2.89**	2.65**	4.46***
	(2.51)	(2.80)	(1.30)	(1.05)	(1.53)
Maximum wind speed	7.81	8.99	4.24	4.29**	3.77
	(5.04)	(5.64)	(2.62)	(2.12)	(3.09)
Day-of-the-week fixed effects	yes	yes	yes	yes	yes
Calendar month fixed effects	yes	yes	yes	yes	yes
Number of observations	407	407	407	407	407
Sum of deviations	7,956	14,413	15,338	10,475	5,246

Note: Standard errors between brackets. Significance levels are indicated by asterisks. * 10%, ** 5%, *** 1% significance level.

Table 5.7: Quantile regression daily parking demand

Parking per peak day	10%	25%	50%	75%	90%
New regime	−87.6***	−62.8	−79.8***	−109.3***	−118.3***
	(34.0)	(40.5)	(19.6)	(11.8)	(21.1)
Sunshine share	−209.8***	−101.8	−128.4***	−142.5***	−127.2***
	(57.2)	(68.0)	(32.9)	(19.9)	(35.4)
Sunshine share	122.8*	−20.8	61.9	109.6***	92.3**
× new regime	(71.6)	(85.2)	(41.2)	(24.9)	(44.4)
Precipitation	0.90	2.07	2.57*	4.46***	5.29***
	(2.40)	(2.86)	(1.38)	(0.84)	(1.49)
Maximum wind speed	9.60**	8.06	3.24	2.16	2.99
	(4.84)	(5.76)	(2.78)	(1.68)	(3.00)
Day-of-the-week fixed effects	yes	yes	yes	yes	yes
Calendar month fixed effects	yes	yes	yes	yes	yes
Number of observations	407	407	407	407	407
Sum of deviations	7,909	14,409	15,273	10,246	5,134

Note: Standard errors between brackets. Significance levels are indicated by asterisks. * 10%, ** 5%, *** 1% significance level.

this suggests that in the new regime days with extremely high parking demand are less common.

5.4.4 Bicycle subsidy

In the previous analyses, we ignored the effect of the bicycle subsidy on car parking demand.[61] As the bicycle subsidy increases the opportunity costs of car parking, it may further reduce car parking demand. The subsidy is only offered during the winter, so we distinguish between the effect of the parking tariff increase on parking demand during the summer months (when there was no bicycle subsidy) and the combined effect of the parking tariff increase and the bicycle parking subsidy during the winter months.[62]

[61] This was included when estimating the effect of the new regime, but excluded when analyzing the effect of prices.

[62] Note that the latter effect is difficult to interpret, because the increase in opportunity costs of parking depends on the probability of using a bicycle.

Bicycle commuting depends on season and weather (see, for example, Nankervis, 1999; Bergström and Magnusson, 2003; Brandenburg, et al., 2004; Heinen, et al., 2010; Stinson and Bhat, 2004). In absence of a bicycle subsidy, one expects a stronger response to parking prices in summer, when it is generally more attractive to substitute to cycling.

We can mitigate any bias by including calendar month fixed effects and weather controls, which allows us to more accurately estimate the effect of bicycle subsidies on car parking demand. Table 5.8 reports the results.

Column (1) shows the results when we do not include calendar month fixed effects and do not control for weather. Demand is reduced in the new regime during summer and winter and the decrease is slightly more pronounced during summer months for employees who live further away. The inclusion of calendar month fixed effects makes the price effect less pronounced in summer, but more pronounced in winter, as shown in Column (2). The results now indicate that employees who live close to the hospital (within 5 kilometers) are more affected by the new parking regime in the winter, which is an indication that they are affected by the bicycle subsidy. The results indicate that for employees residing within 2 kilometers, the bicycle subsidy reduces parking demand by 0.016 (−0.053 +0.037). The inclusion of weather controls in Column (3) does not change this result .[63] In Column (4) we remove the calendar month fixed effects and this result still does not change. The effect of the bicycle subsidy – i.e. the difference in the effects of the new parking regime between summer and winter – as implied by Columns (2) to (4), is statistically significant for employees within 2 kilometers of the hospital as well as those within 2 to 5 kilometers at conventional significance levels according to a standard linear-restriction F-test.[64]

The results strongly suggest that the bicycle subsidy has an impact on parking demand, but the size of the effect is small and only holds for the employees who live closest to the hospital. The relatively weak effect is surprising, given the strong effect of bicycle subsidies found by Wardman et al. (2007). This difference may be a result of cycling being more common in the Netherlands than in Great Britain, which may reduce the effectiveness of financial rewards. Given that the level of the bicycle subsidy (€ 0.50 to 1.00) is very similar to the average parking tariff increase, our results suggests that the bicycle subsidy is an inefficient way to reduce parking demand.

[63] We use 6 temperature categories (<0, 0-5, 5-10, 10-15, 15-20 and >20 °C) , 4 precipitation categories (0, 0-10, 10-20 and >20 mm) and 3 maximum wind speed categories (<5, 5-10 and >10 m/s).

[64] The F-values range from 11.71 to 18.75 for the employees living within 2 kilometers of the hospital, whereas they range from 6.31 to 13.01 for the employees living between 2 and 5 kilometers.

Table 5.8: Peak-parking demand in winter and summer

Peak-parking frequency	(1)	(2)	(3)	(4)
New parking regime in winter:				
<2 km (+€ 2.25 and bicycle subsidy)	−0.048***	−0.053***	−0.053***	−0.053***
	(0.014)	(0.014)	(0.014)	(0.014)
2-5 km (+€ 1.25 and bicycle subsidy)	−0.036***	−0.041***	−0.041***	−0.041***
	(0.005)	(0.006)	(0.006)	(0.005)
5-7 km (+€ 0.75 and bicycle subsidy)	−0.028***	−0.033***	−0.033***	−0.033***
	(0.007)	(0.007)	(0.008)	(0.007)
>7 km (+€ 0.25 and bicycle subsidy)	0.003	−0.001	−0.001	−0.001
	(0.003)	(0.004)	(0.004)	(0.004)
New parking regime in summer:				
<2 km (+€ 2.25)	−0.047***	−0.037***	−0.039***	−0.041***
	(0.014)	(0.014)	(0.014)	(0.014)
2-5 km (+€ 1.25)	−0.040***	−0.030***	−0.031***	−0.034***
	(0.006)	(0.006)	(0.006)	(0.006)
5-7 km (+€ 0.75)	−0.044***	−0.034***	−0.035***	−0.038***
	(0.008)	(0.008)	(0.008)	(0.008)
>7 km (+€ 0.25)	−0.014***	−0.004***	−0.005***	−0.007*
	(0.004)	(0.004)	(0.004)	(0.004)
Day-of-the-week fixed effects	yes	yes	yes	yes
Calendar month fixed effects	no	yes	yes	no
Weather controls	no	no	yes	yes
Temperature (6)				
Precipitation (4)				
Wind speed (3)				
Number of observations	1,920,226	1,920,226	1,920,226	1,920,226
R^2	0.033	0.034	0.034	0.034

Note: commuting distance, day of the week and month fixed effects are included. Standard errors between brackets. Significance levels are indicated by asterisks. * 10%, ** 5%, *** 1% significance level.

5.5. Welfare analysis

In this section we calculate the welfare effects caused by parking overconsumption in different parking pricing schemes. We focus on the welfare losses during peak hours, as peak demand determines the optimal size of the parking lot, which in turn determines the resource costs. Hence, we assume that the optimal price is zero outside peak hours, in line with the hospital's practice.

Welfare losses arise when the parking price is lower than the marginal resource costs. According to the hospital, the resource cost of all 2,100 parking spaces is about € 1.4 million per year, which is about € 3.50 per parking space per peak day on average. We will use € 3.50 for the welfare calculation. Note that the *average* resource costs are likely less than the *marginal* resource costs, so our welfare calculations are conservative.[65] This resource cost is still higher than the highest peak tariff. The deadweight loss is a function of the slope of the demand curve dQ/dp and the difference between parking price p and resource costs c. We use the group-specific demand responses (dQ) estimated in Table

[65] Van Ommeren and Wentink (2012) suggest that the supply function of employer parking is almost perfectly elastic, implying that the underestimate is small. Furthermore, visitors pay (much) more than employees, which also suggests that our welfare estimations are conservative.

Table 5.9: Welfare losses per parking policy

Policy	Welfare loss per year in € Total	Per parking space	As percentage of resource costs
Free parking	116,220	60	8.3
Low tariff (€ 0.75)	71,750	35	5.1
High tariff (€ 1.00-3.00)	40,890	20	2.9
Marginal-cost pricing	0	0	0

Table 5.10: Welfare losses per distance categories

Distance	dQ_j/dp	Annual deadweight loss: Free parking	Low tariff	High tariff
<2 km	−0.021	4,260	2,630	90
2-5 km	−0.030	29,010	17,910	5,330
5-7 km	−0.045	37,320	23,040	12,190
>7 km	−0.012	45,630	28,170	23,280
Total		116,220	71,750	40,890

Note: the welfare losses are calculated at the extensive margin (the combination of daily tariff and subscription fee) and at the intensive margin (daily tariff).

5.4, and we use parking tariff changes (dp) as reported in Table 5.1. We sum the welfare losses of employees in each distance category, based on 200 peak days per year (there are four peak days per week) and the number of employees in each group N_j. The deadweight loss (DWL) is given by:

$$DWL = -200 \sum_{j=1}^{4} \tfrac{1}{2} N_j \frac{dQ_j}{dp} (p_j - c)^2.$$

We compute these welfare losses in case of free parking and those of the different price schemes, compared to the welfare-optimal marginal-cost pricing. The derived welfare losses are shown in Table 5.9.

If parking is free, a deadweight loss of about € 116 thousand arises, which is about 8 percent of the resource costs. If the parking tariff is € 0.75, as in the old regime, the deadweight loss decreases to € 72 thousand per year. In the new regime it is € 40 thousand or € 20 per parking space per year, which is 3 percent of the resource costs. Table 5.10 shows the computed welfare losses per distance category in the three pricing regimes.

Free parking generates the highest deadweight losses. The low tariffs in the old regime reduce the annual deadweight loss by about 40 percent in every category. In the new regime, the deadweight losses have especially reduced for the shorter distance categories, as the tariffs faced by these employees are close to the resource costs, but they remain substantial for the larger distance categories.

5.6. Conclusion

In this paper, we examined the effect of a parking policy change on parking demand of hospital employees. The policy change consisted of two components: a commuting-distance-dependent tariff increase during peak hours, a monthly subscription fee and a bicycle subsidy. Our results indicate that the parking tariff increase reduced parking demand by about 5 percent. The subscription fee reduced parking demand by 2 percent. The implied price elasticity of parking demand is around −0.3.

Using the employees' response to parking tariff changes, we have computed the welfare implications of different pricing schemes. In case of no parking tariffs, the deadweight loss is € 60 per parking space per year compared to marginal-cost pricing, which is 8 percent of the parking resource costs. This is slightly less than what was found in earlier studies.

We offer compelling evidence that bicycle subsidies reduce parking demand. On the other hand, our analysis suggests that the new parking regime especially reduced parking on days with bad weather, when parking demand is usually higher.

Appendix 5.A: Daily and monthly parking demand

A5.1: Aggregated daily parking demand in old and new regime

Table A5.1: Aggregated daily parking demand

	Mean	Standard deviation	Min	Max	Number of obs.
Parking transactions per day	1256	161	788	1616	504
In old regime	1287	160	804	1616	218
In new regime	1233	159	788	1567	286

A5.2: Coefficients of the multinomial logit model

Table A5.2: Daily peak and off-peak demand: estimated coefficients

Parking frequency	Off-peak hours		Peak hours	
New parking regime				
<2 km (+€ 2.25)	−0.096*	(0.054)	−0.694***	(0.030)
2-5 km (+€ 1.25)	−0.250***	(0.024)	−0.374***	(0.011)
5-7 km (+€ 0.75)	−0.154***	(0.022)	−0.234***	(0.010)
>7 km (+€ 0.25)	0.116***	(0.009)	−0.003**	(0.004)
Commuting distance				
<2 km				
2-5 km	0.217***	(0.044)	0.326***	(0.021)
5-7 km	0.531***	(0.044)	0.776***	(0.021)
>7 km	0.948***	(0.041)	1.320***	(0.020)
Number of observations	1,920,226			
Log likelihood	−1,301,595			

Note: We use a multinomial logit model on peak days (Monday to Thursday). Standard errors between brackets. Significance levels are indicated by asterisks. * 10%, ** 5%, *** 1% significance level. Month-of-the-year fixed effects were excluded in order to calculate the marginal effects.

A5.3: Distribution of the monthly parking frequency per employee

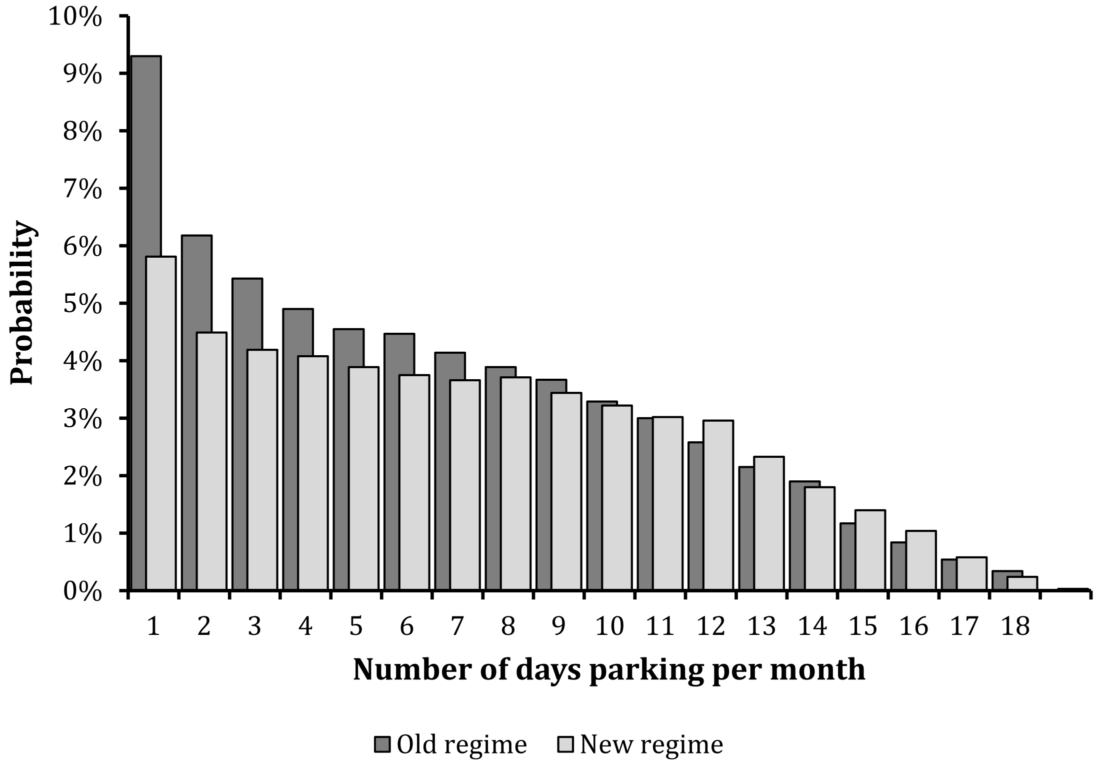


Figure A5.1: Peak-hour parking frequency per employee per month

A5.4: Cumulative distribution of aggregated daily demand

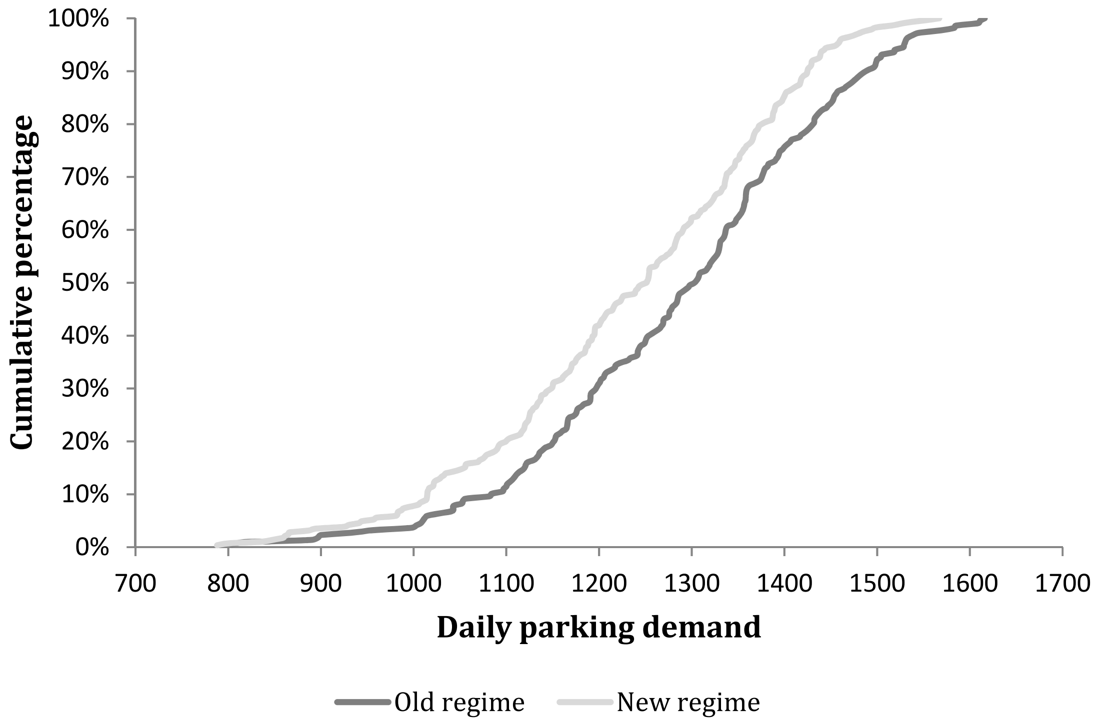


Figure A5.2: Cumulative probability curve of aggregated daily parking demand

6. Summary and policy implications

6.1 Summary

From an economist's point of view the parking market is usually distorted due to government intervention. This distortion may, however, not be confined to the parking market itself, but influences other markets as well. In this dissertation, I look at the effect of parking policy on the parking market, as well as on other associated markets, such as the automobile market, housing market and labor market.

In many places, residential parking is (almost) free for some or all users. In cities with paid parking, residential parking is often subsidized as residents can apply for parking permits that are provided at costs below the market price. It seems that local governments offer parking space at a too low price to residents, as they aim to maximize the welfare of residents at the expense of nonresidents (visitors, shoppers), who usually face much higher parking tariffs. As a result, the available parking space is overused by residents and potentially underused by nonresidents, which is detrimental to welfare.

Residential parking subsidies are detrimental to welfare if the excess residential parking demand results in the provision of more expensive parking space. Parking is particularly costly in city centers, where space is scarce, and the additional parking space has to be provided in the form of large (underground) parking garages. As a result, parking supply costs go up.

Chapter 2 examines the welfare effects for parking due to the provision of permits in shopping districts, where residents and nonresidents share the on-street parking space. In this chapter I estimate the costs of supplying additional parking space to meet excess residential parking demand, assuming that the daily parking price captures the construction costs. The results show that the inverse price elasticity of supply is estimated to be about one, which clearly indicates that the unit costs of providing parking space increase with the amount of parking space supplied. In other words, prices go up if more parking space is provided. The provision of additional parking space to accommodate excess residential parking demand will result in higher prices to nonresidents. This leads to welfare losses of € 275 per permit per year, where 80 to 90 percent is borne by nonresidents.

Parking policy may also affect car ownership. Residential parking permits reduce the car usage costs, which may in turn increase the likelihood of residents' owning a car, which may be especially undesirable in city centers. In Amsterdam, the implicit subsidy (the difference between the price of a permit and the market price for parking) can be over € 3,000 per year, which explains the presence of long waiting lists for these permits in the city center. In the estimation strategy I exploit that, in essence, the waiting lists increase the (non-monetary) price of a parking permit, which can be used to estimate the effect of a permit price increase on car ownership.

Chapter 3 then estimates the effect of waiting-list duration on household car ownership in the city center of Amsterdam. This duration varies from several months to several years between different parking districts. Taking into account differences between households, such as household composition, income, etc., I find that every year of waiting-list duration reduces car ownership by 2 percentage points. The resulting car overconsumption leads to a deadweight loss of about € 270 per permit per year, which is about € 3.5 million in the city center of Amsterdam alone. Longer waiting lists significantly reduce welfare losses, because they increase the non-monetary price of parking. For example, a duration of four years (which is about the maximum in Amsterdam) reduces the deadweight loss by about 65 percent to € 140 per year. A final policy insight is that the parking subsidies predominantly go to high-income households, who tend to have more cars. As a result, high-income households contribute most to the welfare loss.

High levels of street parking may reduce the attractiveness of a neighborhood, as it is harder to find a vacant parking space, which induces cruising for parking. Therefore, parking policy aimed at reducing street-parking demand by both residents and nonresidents may be beneficial to residents. This reduction is usually achieved by introducing paid parking, which also brings additional costs to residents. All in all, it is unclear whether or not the benefits to residents outweigh the costs for residents.

Chapter 4 estimates the impact of the introduction of paid parking on residents by analyzing its effect on house prices in Amsterdam and Utrecht. Both cities have experienced a large-scale introduction of paid parking during the 1990s. In this analysis, I compare house prices before and after the introduction of paid parking, arguably keeping everything else equal. In this way, I identify the residents' preferences for paid parking through house price changes.

The results indicate that the introduction of paid parking does *not* affect house prices, which indicates that the costs are equal to the benefits experienced by residents. This also suggests that paid parking was introduced neither too early or too late from a residents' perspective. Even though there is no effect on house prices, paid parking transfers the costs associated with cruising for parking into government revenue, which is beneficial to society.

Similar to residential parking, employee parking is often subsidized, and usually free. As employee parking is not taxed as income, this encourages parking (and car) use and is expected to be detrimental to welfare. Using paid parking by employees to equalize demand and supply can then be an interesting and inexpensive tool to deal with, for example, negative shocks in parking supply or excess demand. However, employee-paid parking is not very common, except for hospital employees.

Chapter 5 examines the effect of a parking price increase on parking demand for a Dutch hospital in Maastricht. The price increase consisted of a parking tariff increase dependent on commuting distance, a monthly parking subscription fee and a bicycle subsidy. The results suggest that the average tariff increase reduces parking demand by about 5 percent, whereas the subscription fee reduces parking demand by 2 percent. The

Table 6.1: Overview of the main findings per chapter

Chapter	Subsidy	Distortion	Location	Deadweight loss
2	Residents	Residential parking permits	Shopping districts	€ 275/permit
3	Residents	Residential parking permits	Amsterdam	€ 270/permit
4	Residents	Residential parking permits	Amsterdam and Utrecht	Unknown
5	Employees	Subsidized parking	Hospital	€ 60/parking spot

implied price elasticity of parking demand is around −0.3 (regardless of commuting distance). The welfare loss of free parking is € 60 per parking space per year compared to marginal-cost pricing. Furthermore, the analysis offers compelling evidence that bicycle subsidies reduce parking demand.

Table 6.1 summarizes the experimental set-up and the main findings per chapter.

6.2 Policy implications

This dissertation focusses on the distortion in the parking market caused by underpriced parking in the Netherlands. The results indicate that the welfare losses associated with underpriced parking are typically around 10 percent of the parking resource costs in various contexts, ranging from subsidized residential parking permits to cheap parking space provided by employers.

One of the subsidies I examine is for residential parking. Even in case of paid parking, residents do not pay the market price for parking, as they can apply for residential permits. As these permits are too cheap, they are in high demand, which leads to waiting lists. Interestingly, these waiting lists essentially increase the nonmonetary price of a permit, which helps to reduce the market distortion caused by the provision of cheap permits. I find that a waiting-list duration of four years reduces the welfare losses of parking permits, which are typically around € 300 per permit per year, by two thirds.

Increasing the price of a parking permit is a more straightforward way of improving welfare. Ideally, the price of the permits should be much closer to the market price, but even modest price increases can reduce welfare losses significantly. Therefore, increasing the parking tariffs for residents is a good source of government revenue, as it improves, rather than deteriorates, the efficiency of the market. An interesting way of allocating parking permits optimally is by allowing residents to trade these permits among each other. Furthermore, as car ownership increases with income, increasing the price of parking permits reduces the implicit subsidy to high-income households.

6.3 Recommendations for future research

This dissertation covers several topics related to the economics of parking. Nevertheless, there is ample room for further research. As this dissertation focusses on the Netherlands, a natural next step would be to analyze parking policy in different countries. A lot of papers are devoted to the US situation, where parking policy tends to be vastly different. The European situation, with higher street tariffs and more restrictions to nonresidential parking, may be somewhat understudied. An interesting study area might be UK, which tends to have more districts where only residents are allowed to park.

Interesting avenues for further investigation include the effect of parking policy on retail performance, which has not been examined here. This may be important to evaluate the impact of introducing paid parking on changes in retail productivity. The impact of parking policy on the attractiveness of a location to tourists may also be an interesting topic to explore.

Analyzing the substitutability of cars and other transport modes (public transport and, in the Netherlands, the bicycle) was briefly touched upon in Chapter 5, but needs further investigation. Finally, the concept of people actually driving a car themselves may become outdated very soon, given the increasingly advanced technology, allowing for autonomous vehicles. This will likely have a big impact on the parking market.

Bibliography

Anderson, S. P., and De Palma, A. (2004). The Economics of Pricing Parking. *Journal of Urban Economics, 55*(1), 1–20.

Arnott, R. and Rowse, J. (2009). Downtown parking in auto city. *Regional Science and Urban Economics*, *39*(1), 1-14.

Arnott, R., and Rowse, J. (2013). Curbside parking time limits. *Transportation Research Part A: Policy and Practice*, 55, 89-110.

Arnott, R. (2006). Spatial competition between parking garages and downtown parking policy. *Transport Policy, 13*(6), 458-469.

Arnott, R., and Inci, E. (2006). An integrated model of downtown parking and traffic congestion. *Journal of Urban Economics, 60*(3), 418-42.

Arnott, R., and Rowse, J. (1999). Modeling Parking. *Journal of Urban Economics*, *45(1),* 97–124.

Arnott, R., and Rowse, J. (2009). Downtown parking in auto city. *Regional Science and Urban Economics*, *39*(1), 1–14.

Arnott, R., and Rowse, J. (2013). Curbside parking time limits. *Transportation Research Part A: Policy and Practice*, *55*, 89–110.

Arnott, R., De Palma, A., and Lindsey, R. (1991). A temporal and spatial equilibrium analysis of commuter parking. *Journal of Public Economics*, *45*(3), 301-335.

Arnott, R., Inci, E., and Rowse, J. (2015). Downtown curbside parking capacity. *Journal of Urban Economics*, 86, 83–97.

Axhausen, K. W., and Polak, J. W. (1991). Choice of parking: stated preference approach. *Transportation*, *18*(1), 59-81.

Bakis, O., Inci, E., and Senturk, R. O. (2017). *Unbundling Curbside Parking Costs from Housing Prices. Mimeo. Sabancı University*.

Bayer, P., Ferreira, F., and McMillan, R. (2007). A Unified Framework for Measuring Preferences for Schools and Neighborhoods. *Journal of Political Economy*. *115*(4), 588–638.

Bergström, A., and Magnusson, R. (2003). Potential of transferring car trips to bicycle during winter. *Transportation Research Part A: Policy and Practice*, 37(8), 649–666.

Black, S. E. (1999). Do Better Schools Matter? Parental Valuation of Elementary Education. *Quarterly Journal of Economics*, *114*(2), 577–599.

Brandenburg, C., Matzarakis, A., and Arnberger, A. (2004). The effects of weather on frequencies of use by commuting and recreation bicyclists. *Advances in Tourism Climatology*, (4), 189–197.

Brown, J. M., and Rosen, H. S. (1982). On the Estimation of Structural Hedonic Price Models. *Econometrica, 50*(3), 765–768.

Brueckner, J. K., Thisse, J. F., and Zenou, Y. (1999). Why is central Paris rich and downtown Detroit poor? An amenity-based theory. *European Economic Review*, *43*(1), 91–107.

Bureau Onderzoek en Statistiek. (2007). Inkomensontwikkelingen in Amsterdam. *Retrieved from http://www.os.amsterdam.nl*

Bureau Onderzoek en Statistiek. (2013). Stadsdelen in cijfers 2013. Amsterdam. *Retrieved from http://www.os.amsterdam.nl*

Bureau Onderzoek en Statistiek. (2014). Kerncijfers inkomen naar stadsdelen. *Retrieved from http://www.os.amsterdam.nl*

Button, K. (2006). The Political Economy of Parking Charges in "First" and "Second-best" Worlds. *Transport Policy, 13*(6), 470–478.

Button, K. J., Fowkes, A. S., and Pearman, A. D. (1980). Car ownership in West Yorkshire: The influence of public transport accessibility. *Urban Studies*, *17*(2), 211–216.

Calthrop, E. and Proost, S. (2006). Regulating on-street parking*. Regional Science and Urban Economics, 36*(1), 29-48.

Calthrop, E., Proost, S., and Van Dender, K. (2000). Parking policies and road pricing. *Urban Studies*, 37(1), 63–76.

CBS New York (2011). City council approves residential parking permit plan. *Retrieved from www.newyork.cbslocal.com*

CBS (2004). Zes van de tien mensen in woon-werkverkeer nemen de auto. *Retrieved from https://www.cbs.nl/nl-nl/nieuws/2004/08/zes-van-de-tien-mensen-in-woon-werkverkeer-nemen-de-auto*

Cition (2014). Parkeertarieven. *Retrevied from https://www.cition.nl/*

Clark, S. D. (2007). Estimating local car ownership models. *Journal of Transport Geography*, *15*(3), 184–197.

CROW (2008). Parkeercijfers - Basis voor Parkeernormering. Ede, the Netherlands.

Cullinane, S. (2002). The relationship between car ownership and public transport provision: A case study of Hong Kong. *Transport Policy*, *9*(1), 29–39.

Cullinane, S., and Cullinane, K. (2003). Car dependence in a public transport dominated city: Evidence from Hong Kong. *Transportation Research Part D: Transport and Environment*, *8*(2), 129–138.

Cutter, W. B., and Franco, S. F. (2012). Do parking requirements significantly increase the area dedicated to parking? A test of the effect of parking requirements values in Los Angeles County. *Transportation Research Part A: Policy and Practice*, *46*(6), 901–925.

Dargay, J. M. (2002). Determinants of car ownership in rural and urban areas: A pseudo-panel analysis. *Transportation Research Part E: Logistics and Transportation Review*, *38*(5), 351–366.

Dargay, J., and Gately, D. (1999). Income's effect on car and vehicle ownership, worldwide: 1960–2015. *Transportation Research Part A: Policy and Practice.* 33(2), 101-138.

Dargay, J., Gately, D., and Sommer, M. (2007). Vehicle ownership and income growth, worldwide: 1960-2030. *Energy Journal*, *28*(4), 143–170.

De Borger, B., and Proost, S. (2012). A Political Economy Model of Road Pricing. *Journal of Urban Economics, 71*(1), 79–92.

De Groote, J., Van Ommeren, J. N., and Koster, H. R. A. (2016). Car Ownership and Residential Parking Subsidies : Evidence from Amsterdam. *Economics of Transportation, 6*, 25–37.

Denktank Markt en Overheid (2011). *Woonmanifest Amsterdam 2012*.

Dijken, K. V. (2002). Parkeren in Nederland. *IOO/AVV, Zoetermeer/Rotterdam*.

Feeney, B. P. (1989). A review of the impact of parking policy measures on travel. *Transportation Planning and Technology, 13*(4), 229-244.

Frankena, M. (1973). Income distributional effects of urban transit subsidies. *Transport Economics and Policy*, 215–230.

Gabbe, C. J., and Pierce, G. (2017). Hidden Costs and Deadweight Losses: Bundled Parking and Residential Rents in the Metropolitan United States. *Housing Policy Debate, 27*(2), 217–229.

Gemeente Amsterdam (2000). *Parkeren is manoeuvreren*, Dienst Infrastructuur Verkeer en Vervoer.

Gemeente Amsterdam (2005). *Fiscaal parkeren in deelgebied Oostelijke Eilanden van Stadsdeel Amsterdam-Centrum*. Dienst Infrastructuur Verkeer en Vervoer.

Gemeente Amsterdam (2011). *Bestedingsprogramma parkeeropbrengsten Nieuw-West 2012*. Stadsdeel Nieuw-West.

Gemeente Amsterdam (2011). *Amsterdam in cijfers 2011*. Dienst Infrastructuur, Verkeer en Vervoer.

Gillen, D. W. (1977). Estimation and specification of the effects of parking costs on urban transport mode choice. *Journal of Urban Economics*, 4(2), 186–199.

Giuliano, G., and Dargay, J. (2006). Car ownership, travel and land use: A comparison of the US and Great Britain. *Transportation Research Part A: Policy and Practice*, *40*(2), 106–124.

Glaeser, E. L., and Kahn, M. E. (2004). Sprawl and urban growth. *Population English Edition*, *4*(04), 2481–2527.

Glaeser, E. L., Kahn, M. E., and Rappaport, J. (2008). Why do the poor live in cities? The role of public transportation. *Journal of Urban Economics*, *63*(1), 1–24.

Glazer, A., and Niskanen, E. (1992). Parking fees and congestion. *Regional Science and Urban Economics*, *22*(1), 123-132.

Gragera, A., and Albalate, D. (2016). The impact of curbside parking regulation on garage demand. *Transport Policy*, 47, 160–168.

Guo, Z. (2013). Does residential parking supply affect household car ownership? The case of New York City. *Journal of Transport Geography, 26*, 18–28.

Handy, S., Cao, X., and Mokhtarian, P. (2005). Correlation or causality between the built environment and travel behavior? Evidence from Northern California. *Transportation Research Part D: Transport and Environment*, *10*(6), 427–444.

Hasker, K., and Inci, E. (2014). Free parking for all in shopping malls. International *Economic Review*, 55(4), 1281-1304.

Havranek, T., Irsova, Z., and Janda, K. (2012). Demand for gasoline is more price-inelastic than commonly thought. *Energy Economics*, *34*(1), 201–207.

Heinen, E., Van Wee, B., and Maat, K. (2010). Commuting by bicycle: An overview of the literature. *Transport Reviews*, 30(1), 59–96.

Hensher, D. A., and King, J. (2001). Parking demand and responsiveness to supply, pricing and location in the Sydney central business district. *Transportation Research Part A: Policy and Practice*, *35*(3), 177–196.

Hu, L., and Schneider, R. J. (2015). Shifts between Automobile, Bus, and Bicycle Commuting in an Urban Setting. *Journal of Urban Planning and Development*, 141(2), 04014025.

Huang, B. (2007). The Use of Pseudo Panel Data for Forecasting Car Ownership. Dissertation, University of London, London.

Inci, E. (2015). A review of the economics of parking. *Economics of Transportation*, 4(1–2), 50–63.

Ingram, G., and Liu, Z. (1999). Determinants of motorization and road provision. *World Bank Policy Researach Working Paper*.

Jia, W., and Wachs, M. (1999). Parking Requirements and Housing Affordability: A Case Study of San Francisco. *Transportation Research*, (380), 156–160.

Kelly, J. A., and Clinch, J. P. (2006). Influence of varied parking prices on parking occupancy levels by trip purpose. *Transport Policy*, *13*(6), 487–495.

Kelly, J. A., and Clinch, J. P. (2009). Temporal variance of revealed preference on-street parking price elasticity. *Transport Policy*, *16*(4), 193–199.

Kensington and Chelsea (2012). *Retrieved from www.rbkc.gov.uk.*

Kim, J. (2012). Endogenous vehicle-type choices in a monocentric city. *Regional Science and Urban Economics*, *42*(4), 749-760.

Kobus, M. B., Gutiérrez- i-Puigarnau, E., Rietveld, P., and Van Ommeren, J. N. (2013). The on-street parking premium and car drivers' choice between street and garage parking. *Regional Science and Urban Economics , 33* (2), 395-403.

Kodransky, M., and Hermann, G. (2011). Europe’s Parking U-turn: From Accommodation to Regulation. *Institute for Transportation and Development Policy, 84*.

Koenker, R., and Bassett, G. (1978). Regression Quantiles. *Econometrica*, 46(1), 33.

Koenker, R., and Hallock, K. (2001). Quantile regression: An introduction. *Journal of Economic Perspectives*, 15(4), 43-56.

Koster, H. R., van Ommeren, J. N., and Rietveld, P. (2014). Historic amenities, income and sorting of households. *Journal of Economic Geography*, 16(1), 203-236.

Kunreuther, H., and Kleindorfer, P. R. (1986). Sealed-bid auction mechanism for siting noxious facilities. *American Economic Review*, *76*(2), 295-299.

Leichenko, R. M., Coulson, N. E., and Listokin, D. (2001). Historic Preservation and Residential Property Values: An Analysis of Texas Cities. *Urban Studies 38*(11): 1973-1987.

LeRoy, S. F., and Sonstelie, J. (1983). Paradise lost and regained: Transportation innovation, income, and residential location. *Journal of Urban Economics.*

Litman, T. (1995). Parking Requirement Impacts on Housing Affordability. Victoria *Transport Policy Institute*, (February), 36.

Litman, T. (2012). *Understanding transport demands and elasticities*. Victoria Transport Policy Institute

Liu, C., Susilo, Y. O., and Karlström, A. (2015). The influence of weather characteristics variability on individual's travel mode choice in different seasons and regions in Sweden. *Transport Policy*, 41, 147–158.

London datastore (2014). Office for National Statistics (ONS) Population Estimates, Borough and Ward. *Retrieved from http://data.london.gov.uk/*

Machado, J. A. F., and Mata, J. (2005). Counterfactual decomposition of changes in wage distributions using quantile regression. *Journal of Applied Econometrics*, 20(4), 445–465.

Manville, M. (2013). Parking Requirements and Housing Development. *Journal of the American Planning Association, 79*, 49–66.

Marcucci, E., Marini, M., and Ticchi, D. (2005). Road Pricing as a Citizen-candidate Game. *European Transport, 31*, 28–45.

Mingardo, G., and Van Meerkerk, J. (2012). Is parking supply related to turnover of shopping areas? The case of the Netherlands. *Journal of Retailing and Consumer Services*, *19*(2), 195-201.

Mingardo, G., Van Wee, B., and Rye, T. (2015). Urban parking policy in Europe: A conceptualization of past and possible future trends. *Transportation Research Part A: Policy and Practice*, 74, 268–281.

Molenda, I., and Sieg, G. (2013). Residential parking in vibrant city districts. *Economics of Transportation*, *2*(4), 131–139.

Nankervis, M. (1999). The effect of weather and climate on bicycle commuting. *Transportation Research Part A: Policy and Practice*, *33*(6), 417–431.

National Parking Association (2009). *Parking in America: The second annual review of parking rates in North America.* National Parking Association, Washington DC.

Nibud (2015). Wat kost een auto? *Retrieved from www.nibud.nl*

Palmquist, R. B. (1984). Estimating the Demand for the Characteristics of Housing. *The Review of Economics and Statistics, 66*(3), 394–404.

Parkin, J., Wardman, M., and Page, M. (2008). Estimation of the determinants of bicycle mode share for the journey to work using census data. *Transportation*, *35*(1), 93–109.

Potoglou, D., and Kanaroglou, P. S. (2008). Modelling car ownership in urban areas: a case study of Hamilton, Canada. *Journal of Transport Geography*, *16*(1), 42–54.

Q-Park. (2014). Parkeren in Amsterdam. *Retrieved from www.q-park.nl*

Rosen, S. (1974). Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *Journal of Political Economy, 82*(1), 34.

Russo, A. (2013). Voting on Road Congestion Policy. *Regional Science and Urban Economics, 43*(5), 707–724.

Saneinejad, S., Roorda, M. J., and Kennedy, C. (2012). Modelling the impact of weather conditions on active transportation travel behaviour. *Transportation Research Part D: Transport and Environment*, *17*(2), 129–137.

Shoup, D. C. (1999). The trouble with minimum parking requirements. *Transportation Research Part A: Policy and Practice*, *33*(7), 549–574.

Shoup, D. C. (2004). The ideal source of local public revenue. *Regional Science and Urban Economics, 34*(6), 753-784.

Shoup, D. C. (2005). *The High Cost of Free Parking*. Planners Press, Chicago.

Shoup, D. C. (2006). Cruising for parking. *Transport Policy, 13*, 479–486.

Statistics Netherlands (2008). Central Bureau of Statistics, the Hague.

Stinson, M., and Bhat, C. (2004). Frequency of Bicycle Commuting: Internet-Based Survey Analysis. *Transportation Research Record: Journal of the Transportation Research Board*, *1878*(512), 122–130.

Topp, H. H. (1991). Parking Policies in Large cities in Germany. *Transportation, 18*(1), 3–21.

Trajan (2009). Onderzoek korte ritten en optimale grootte vergunningsgebieden.

UK government. (2013). Travel by Region and Area Type of Residence (NTS99). *Retrieved from www.gov.uk*

Van Dijken, K. (2002). *Parkeren in Nederland*.

Van Ommeren, J. N., and Wentink, D. (2012). The (hidden) costs of employer parking policies*. International Economic Review*, *53*(3), 965-977.

Van Ommeren, J. N., De Groote, J., and Mingardo, G. (2014). Residential parking permits and parking supply. *Regional Science and Urban Economics, 45*(1), 33–44.

Van Ommeren, J. N., Wentink, D., and Dekkers, J. (2011). The real price of parking policy. *Journal of Urban Economics*, *70*(1), 25-31.

Van Ommeren, J. N., Wentink, D., and Rietveld, P. (2012), Empirical evidence on cruising for parking, *Transportation Research Part A: Policy and Practice, 46*(1), 123-130.

Van Ommeren, J. N., and Russo, G. (2014). Time-varying parking prices. *Economics of Transportation*, *3*(2), 166–174.

Verhoef, E., Nijkamp, P., and Rietveld, P. (1995). The economics of regulatory parking policies: The (im)possibilities of parking policies in traffic regulation. *Transportation Research Part A: Policy and Practice*.

Verkeersnet. (2013). Utrecht Schrapt Draagvlakmetingen bij Invoering Betaald Parkeren. *Retrieved from https://www.verkeersnet.nl/*

Vickrey, W. S. (1954). The economizing of curb parking space. *Traffic Engineering*, *November, 29,* 62-67, reprinted in *Journal of Urban Economics*, 1994, 36, 42-65.

Wardman, M., Tight, M., and Page, M. (2007). Factors influencing the propensity to cycle to work. *Transportation Research Part A: Policy and Practice*, 41(4), 339–350.

Whelan, G. (2007). Modelling Car Ownership in Great Britain. *Transportation Research Part A: Policy and Practice, 41*(3), 205–219.

Whelan, G. A., Wardman, M., and Daly, A. J. (2000). Is there a Limit to Car Ownership Growth? An Exploration of Household Saturation Levels Using Two Novel Approaches. *Proceedings of the European Transport Annual Meeting, PTRC, London*.

Willson, R. W. (1992). Estimating the travel and parking demand effects of employer-paid parking. *Regional Science and Urban Economics*, *22*(1), 133–145.

Willson, R. W., and Shoup, D. C. (1990). Parking subsidies and travel choices: Assessing the evidence. *Transportation*, *17*(2), 141–157.

Samenvatting

In Nederland is heel veel parkeerruimte. Doorgaans is het niet rendabel om zoveel parkeerruimte aan te bieden, omdat de baten hiervan in geen verhouding staan tot de kosten (bestaande uit niet alleen de aanleg- en onderhoudskosten, maar vooral ook de alternatieve kosten). Dit is een bekend probleem in de parkeermarkt, die vaak wordt verstoord omdat de overheid te hoge parkeernormen voortschrijft of parkeren (impliciet) subsidieert. De verstoring in de parkeermarkt heeft implicaties voor andere markten. In dit proefschrift heb ik de welvaartsverliezen van verstoringen op de parkeermarkt in beeld gebracht.

Parkeren is vaak gratis. Stadscentra zijn daarop de uitzondering, want daar moeten bezoekers al sinds jaar en dag flink voor een parkeerplek betalen. Bewoners kunnen daarentegen vaak gebruikmaken van parkeervergunningen. Deze vergunningen worden onder de marktprijs verstrekt, wat betekent dat de lokale overheid het gebruik van parkeerruimte door eigen bewoners impliciet subsidieert. Een mogelijk gevolg van de parkeersubsidie is dat de vraag naar parkeerruimte door bewoners stijgt, hetgeen stimuleert dat er meer parkeerruimte wordt aangelegd. De kosten daarvan zijn hoog, vooral bij ondergrondse parkeergarages.

In hoofdstuk 2 heb ik de maatschappelijke kosten (het welvaartsverlies) berekend dat ontstaat door de uitgifte van parkeervergunningen aan bewoners in de buurt van winkelcentra. In deze winkelcentra maken zowel de bewoners als het winkelend publiek gebruik van dezelfde parkeerplaatsen, maar betalen ze een verschillende prijs. Doordat de bewoners een lage prijs betalen, neemt de vraag naar parkeerruimte door bewoners toe. Dit blijkt een prijsopdrijvend effect te hebben, omdat de aanlegkosten van parkeerplaatsen toenemen naarmate er meer parkeerruimte wordt aangeboden (de elasticiteit hiervan is ongeveer 1). De rekening hiervan komt grotendeels bij de bezoekers te liggen in de vorm van hogere parkeertarieven voor bezoekers. Zij nemen 80 tot 90 procent van het welvaartsverlies van 275 euro per vergunning per jaar voor hun rekening.

Een ander effect van goedkope parkeervergunningen is een stijging van autobezit. In het stadscentrum van Amsterdam bespaart een parkeervergunning een autobezitter jaarlijks ongeveer drieduizend euro aan parkeerkosten, waardoor er jarenlange wachtlijsten voor vergunningen zijn ontstaan. De wachtlijsten verhogen de kosten van autobezit, omdat (nieuwe) bewoners die op de wachtlijst staan de marktprijs voor parkeren betalen.

In hoofdstuk 3 heb ik becijferd dat het autobezit van huishoudens met twee procentpunten afneemt voor ieder jaar dat ze op de wachtlijst staan. Dit impliceert dat extra parkeervergunningen autobezit en daarmee parkeerdruk verhoogt. De maatschappelijke kosten van extra parkeerruimte zijn ongeveer 270 euro per vergunning per jaar, ofwel drieënhalf miljoen euro voor het stadscentrum van Amsterdam. De maatschappelijke kosten worden grotendeels door de rijkere huishoudens veroorzaakt,

omdat zij meer auto's bezitten, waardoor ze het grootste gedeelte van de parkeersubsidies opstrijken. Langere wachtlijsten kunnen de maatschappelijke kosten echter met wel 65 procent terugdringen.

Door de uitgifte van parkeervergunningen ligt het autobezit in stadscentra hoger dan wat maatschappelijk gezien optimaal is. Toch is de situatie niet meer zo problematisch als in de jaren 80, toen de auto in krappe steden als Amsterdam aan zijn succes ten onder leek te gaan. De voertuigen hadden vaak niet alleen alle voor hen beschikbare parkeerruimte in gebruik, maar daarnaast vaak ook de straat en de stoep. Om de overlast door de vele geparkeerde auto's weg te nemen, werd in de jaren 90 in de grote steden in Nederland op grote schaal betaald parkeren ingevoerd. Hebben de bewoners daar ook van geprofiteerd?

In hoofdstuk 4 heb ik die mogelijkheid onderzocht voor Amsterdam en Utrecht door de effecten van beleid op huizenprijzen te analyseren. Het idee is dat als de leefbaarheid in een straat of buurt omhooggaat door de invoering van betaald parkeren, dit is terug te zien in *hogere* huizenprijzen. Omgekeerd jaagt de invoering van betaald parkeren de bewoners op extra kosten vanwege de kosten van een parkeervergunning, wat juist tot *lagere* huizenprijzen kan leiden. De analyse wijst uit dat de twee effecten tegen elkaar opwegen en dat de invoering van betaald parkeren *geen* effect heeft gehad op de huizenprijzen. Hoewel de bewoners zelf niet direct hebben geprofiteerd van betaald parkeren, profiteert de stad er wel van door hogere inkomsten uit parkeren.

Net als bewoners betalen werknemers mede vanwege belastingtechnische redenen vaak niet voor parkeren bij de werkgever. Hierdoor gaan ze eerder met de auto naar het werk, wat maatschappelijke kosten met zich meebrengt. Wanneer het aantal werknemersparkeerplaatsen wordt verminderd (bijvoorbeeld omdat een deel van de parkeerruimte een andere bestemming krijgt), kan het invoeren van betaald parkeren voor medewerkers een interessante en kostenefficiënte oplossing zijn om de vraag naar parkeren beter op het aanbod aan te laten sluiten. Betaald parkeren voor werknemers is in het algemeen zeldzaam, maar wel gebruikelijk bij ziekenhuizen.

In hoofdstuk 5 heb ik de invloed van tariefsverhogingen op de vraag naar parkeren geschat voor het *academisch ziekenhuis Maastricht*. Dit ziekenhuis besloot de parkeertarieven voor de werknemers te herzien nadat een deel van het parkeerterrein een andere bestemming had gekregen. De tarieven gingen het sterkst omhoog voor de werknemers die dichtst bij het ziekenhuis woonden. Daarnaast was er een beloning voor werknemers die in de wintermaanden met de fiets naar het werk kwamen. Uit de resultaten blijkt dat de verhoging van het dagtarief de parkeervraag met 5 procent doet afnemen, terwijl de ingevoerde maandtarieven voor een verdere afname van 2 procent zorgen. De prijselasticiteit van parkeren door werknemers wordt op −0,3 geschat, en is onafhankelijk van de woon-werkafstand. Het welvaartsverlies van gratis parkeren is in dit geval 60 euro per parkeerplaats per jaar. Daarnaast is er sterk indirect bewijs dat de fietsbeloning de parkeervraag doet verminderen.

Samenvattend brengt gratis parkeren hoge maatschappelijke kosten met zich mee. De invoering van betaald parkeren in veel steden heeft deze kosten sterk verminderd, maar niet helemaal, omdat bewoners een beroep kunnen doen op parkeervergunningen, waardoor ze alsnog (te) goedkoop kunnen parkeren. In de binnensteden en Nederlandse winkelcentra schat ik de maatschappelijke kosten op ongeveer 300 euro per vergunning per jaar. De invoering van betaald parkeren heeft geen invloed op de huizenprijzen gehad, wat betekent dat de afgenomen parkeeroverlast opweegt tegen de kosten van deze vergunningen.