The Marginal External Costs of Street Parking, Optimal Pricing and Supply: Evidence from Melbourne

Jos van Ommeren [a], Michael McIvor [b]

29 October 2018

Abstract — We introduce a nonparametric methodology to estimate the full distribution of marginal external costs of street parking. This information is shown to be a sufficient statistic for the optimal setting of parking prices as well as parking supply across time and space. We focus on Melbourne, which has a policy of low on-street parking prices and restrictive parking time limits during the day. For most of the time, the marginal external costs are far below parking prices, implying that relaxing current time limits increases welfare. Conversely, we show that there are substantial welfare losses towards the end of the day when these time limits expire, which can be avoided by extending paid parking further into the evening. A reduction in parking supply in several suburban areas is welfare improving.

Keywords — marginal external costs of parking, time limits.

JEL codes— H76, R41.

[a] Jos van Ommeren: Department of Spatial Economics, VU University, De Boelelaan 1105 1081 HV Amsterdam, email: jos.van.ommeren@vu.nl. Jos van Ommeren is a Fellow of the Tinbergen Institute, Amsterdam; jos.van.ommeren@vu.nl.

[b] Michael McIvor: Infrastructure Advisory, Ernst & Young, 8 Exhibition Street, Melbourne, VIC 3000, Australia. Email: mtmcivor@gmail.com.

We thank the City of Melbourne for making their sensor data publically available, as well as Jess Chadderton for assistance with on-street observations. We thank Richard Arnott, Albert Gragera, Jesper de Groote and audiences at the Urban Economics Association in Düsseldorf and the International Transport Economics Association in Hong Kong for useful comments.

1 Introduction

On-street parking pricing receives much attention in economic theory, which recommends that governments optimally set prices to allocate on-street parking spaces to drivers in order to avoid excessive cruising (Vickrey, 1969; Arnott et al., 1991; Verhoef et al., 1995). In essence, drivers who decide upon their parking duration ignore cruising for parking by other drivers who aim to park at the same location (Zakharenko, 2016; Inci et al., 2017). A longer duration increases the occupancy rate of parking, and therefore other drivers' cruising costs, which encompass in-vehicle search and walking time costs. Hence, we aim to have information about the marginal external cost of parking, i.e. the external costs of marginally increasing the parking duration. It has been shown that parking prices which are set equal to the marginal external costs of parking are welfare maximising (Zakharenko, 2016).

In the current paper, we introduce and apply a nonparametric methodology to estimate *the full distribution* of marginal external cost of parking, i.e. the external costs of marginally increasing the parking duration, across time and space. This information, combined with information about parking prices, provide us with sufficient statistics to derive welfare implications of parking pricing as well as parking quantity policies.[1] For example, we show that the full distribution of marginal external cost of parking can be used to calculate the marginal benefit of on-street parking supply. Moreover we show that given optimal policy, supply of street parking is self-financing, i.e. the parking revenues are exactly sufficient to finance the supply cost of the optimal quantity of on-street parking.

We apply our methodology to the central city of Melbourne, Australia, which – similar to many US cities – has a policy of below-market on-street parking prices (on Sundays parking is even free) combined with restrictive parking time limits during the day.[2] We estimate the marginal external cost of parking at the block level for half hour intervals, so we have time-varying and spatially detailed information.

We demonstrate that during most hours of the week, the marginal external costs of parking are low – i.e. less than the parking price – implying that relaxing time limits would increase welfare, because there is little cruising. There are exceptions though: in the evening, just before time limit restrictions are lifted and parking becomes free, we observe that marginal external costs far exceed the price, hence there are high levels of cruising. A policy of paid parking extending further into the evening would substantially increase welfare. On Sundays, the external costs due to cruising are substantial for a significant part of the day. We

[1] In essence, information on where and when drivers park their car combined with information on supply of parking spaces allows one to calculate the time-varying and location-specific marginal external time cost of parking, as well as the marginal benefit of increasing on-street supply.

[2] Below market street prices refer to prices which are substantially below commercial off-street prices. Time limits may reduce the demand in two ways: drivers with an intended parking duration exceeding the limit may either leave earlier or choose not to park. We demonstrate that the latter is the dominant behavioural reaction: the large majority of parked drivers depart substantially before the time restriction becomes effective.

also show that parking supply is not welfare optimal: a reduction of parking supply in many suburban areas around the central business district is strictly welfare improving.[3]

Our paper relates to large empirical transport economics literature on the externalities of traffic, including accident, congestion and environmental externalities (Keeler and Small, 1977; Chay and Greenstone, 2005; Davis, 2008; Anderson and Auffhammer, 2013) and on the effects of highway expansion (Baum-Snow, 2010; Duranton and Turner, 2011; 2012; 2016; Duranton et al. 2014). In this literature there is little attention to the role of parking externalities and optimal pricing and supply of parking. This may be justified for highway travel, but not for travel within busy urban areas, where the cost of parking supply tends to be substantial and where parking policies are economically and politically relevant, as discussed in a growing number of theoretical papers, e.g. Brueckner and Franco (2017; 2018).[4]

Our paper contributes to a small – but growing – empirical urban economics literature which examines the welfare consequences of parking policies. For example, Van Ommeren and Wentink (2012) derive the welfare cost of not taxing employer parking as a fringe benefit and of setting minimum parking requirements. Millard-Ball et al. (2014) analyses the consequences of San Francisco's adaptive parking pricing policy. Van Ommeren et al. (2011) show that cruising for parking by residents capitalizes into lower house prices.

Our paper improves on a descriptive empirical literature which attempts to estimate cruising time (for example Shoup, 2005, 2006). A key difficulty in this field is observing cruising.[5] We advance the literature by showing that with commonly held administrative data about arrival rates and vacancy rates one can estimate the full distribution of cruising time. The data requirement is not restrictive: it is regularly collected on a large scale by many cities and towns throughout the world.[6] More interestingly, one can also estimate the full distribution of *marginal* external costs of parking due to cruising, which means that one can examine whether current parking policies are economically efficient. Thus, our methodology can be easily implemented (by parking authorities and researchers) to inform this politically and economically important issue.[7]

[3] Our welfare evaluations are partial, in the sense that we consider changes in one parking policy parameter (e.g. the hourly price), conditional on other policy parameters (e.g., current supply, time limits). Furthermore, we ignore congestion traffic externalities.

[4] For example, Inci et al. (2017) focus on a very expensive shopping street in the city centre of Istanbul. They show that the marginal external cost of one driver who parks for two hours in a shopping street in Istanbul is about equal to the marginal external cost of traffic congestion imposed by this driver.

[5] Information about cruising time is usually obtained by manual or automatic counting (such as by videoing traffic flows), experimental approaches (in which drivers are asked to park in certain areas), or estimates deduced from surveys (e.g. van Ommeren et al. 2012; see Shoup, 2005, for a review). These approaches are too expensive to be undertaken on a large scale.

[6] Although administrative parking data have existed for a long time, they have only been utilized in research very recently (see, e.g., Kelly and Clinch, 2009; Bakis et al., 2015).

[7] Our methodology improves on Inci et al. (2017) which introduces an alternative way to derive these costs. The current paper offers three key advantages: i) it requires less data; ii) it avoids the estimation of a causal effect; iii) it is nonparametric and allows the estimates of the marginal external costs to be time-varying rather than time invariant.

Our paper is complementary to a large theoretical literature on the optimal pricing and supply of congestible facilities, and particular highway capacity. An important theme in this literature under which conditions the road price is exactly sufficient to pay for the capacity costs, implying self-financing (e.g. Small, 1999). Self-financing of highway capacity is examined in many theoretical settings.[8] We are not aware of any study which examines self-financing of *parking supply*. We show that, conditional on a constant-return-to-scale assumption, given optimal policy (including a time-varying parking price), the total revenue of parking is equal to the total supply cost of parking, including the cost of land, implying self-financing. This result is useful for two reasons. First, it implies that when the self-financing rule does not hold, parking policy is not optimal. Second, it implies that parking should be a cash cow for local authorities as revealed in their budgets as these authorities own street parking but do not include the opportunity cost of land, which is the main cost of on-street parking, in their budget.

Our paper also adds new insights to the existing theoretical literature of parking (e.g., Anderson and De Palma, 2004) and in particular cruising for parking (Arnott et al., 1991; Arnott and Rowse, 1999; Arnott, 2014; Arnott and Inci, 2006; Arnott, 2014; Arnott and Williams, 2017; Martens et al., 2010; Zakharenko, 2016) by introducing a driver's optimal spatial cruising strategy where drivers optimally circle around their destination in order to reduce walking time between the parking bay and their destination. Walking does not receive much attention in this literature, although it is shown to be relevant for defining the marginal search externalities and interpreting of the empirical results.

The remainder of this paper is structured as follows. In Section 2, we discuss the theoretical framework that guides the empirical methodology. Section 3 extends this model by elaborating on driver's different cruising for parking strategies and their effect on walking time. Section 4 discusses the empirical methodology. Section 5 outlines the institutional context, the data and descriptive statistics. In Section 6, we present the main results. Section 7 provides a sensitivity analysis. We draw conclusions in Section 8.

2 Theoretical Framework

2.1 The Theoretical Model

In this section, we first introduce a model developed by Zakharenko (2016), which makes clear how to calculate the marginal external costs of parking. For convenience, we present a simplified version with identical drivers and assume that the number of drivers who aim to

[8] Perfect divisibility of capacity is one of the critical underlying assumptions, which may not necessarily hold for road capacity, as the number of lanes is discrete (Small and Verhoef, 2007), but which is a more natural one in the context of parking.

park is given.[9] We extend Zakharenko (2016) by allowing for optimally-chosen parking supply by parking authorities and by analysing self-financing.

Drivers arrive with an exogenous rate $A(t)$ at a block with a given number of parking bays. Drivers pay the expected search cost to park in this block. Parked drivers leave at a self-chosen and therefore *endogenous* rate $L(t)$. Drivers have a value of time equal to c. A parked driver who decides to continue parking at time t during a certain day (from $t = 0$ to T) imposes a marginal search externality on arriving drivers.

The drivers' walking time to the final destination is proportional to in-vehicle search time, with an exogenous walking multiplier ψ, which exceeds 1. In the absence of walking, ψ is equal to 1. Later on we will allow for endogenous walking multipliers.

We ignore any changes over time of the search environment while a driver is searching. This is a reasonable assumption because the search time for parking is typically short. One consequence is that the occupancy rate, $q(t)$, and hence the vacancy rate, $v(t) = 1 - q(t)$, remains constant through the search. The other consequence is that when drivers arrive at a block, they park instantaneously, although incurring search time costs. This has important consequences for our empirical methodology: the number of cars that we observe parking in a given area is (assumed to be) equal to those that search for parking in that area. We denote the number of parked drivers by $n(t)$ and the total number of bays per block by N. The vacancy rate is therefore $v(t) = 1 - \frac{n(t)}{N}$, where $n(t) = \int_0^t [A(x) - L(x)]dx$.

A searching driver randomly samples bays at a rate r (e.g. one bay per second) from a block with a vacancy rate $v(t)$. Once they have found a vacant bay they park their car and the search ends. The success of parking search follows a Poisson distribution with a rate of $rv(t)$.[10] The expected search time, including walking, $Z(t)$ for an arriving driver at time t is therefore:

$$Z(t) = \frac{\psi}{rv(t)}. \tag{1}$$

Equation (1) can be used to estimate the full distribution of cruising time, for each time and block, improving on previous studies' difficulties of observing cruising. It follows that the expected total search cost $C(t)$ of all drivers who arrive at time t can then be written as:

---

[9] This simplified version is less elegant, and more restrictive, than the elaborate model developed by Zakharenko (2016), but it is mathematically less demanding. All our results can be shown to hold in the more elaborate model . These results can be received upon request.

[10] Arnott and Williams (2017) investigated this assumption, which we interpret as an approximation, using a simulation approach. They show that it is plausible that we *underestimate* the marginal external cost of parking, particularly if the average vacancy rate is below 0.1. So our estimates for lower vacancy rates should be interpreted as conservative. However, we will see that for only 7 percent of the 30-minute interval observations, the vacancy rate is below 0.1, so the share of observations with an *average* vacancy rate below 0.1, where the average is taken over longer time intervals, is even smaller. Arnott and Williams (2017) show that there are several reasons why this assumption does not strictly hold (e.g., occupied parking spaces are spatially correlated). We will test whether we have an overestimate because there is variation in the occupancy rate *within* the time interval, but it appears that this is not the case..

$$C(t) = \frac{c\psi}{r}\frac{A(t)}{v(t)}. \tag{2}$$

We are interested in the marginal external cost of a parked driver who decides at time t whether to extend their parking duration, hence reducing $L(t)$. Note that reducing the departure rate is the same as increasing the number of parked drivers as $\partial n(t)/\ \partial L(t)= -1$. If a driver decides to stay, the number of parked cars will marginally increase, decreasing the vacancy rate and marginally increasing search time for arriving drivers. The marginal external cost imposed by a parked driver upon searching drivers is the first derivative of the expected total search costs with respect to $n(t)$.

$$\frac{\partial C(t)}{\partial n(t)} = \frac{\partial\left(\frac{c\psi}{r}\frac{A(t)}{v\ (t)}\right)}{\partial v(t)}\frac{\partial v\big(n(t)\big)}{\partial n(t)} = \frac{c\psi}{r}\frac{A(t)}{Nv(t)^2}. \tag{3}$$

This is the first result that is fundamental to our empirical study. Equation (3) allows us to estimate *marginal* external costs of parking for each time and block.

2.2 Estimating the Marginal External Cost of Parking

Here, we will explain our estimation procedure shortly, but we will elaborate on this further in Section 4. Equation (3) states that the marginal external cost of parking is a function of the arrival rate of drivers per parking bay in the block, $A(t)/N,$ and the vacancy rate, $v(t)$, which both vary per block and over time. Information about $A(t)/N$ as well as $v(t)$ is observed in administrative data. The costs also depends on the sampling rate, r. In our empirical application we estimate a block-specific sampling rate using the spatial density of parking bays combined with assumptions on driving speed. The walking multiplier ψ, which determines the impact of walking time in addition to the in-vehicle cruising time, will be derived given a number of assumptions regarding the chosen search strategy. The value-of-time parameter c is not observable, but can be deduced from other studies.[11] Given this information, the marginal external cost of parking can be calculated in a nonparametric way.

2.3 Optimal Policies

2.3.1 The Optimal Parking Price

We now derive the optimal price of parking. The total benefit of parking by parked drivers is denoted as $U\big(n(t)\big)$, which is assumed to be an increasing concave function of the number of parked drivers. The total cost of parking is equal to the sum of the search cost of parking $C(t)$, defined by (2) and the (time-invariant) capital costs of parking supply, denoted by

[11] Let us provide an example for a block with 20 bays, so N = 20. We observe that the vacancy rate, v, is 0.10, and the hourly arrival rate, A, is equal to 30. The estimated sampling rate of a bay for this block is one per second, so r = 1600 per hour. Let us assume that there is no walking time, so ψ = 1, which provides as with an underestimate. We further assume a hourly value of time, c, of 25. The marginal external cost of parking for one hour of parking is then estimated as about one dollar (25/3600) · (30/(20 · 0.01) ≈ \$1.04).

$K(N)$, which increase in the number of parking bays N.[12] The social welfare aggregated during the day (from $t = 0$ to T) across all drivers, W, is the total parking benefit minus the sum of the search and capital costs:

$$W = \int_0^T \Big(U\big(n(t)\big) - C(t)\Big)\, dt \; - \; K(N)\,. \tag{4}$$

To find the socially optimal parking price, we maximise welfare with respect to the number of parked drivers across the day, $n(t)$. The first-order condition implies:

$$\frac{\partial U\big(n(t)\big)}{\partial n(t)} = \frac{\partial C(t)}{\partial n(t)}\,. \tag{5}$$

A driver will continue to park until the marginal utility of parking is equal to the marginal price:

$$\frac{\partial U\big(n(t)\big)}{\partial n(t)} \; = \; p(t)\,. \tag{6}$$

Combining (3), (5) and (6), the optimal price of parking can be written as (Zakharenko, 2016):

$$p^*(t) = \frac{\partial C(t)}{\partial n(t)} = \frac{c\psi}{r}\frac{A(t)}{Nv(t)^2}\,. \tag{7}$$

Consequently, the optimal price of parking *per unit of time* internalises the external search cost, effectively as a Pigouvian tax.[13] Equation (7) is fundamental to the welfare interpretations of our empirical results. It states that in the optimal equilibrium, the marginal external cost of parking must be equal to the actual price of parking administered by the parking authority. Therefore, if the actual parking price is less than the marginal external cost, we have undesirable cruising and can increase welfare by increasing the parking price. Conversely, if the parking price exceeds the marginal external cost, the on-street parking is not being effectively utilized, and welfare can be increased by reducing the price. Hence, our estimates of the marginal external costs, and the unpriced marginal externality, i.e. the price minus the marginal external costs, can be used as a sufficient statistic for welfare analysis.

We note a number of intuitive features of the optimal price. First, it is inversely proportional to the vacancy rate squared. Given few vacancies, the marginal increase in cruising time caused by staying for longer increases steeply. Having a higher price when vacancy is low is a key argument of Shoup (2005). Second, the optimal price is proportional to the number of arrivals. When there is a low number of arrivals (such as overnight), the marginal external cost is low, and so it is preferable to aim for a higher occupancy rate.

---

[12] This includes the opportunity cost for competing use, such as café seating, transport lanes or green space.

[13] We ignore here externalities due to the travel congestion costs associated with each trip, see Glazer and Niskanen (1992), which can be partially internalised by taxing parking *not* per unit of time, but by taxing parking independent of the duration of parking.

2.3.2 Optimal Parking Supply

We now consider the marginal benefit of parking supply and the optimal supply of parking. We calculate the marginal benefit of a parking bay at time *t*, by calculating the reduction in search costs at that time due to the increase in total parking bays, N. It is straightforward to show that:

$$\frac{\partial C(t)}{\partial N} = \frac{\partial\left(\frac{c\psi}{r}\frac{A(t)}{v\,(t)}\right)}{\partial v(t)}\frac{\partial v(t)}{\partial N} = -q(t)\frac{\partial C(t)}{\partial n(t)}. \tag{8}$$

Consequently, in line with intuition, the decrease in search costs by adding one parking bay is equal to the occupancy rate times the marginal search costs of one parked car.

It is now straightforward to calculate the marginal benefit of parking supply, i.e. the total reduction in search cost by increasing supply, by integrating over time *t*:

$$\int_0^T \left(\frac{\partial C(t)}{\partial N}\right) dt = \int_0^T \left(-q(t)\frac{\partial C(t)}{\partial n(t)}\right) dt \ . \tag{9}$$

In our empirical application, we will estimate $\partial C(t)/\partial n(t)$ using (3), and therefore able to calculate the marginal benefit of parking supply during the day using (9), and then by aggregating the daily marginal benefits over all time periods. Note that when the occupancy rate is low (during the whole day), then the marginal search cost of one parked car is also low, and therefore the marginal benefit of parking supply is low.

To find the socially optimum supply of parking, we maximise social welfare with respect to N. The first-order condition of optimal supply reads as follows:

$$\int_0^T \left(-\frac{\partial C(t)}{\partial N}\right) dt - \frac{\partial K}{\partial N} = 0. \tag{10}$$

Hence, in the optimum, the marginal benefit of a parking bay due to the reduction in the search cost is equal to the marginal capital costs.[14] This intuitive result is the second result fundamental to our empirical study. Hence, given estimates of the marginal benefit of a parking bay and given information about the marginal capital cost of street parking, one can determine to what extent parking supply should be increased or decreased from a welfare perspective.[15] An estimate of the marginal benefit of a parking bay minus the marginal capital cost can be used as a sufficient statistic to determine whether to increase or decrease the current supply of on-street parking.

[14] It seems we have not assumed optimal pricing, but note that the arrival rate is held fixed when deriving (8). If we assume that this rate is endogenous, it would be necessary to assume that the authority sets optimal prices per unit of time to obtain the above result.

[15] In the empirical analysis, we will derive the marginal capital cost of on-street parking using information about close substitutes in the private carpark rental market, for which we observe rents.

2.3.3 Self-Financing of Parking Supply

Let us now make the additional – but not too restrictive – assumption that the capital cost of parking is proportional to the number of parking bays, with proportionality factor k $(K(N) = kN)$. Let us suppose further that the parking price is optimally set. Using (7) and (8), we get:

$$\int_0^T \left(\frac{\partial C(t)}{\partial N}\right) dt \ = \int_0^T \big(q(t)p(t)\big) dt\,. \tag{11}$$

Hence, given the optimal price, the marginal benefit of a bay is equal to the marginal revenue of a bay. Using (10) and (8), it follows that:

$$N \int_0^T \big(q(t)p(t)\big) dt \ = kN\,. \tag{12}$$

Note that the left-hand side denotes the revenue per block, whereas the right-hand side is equal to the capital costs per block. Hence, given optimal pricing and supply, revenue is equal to capital expenditure, so we have a self-financing result.

2.4 Maximum Parking Time Limits

In our empirical investigation, we focus on a market where paid parking is combined with maximum parking time limits (usually, one or two hours). An optimal policy using prices does not require time limits from a welfare perspective (Zakharenko, 2016).[16] Nevertheless, the presence of time limits raises the question to what extent the above results still apply. Parking time limits induce an implicit price of parking for drivers (if they would like to park longer than the time limit) which has to be added to the monetary price, hence the perceived 'total price' (including time limits) exceeds the monetary price.[17]

Let us focus on the case where the monetary parking price exceeds the marginal external cost of parking – which we will show is the dominant finding for Melbourne. In this case, the presence of time limits does *not* change the conclusion that the total price is too high. The policy consequence is that the total parking price should be reduced. This can be established in two ways: by reducing the monetary price or by relaxing the time limit. We favour the former: welfare would increase if time limits were marginally relaxed (e.g. extended from 60 minutes to 120 minutes). As a result, drivers will park longer (and the arrival rate of drivers would go up) and the marginal external cost of parking will increase.

As an alternative, let us assume the opposite: i.e. the monetary parking price is lower than the marginal external cost (which we find for Sunday, when the monetary parking price is zero). In this case it is not clear whether the *overall* parking price is higher or lower for

[16] Given homogeneous drivers, time limits may be optimal. This is never the case given heterogeneous drivers (Zakharenko, 2016).

[17] Time limits may be welfare increasing compared to the absence of any parking policy (Arnott and Rowse, 2003). One common justification for time limits is that they aim to subsidise short-term parking (City of Melbourne, 2008). However, drivers parking for a short-term have a higher willingness to pay *per unit of time* than those parking for a longer term, because alternatives, such as parking elsewhere, are relatively less attractive. Therefore using prices rather than time limits results in on-street parking mostly being used by drivers parking for a short-term anyway (Kobus et al. , 2013).

arriving drivers who intend to park longer than the time limit. Consequently, it is not clear whether it would be welfare optimal to increase or decrease the overall price of parking. This shows another disadvantage of the presence of time limits: time limits hamper the optimal setting of parking prices.[18]

Similarly, in order to determine whether the current parking supply is optimal, the presence of time limits may hamper the welfare evaluation (because it is not clear whether the overall price is too high or too low compared to the marginal external cost). However, when the marginal external costs are lower than the monetary price, which, as has been emphasised above, is the dominant case in Melbourne, then the effect of increasing parking on inducing demand – i.e. increasing the number of drivers who we will search for parking – will reinforce the argument that there is too much parking, so parking supply should be decreased. In fact, we show that in general the marginal external costs in Melbourne are *much* lower than the monetary price, and hence the occupancy rate is low such that the increase in the number of drivers who will search is likely negligible.

3 Search Strategies Allowing for Walking and Circling

We will now analyse several search strategies which include walking and identify the walking multiplier ψ for each strategy.[19] ψ will be shown to depend on the ratio between the speed of driving (while searching) and speed of walking, defined as θ, where $\theta \geq 1$. We will give numerical examples for $\theta = 4$, which is consistent with a walking speed of 5 km/h, and a driving speed of 20 km/h.

3.1 Linear Search Strategies

We first focus on linear search strategies, where drivers search on a road in a straight line. A *naive* search strategy is then to drive towards the destination and then start searching. After having parked, the drivers has to walk twice between the car and the destination. Given these assumptions, $\psi = 2\theta + 1$. Given $\theta = 4$, $\psi = 9$. Hence the multiplier is *much* higher than 1, the multiplier value in the absence of walking.[20]

The naive strategy overestimates walking time, as a rational driver also searches *before* reaching the destination. A rational strategy is that the driver optimally chooses where to start

[18] There are other arguments to favour parking prices compared to time limits: i) time limits require greater enforcement costs (as parked cars need to be checked multiple times to determine if they are violating regulation); ii) time limits induces parked drivers to move their car to another location nearby when reaching the limit, which is costly.

[19] In general it is believed that motorists have a strong dislike of walking and typically aim to park very close to final destination. There is hardly any empirical information about the extent of walking due to cruising. De Vos and van Ommeren (2018) demonstrate that residents' walking time from the parking location to their homes is strongly increasing with the occupancy parking rate supporting the above assumptions made here.

[20] We ignore here the effect of searching on the travel time in the car to the next destination. If the driver searches in the direction of the next destination, then ψ is slightly lower.

searching before reaching the destination by minimising expected travel time, i.e. the sum of in-vehicle driving and walking time (here we deviate from Zakharenko (2016), who minimises expected in-vehicle driving time, and therefore obtains a larger multiplier). In Appendix A, we show that:

$$\psi \; = \; (2\theta - 1)\ln\left(\frac{4\theta}{2\theta - 1}\right), \tag{13}$$

which is less than $2\theta + 1$. For example, given θ = 4, ψ = 5.8, which is about 35 percent below the numerical value implied by the naive search strategy.

3.2 Circling Search Strategy

A linear search strategy overestimates ψ, when a searching driver starts to circle around to reduce walking *after* reaching the destination – in line with empirical findings (Inci, 2015). To capture this, we assume that drivers only search within a block, and that the destination is at one end of that block.[21] In Appendix A, we show that:

$$\psi \; = \; (2\theta - 1)\ln\left(\frac{4\theta - 2\theta e^{-\,0.5\,vN}}{2\theta - 1}\right). \tag{14}$$

Consequently, ψ is increasing in vN. When vN is large, i.e. when the vacancy rate is substantial and the block is large, ψ approaches (13) from below, as the driver will search in a straight line. In contrast, when vN approaches zero, i.e. when the vacancy rate or the block is small, drivers will circle around to reduce walking time and ψ approaches 1 from above.[22] Given $\theta \; = \; 4$, ψ will be between 1.0 and 5.8.

Arguably, the circling search strategy is the most realistic and will be used in the empirical analysis. Previous studies typically point out that cruising is rare for vacancy rates above 0.1 and the same is implied by our data. Hence, the multiplier level only matters for vacancy rates below 0.1. Let us focus on $\theta = 4$ and a typical block size of 20. Given a vacancy rate of 0.1, $\psi \; = \; 4.4$. With a rate of 0.01, it drops to 2.5. Given the latter, the additional external time losses due to walking are 150 percent higher than external time losses due to in-vehicle search.

[21] Hence, a driver that obtains a random bay will expect to walk half a block. If destinations are distributed uniformly along the block then the expected walking distance will be a quarter of the block. Alternatively, if a driver drives in a square search pattern around four blocks with identical occupancy, bays and spatial bay density, then the expected walking distance will be two blocks.

[22] Note that (2θ-1)ln(2θ/(2θ-1)) = (2θ-1)ln(1 + 1/(2θ-1)) ≈ (2θ-1)/(2θ-1) = 1 for θ much larger than one.

4 Estimation Method

We aim to estimate the marginal external cost of parking as defined by equation (3) using information about blocks for 30-minutes intervals. We will discuss here a number of important issues which arise when calculating (3). First, it is based on the assumption that drivers search for parking *within one block and end up parking in this block*. This assumption allows us to approximate the unobserved number of searching drivers by the number of drivers that park on a block within a given time interval, which we can observe. However, the assumption may be inaccurate when a substantial share of on-street searching drivers end up parking off-street or also search in other blocks with different vacancy levels. To deal with the latter, we will focus on blocks with at least 10 parking bays, which reduces – but does not eliminate – the probability that drivers also search in blocks with different vacancy levels. Our sensitivity analysis suggests that our estimates are slightly conservative because of this minimum block size selection.

Second, the method assumes that the number of arrivals and vacancy rate is constant within an interval of 30 minutes. A sensitivity analysis – using intervals of five minutes – shows that our results are insensitive to this assumption.[23] Third, we assume that *within* blocks, parking is homogeneous with respect to time limits. This assumption does not hold. For about a quarter of blocks, parking bays differ in their time limit restrictions within blocks.[24] In a sensitivity analysis, we will show that by distinguishing between different time limits within blocks, the estimates of the marginal external cost are only slightly higher.

Fourth, the marginal external cost of parking of a block is not defined by (3) when there are no vacancies during a time interval. This turns out not to be an important issue given the chosen interval length of 30 minutes, as observations without vacancies occur seldom. One may exclude these observations, but we include these observations making some assumptions. [25] When the number of arrivals is zero, we set the marginal external costs to 0. This slightly underestimates the marginal external cost.[26] When the arrival rate is positive, we use (3), while assuming that the vacancy rate is small, but positive, and equal to about 0.1/N.

Fifth, the search process assumes that drivers sample parking bays "with replacement", which overestimates the marginal external cost of parking if drivers in reality sample "without replacement". We have investigated this further with numerical simulations.

[23] Arnott and Williams (2017) simulation results imply that that one get underestimates when the time interval is too long, because the vacancy rate varies within the time interval. Apparently, a 30-minute interval short enough to avoid this bias.

[24] Some parking blocks also contain extremely short-term bays (which allow for parking durations of 15 mins or less), or other restrictions, such as loading bays for commercial use or disabled bays for eligible drivers. These bays are excluded from the analysis.

[25] Observing a positive number of arrivals combined with zero vacancies may occur because the vacancy rate is observed with a small measurement error as explained later on.

[26] The underestimate becomes more severe for shorter intervals, because the share of observations with zero vacancies increases. Nevertheless, the marginal external cost reduces only slightly even when we reduce the interval length to 5 minutes.

Note that the results are quite different for small blocks, but that both sampling methods converge to each other for larger blocks, which supports using a minimum block size of 10. For vacancy rates above 0.20, the results are almost identical for sampling with and without replacement. When the quitting rate is high, both methods converge to each other. For example, for a block of 20 bays, and a parking limit of one hour, there is at least a 30 percent chance that a block that is completely full at a certain moment has at least one vacancy one minute later.[27] Consequently, when vacancy rates are below 0.20, it seems not unreasonable to assume that drivers search with replacement, because drivers are re-searching bays hoping that one has become vacant since they last looked.

5 Institutional Environment, Data and Descriptive Statistics

We aim to estimate the marginal external parking costs for about 4000 on-street bays in central Melbourne for the month March 2014, using publically available data collected by the local council (City of Melbourne, 2015).[28] In this area, there are also about 70,000 off-street car parking spaces, predominantly privately owned, which are open to the public (City of Melbourne, 2016).[29] Around 40 percent of on-street parking trip purposes are for work, 20 percent are for personal business, 20 percent are for delivery or servicing, and the remaining 20 percent are for shopping or other activities (City of Melbourne, 2008).

Prices for on-street parking during 2014 varied slightly over space, with higher prices closer to the CBD. If one has to pay for parking at a bay, then the price is the same for all days of the week except for Sunday. We will distinguish between three different parking price regimes: i) the city centre with an hourly price of $5.50; ii) inner suburbs where prices usually are around $1.70 or around $3.20, and some free (but time-limit restricted) parking is available, and iii) and on Sundays when parking is everywhere free.[30]

Information about whether a parking bay is occupied is obtained from in-ground sensors. The sensors are used to assist enforcement of time limits, and record the time of arrivals and subsequent departures of vehicles (to the nearest 10 seconds) and only operate when time-limit restrictions are in place.[31] Time limits are used when the parking price is positive, but

[27] We assume that drivers arrive randomly with a constant inflow rate for the last hour and each driver parks for exactly 60 minutes. On can then calculate the expected level of the vacancy rate.

[28] Melbourne contains around 4.5 million people in the state of Victoria, Australia, with a busy central city area. It's central city area – the City of Melbourne – contains 140,000 residents and 450,000 workers. On an average weekday around 900,000 people are present in the central city (City of Melbourne, 2017).

[29] These figures apply to the council area which is slightly larger than the study area, consequently the supply of off-street parking is somewhat overestimated here. There are also 130,000 parking spaces that are not open to the public (e.g., employer parking or residential parking).

[30] Commercial off-street parking prices vary a lot over space and time, but these prices are *much* times higher than on-street parking prices. For example, in the city centre, a typical garage charges *at least* $20 per hour during the workday and at least $10 per hour during the weekend and in the evenings.

[31] We do not have information about the reliability of sensors. Most likely, reliability is very good, because the sensors are continuously monitored, as they determine potential fines motorists have to pay. Furthermore,

not always when parking is free. Hence we do not have any information, when parking is free and there are no time limits used.

Our information comes from about 4245 parking sensors which are active during daytime hours – between 07:30 and 20:30 (virtually all bays do not have restrictions outside these hours). In the weekends, there are fewer time restrictions; hence not all bays are monitored (90 percent Saturday mornings, 65 percent Saturday afternoons and 45 percent on Sundays).[32]

The council sets time limits using a target occupancy range (City of Melbourne, 2008), which vary from five minutes up to four hours, but may have different time-limit restrictions throughout the week, or even throughout the day. Time limits frequently vary between bays that are spatially close to each other, sometimes even within the same block. The majority of bays have a limit of one or two hours.[33]

We use information on 3609 bays that are open to the public (e.g. we exclude residential parking, parking obstructed due to construction) and which allow drivers to park for at least 15 minutes. These bays are distributed over 218 blocks. Most blocks have between five and 15 bays, and a few blocks have more than 40 bays. See Figure B in Appendix B, which shows the blocks in a map.

Our analysis focuses on 3159 bays belonging to 135 blocks that have at least 10 bays. We have information about the occupancy rate and the number of arrivals for 5-minutes intervals and aggregate this to 30-minutes intervals, which is our unit of measurement. In total, we have 81,535 observations.[34] Accordingly, we use information about the (time-averaged) occupancy rate, the ratio of the number of arrivals to the number of bays and the price of parking per block for each 30-minutes interval. On average, the occupancy rate is equal to 0.50 (the interquartile range is 0.25 to 0.70) and the ratio of number of arrivals to the number of bays in a block is equal to 0.75 arrivals per bay per hour (the interquartile range is 0.29 to 1.05). The sampling rate r is derived from an assumed search driving speed of 20km/h combined with information about the spatial density of bays within blocks. The average sampling rate is about 0.75 bays per second.

In Appendix B, Figures B2-B4, we provide information about the distributions of i) occupancy rate, ii) the ratio of number of arrivals to the number of bays in a block, and iii) the sampling rate. It shows that there is a lot of variation in occupancy levels and occupancy is generally, for 93 percent of the observations, lower than 90 percent. These distributions

motorists may complain about malfunctioning sensors. In contrast, when sensors are not used for financial purposes, as in SFPark, authorities and motorists have less incentive to ensure that sensors are reliable.

[32] Blocks without restrictions likely have a higher marginal external cost. Consequently, for Sundays, our estimate is likely a severe underestimate. This is not problematic for our conclusions.

[33] To be more precise, the workweek, about 5 percent have a limit of 30 minutes, 30 percent have a limit of 60 minutes, 44 percent have a limit of two hours, 6 percent have a limit of three hours and 13 percent have a limit of four hours. On Saturdays, the time limits are similar, but time limits of four hours occur less (only 7 percent). On Sundays, 45 percent have a limit of one hour, 51 percent a limit of two hours and 4 percent a limit of three hours.

[34] Note that this introduces a small measurement error for the occupancy rate, as it is averaged over time.

mask a lot of heterogeneity over time and space. We therefore group blocks into eight areas also provide information about the average occupancy for these areas for different periods of the day (see Figure B6 in Appendix B). It shows, for example, that occupancy in the south-east CBD tends to be higher and particularly so in the evening.

We allow for in-vehicle search in a circle, as discussed above. We assume that the ratio of driving and walking speed equal to 4. Hence, the walking time multiplier ψ has values between 1 and 5.8. Its average value is equal to 4.3 (the interquartile range is 3.1 to 5.7), with higher values when occupancy and search time are lower. For the value of cruising time, we use \$33 per hour using Australian Transport Assessment and Planning Guidelines (Commonwealth Department of Infrastructure and Regional Development, 2016).[35]

6 Main Results

6.1 Search Time

Figure 1 shows the cumulative distribution of drivers' search time $Z(t)$, the sum of cruising and walking time. It shows that for a large majority of drivers, search time is very short. For 80 percent of drivers the search time is less than 30 seconds, of which less than one third is in-vehicle. Very few drivers search for more than two minutes. This result is consistent with our descriptive finding that the occupancy rate is most of the times below 0.90. When we focus on occupancy rates between 0.90 and 0.95, the average search time is estimated to be about 1 minute, of which one third is in-vehicle. Figure 2 shows the full search then distribution for occupancy rates between 0.90 and 0.95. It appears that a substantial proportion of drivers search then for more than 1.5 minutes.

6.2 The Marginal Search Externality of Parking

We now focus on the *marginal* search externality of parking. Recall that we have observations for 30-minute intervals. For convenience, we provide this metric *for one hour of parking*, facilitating comparisons with hourly parking prices. We are particularly interested whether the unpriced marginal parking externality– i.e. the marginal externality minus the marginal *monetary* price – is positive or negative.

It appears that in 97 percent of the observations, the unpriced marginal externality is negative: the marginal unpriced externality is lower than -\$1.00. Recall that time limits imply that the total price exceeds the monetary price. Consequently, in general, the *total* price of parking – the combined effect of the monetary on-street price and the time limit restriction –

[35] We use travel value of time values that are specific with trip purpose and vehicle occupancy. We assume a vehicle occupancy of 1.5 and that 18 percent of drivers travel for business, which is a conservative assumption, as Melbourne's city centre has a high proportion of business travel and higher wages. We ignore that drivers may have a higher willingness to pay to avoid cruising than travelling. Inci et al. (2017) use a value of search time which is 30 percent higher than the value of travel time.

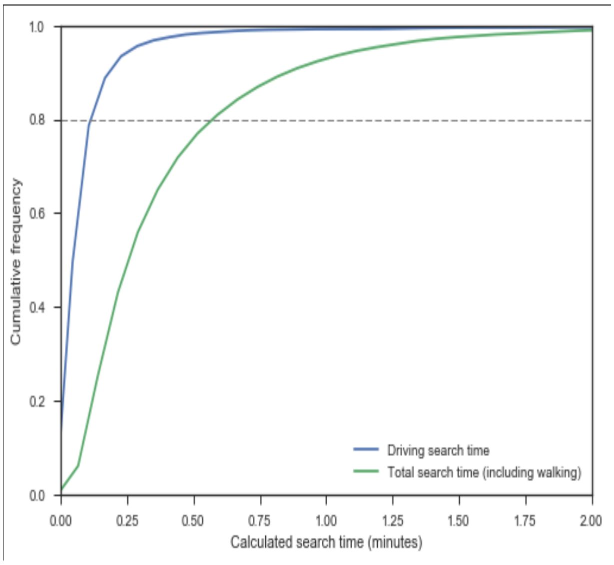

Figure 1: The cumulative distribution of search time.

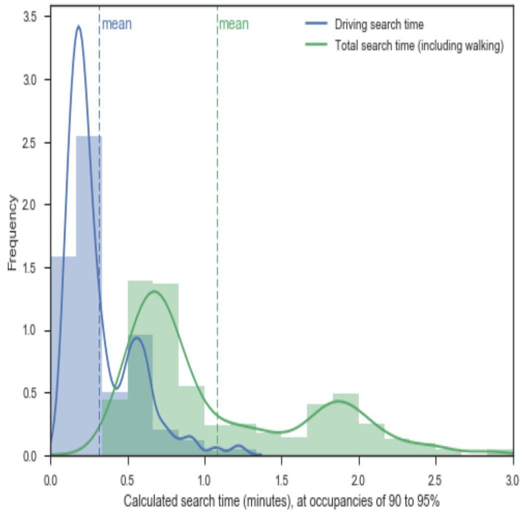

Figure 2: The distribution of search time for blocks with an occupancy of 90 to 95 percent.

is much too high. Since the on-street monetary price is far below the off-street price, this implies that the time limit restrictions are almost always *much* too strict from a welfare perspective.

In 1.5 percent of observations, the marginal unpriced external cost is within \$1.00 of the price, so the *monetary* price of parking is (approximately) equal to the marginal external cost. Furthermore, in the remainder of the sample, also 1.5 percent, the unpriced external cost exceeds \$1.00, so the external costs exceed the monetary price. In this case it is not clear whether the *overall* parking price is too high or too low for arriving drivers who intend to park longer than the time limit.[36] Consequently, it is, in principle, not immediately clear whether it would be welfare optimal to increase or decrease the overall price of parking.

This exhibits another disadvantage of time limits: time limits hamper the optimal setting of parking prices. Furthermore, we will see that these high levels are caused by time limits as well. It appears that very high levels of unpriced external costs frequently occur *just before* time limits expire and parking becomes free, so arrival rates strongly increase before time limits expire, indicating that increasing the monetary price of parking *after* the time limits expire would be strongly welfare improving.

[36] Arriving drivers will either i) decide not to park or ii) will park their car up to the maximum time limit. Our data indicate that few drivers do the latter: only 22 percent of parked drivers depart with less than 15 minutes remaining before the time limit expires. Moreover, the quit rate out of parking hardly increases just before or after the time limit also suggesting that most parked drivers with durations close to the time limit are not constrained.

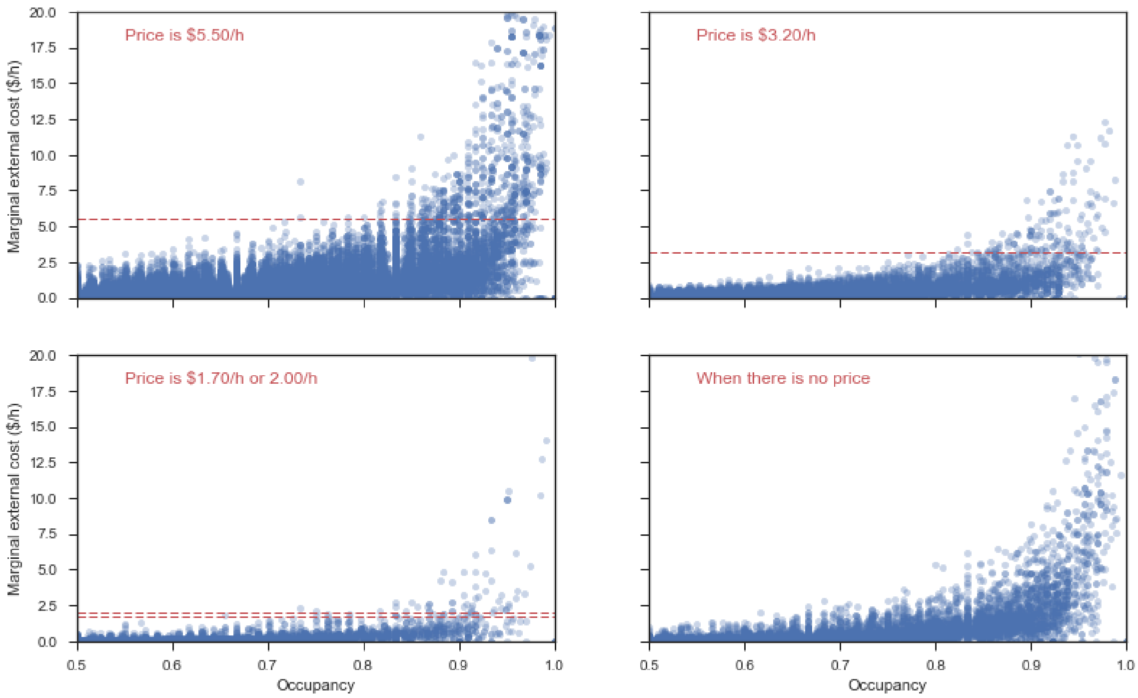

Figure 3: Marginal external costs of parking as a function of occupancy rate.

It is insightful to examine the marginal external costs where we distinguish different parking prices. Figure 3 shows the results as a function of the occupancy rate. It shows for example that in the absence of paid parking, about 75 percent of the time, the marginal cost is less than $1.00, so rather small, but for about 25 percent of the time it exceeds $1.00, so the marginal external cost is non-negligible. It also shows that when the price is between $1.70 and $3.20, the externality is almost always negative indicating that the time limits are too restrictive. The same holds in the city centre areas with the highest prices, but for a non-negligible share of the sample – about 2 percent – the marginal external cost exceeds the price by at least $1.00, of which for 1 percent, the marginal external cost exceeds the price by at least $5.00.

We have also analysed the temporal-spatial distribution of these costs. The marginal external costs differ across hours of the day and days of the weeks, and there are strong patterns in the data. Figure 4 shows that on Sundays, the marginal external costs fluctuate around $4 per hour between 10:00 and 15:00. [37] They are substantial in the morning around the Queen Victoria market in the north of the central city (a popular market area with relatively few private car parks).

[37] The model predicts the worst cruising on Sunday afternoons. We undertook observations on identified high cruising areas in the central city on Sunday 4 June 2017 and found very strong evidence of cruising. Occupancy was near 100 percent with substantial turnover (at least two departures per five minutes) and with vacant bays becoming almost immediately filled. Self-reported average cruising time was about 15 to 20 minutes. The percentage of cars driving past vacant bays was only 20 percent, suggesting that 80 percent of travelling cars are cruising. The worst cruising is predicted by our model is on Therry Street, near the Queen Victoria Market, between 12:00 and 15:00 on weekends with an average hourly marginal external cost of $65. Our field observations confirmed this.

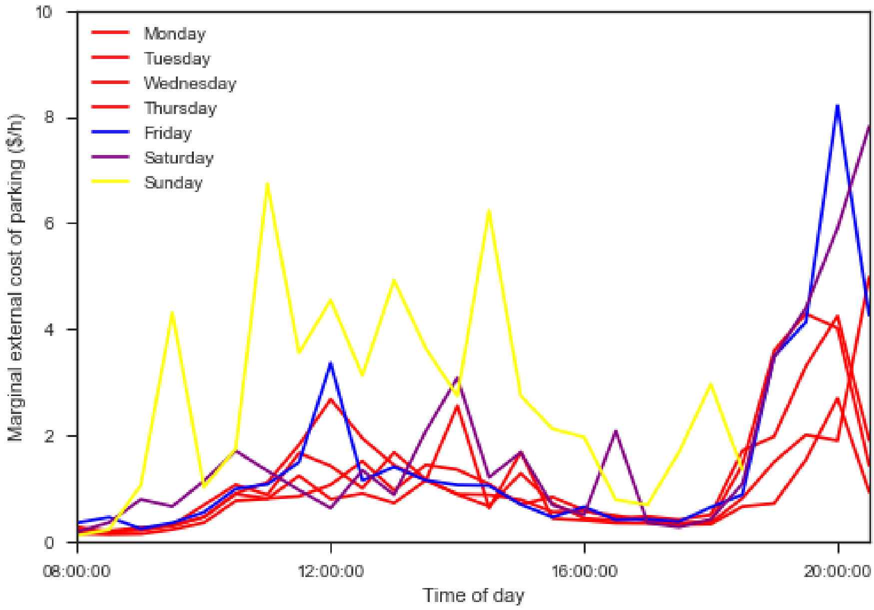

Figure 4: Daily profiles of marginal external parking costs

Figure 4 also shows that these costs have similar patterns throughout the day for the other days of the week. They peak during the middle of the day and in the evening, just before time limits end (because parking is free after the restrictions).[38] Particularly, Fridays and Saturdays have a very large second peak because parking demand is high in the evenings. This is especially so in the southeast of the central city, a busy entertainment area with restaurants, bars and nightclubs. This implies that the extension of paid parking further into the evening would strongly increase welfare. In the central city, these costs are negligible early in the morning – just after restrictions start – implying that removing time limit restrictions in the morning would increase welfare.

6.3 The Marginal Benefits of Parking Supply

We now turn to the estimates of the marginal benefit of one month of parking supply using (9), for which we have to aggregate all marginal benefits during all time periods within the month. It is then interesting to compare the marginal benefits of supply with the capital costs of parking, in order to find out whether or not parking is under or oversupplied (conditional on current parking policy). We have derived the capital cost of parking from the rental asking price for off-street parking, which is typically around $400 per month in the central business district and $200 and in the inner suburbs around the central city.

There is one important caveat to our analysis. We only calculate benefits for time intervals for which we have sensor data, i.e. not in the evenings and overnight. Consequently, we will underestimate the marginal benefit of supply, because cruising will occur outside

[38] For example, drivers who arrive 50 minutes before a one hour time limit ends, pay only for 50 minutes and then park for free.

observed hours. This underestimate will however be small – and likely negligible – in three of the eight areas examined, to be precise East Melbourne, West Melbourne and Southbank, because in these areas the marginal benefit is small during the observed hours and we don't observe a peak in the marginal external cost just before the time restrictions end. For these areas, we find that the marginal benefit of supply is only about 20 to 30 percent of the capital costs.[39] Consequently, removing on-street bays in the inner suburbs of East Melbourne, Southbank and West Melbourne will increase welfare.

7 Sensitivity Analysis

There are several simplifications and assumptions in the above method worth further discussion. First, we have ignored vehicle operating costs and travel congestion costs by drivers during their driving search, which would increase the search cost estimates. For example using a vehicle operating cost of $16 per hour and a marginal external time cost of congestion at 30 percent of travel time, then the total external costs increase by 30 percent for occupancies of 85 to 95 percent.

Second, we used a minimum block size of 10 bays. We have also examined minimum block sizes of 15 and 20 bays. This tends to give similar results except for areas with extensive cruising when the costs are somewhat lower with the higher thresholds. This suggests that we tend to underestimate the marginal external cost (and therefore the marginal benefit of supply) for the whole area by selecting minimum block size of 10 bays, potentially due to higher levels of cruising on smaller blocks.

Third, we have assumed that bays within a block are identical (after excluding short-term bays, loading zones etc.). This ignores that bays within blocks frequently differ with respect to time limits. We underestimate cruising if arriving drivers with longer intended parking durations disregard bays with shorter time limits.[40] In our data 25 percent of observed blocks have multiple time limits. We therefore calculate the marginal external cost allowing for multiple time limits. We have proceeded as follows: using the observed parking duration of each driver as a proxy for the intended parking duration, we calculate the time-limit specific arrival rate (e.g., the number of arriving drivers who intend to park for more than two hours) and the time-limit specific vacancy rate per block (e.g., the vacancy rate of parking bays which allow to park for more than two hours). We then calculate the time-limit specific marginal external cost (e.g., the marginal external cost of a driver who parks at a bay with a time limit of two hours). For the bays belonging to blocks with multiple time limits, the marginal external cost is higher than our original measure, with a (trimmed) mean increase of

[39] These results, which can be received upon request, show that the upper limit of the marginal benefits of a bay is high in the city centre and strongly reduce as we move further away from the city centre.

[40] Another, less important, difficulty is that a limited number of blocks have a combination of priced and non-priced bays. Because on-street prices are substantially below off-street parking prices, it is likely that this difficulty is hardly relevant for our estimation procedure.

33 percent.[41] On average, marginal external costs are then about 8 percent higher (0.25 times 33 percent). Hence, using this alternative measure does not fundamentally change our conclusions.

8 Conclusion

The findings of this paper add to our understanding of the marginal external costs of parking, optimal parking prices and parking supply. We introduce a nonparametric methodology to estimate the marginal external costs of parking due to cruising, which varies over time and space, using the theoretical study by Zakharenko (2016). We demonstrate that this methodology can also be used to estimate the marginal benefits of parking supply. We show that if a parking authority introduces an optimal parking policy, then the cost of parking supply is fully self-financing.

We apply our methodology to estimate the marginal external costs of parking for the city centre of Melbourne, where on-street parking prices are far below off-street parking prices and cruising for parking is reduced with very strict limits on the maximum parking duration (typically one or two hours). We demonstrate that in general, the marginal external cost of parking in Melbourne are low and far below the optimum. Relaxing parking time limits will therefore increase welfare for all but a few blocks and time periods. Conversely, we show that there are substantial welfare losses towards the end of the day when time limits expire, particularly on Friday and Saturday evening, which can be avoided by extending paid parking further into the evening. Finally we show that removing on-street parking bays in several suburban areas of Melbourne is strictly welfare improving.

Our approach relies on the underlying assumption that the search process of motorists can be approximated using a Poisson distribution. The study by Arnott and Williams (2017) suggests that our estimates of the marginal external costs may be underestimates, and are therefore conservative. We suggest that future work should concentrate on testing for, and relaxing of, this underlying assumption.

[41] We use the trimmed mean (we exclude bottom and top 5 percent) because of extreme positive outliers. Note that the median increase is even lower and equal to only 13 percent.

References

Anderson, M. L., & M. Auffhammer (2013). Pounds that kill: The external costs of vehicle weight. *The Review of Economic Studies*, 81(2), 535-571.

Anderson, S.P., & A. De Palma (2004). The economics of pricing parking, *Journal of Urban Economics*, 55, 1-20.

Arnott, R. (2014). On the optimal target curbside parking occupancy rate. *Economics of Transportation* 3, 133–144.

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

Arnott, R., & E. Inci (2006). An integrated model of downtown parking and traffic congestion, *Journal of Urban Economics*, 60, 418-442.

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

Arnott, R. & J. Rowse (1999). Modeling parking. *Journal of Urban Economics* 45, 97–124.

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

Arnott, R. & P. Williams (2017). Cruising for parking around a circle, *Transportation Research Part B*, 104, 357-375.

Baum-Snow, N. (2010). Changes in transportation infrastructure and commuting patterns in US metropolitan areas, 1960-2000. *American Economic Review*, 100, 2, 378-82.

Brueckner, J. K. & S.F. Franco (2017). Parking and urban form, *Journal of Economic Geography*, 17, 1, 95–127

Brueckner, J. K. & S.F. Franco (2018). Employer-paid parking, mode choice, and suburbanization, *Journal of Urban Economics*, 104, 35-46

Chay, K.Y. & M. Greenstone (2005). Does air quality matter? Evidence from the housing market. *Journal of Political Economy* 113, 376-424.

City of Melbourne (2008). CBD and Docklands Parking Plan 2008-2013. Melbourne, VIC Australia.

City of Melbourne (2015). Parking bay arrivals and departures 2014.

City of Melbourne (2016). Census of land Use and Employment (CLUE) 2016. Melbourne, VIC Australia.

City of Melbourne (2017). Facts about Melbourne.

Commonwealth Department of Infrastructure and Regional Development (2016). Australian Transport Assessment and Planning Guidelines: PV2 Road Parameter Values. Canberra.

Davis L. (2008). The effects of driving restrictions on air quality in Mexico City. *Journal of Political Economy, 116.*

De Vos, D. & J.N. van Ommeren (2018). Parking occupancy and external walking costs in residential parking areas, *Journal of Transport Economics and Policy*, 52, 3, 221-238

Duranton, G. & M. A. Turner (2011). The fundamental law of road congestion: Evidence from US cities. *The American Economic Review*, 2616-2652.

Duranton, G. & M. A. Turner (2012). Urban growth and transportation. *The Review of Economic Studies*, 79(4), 1407-1440.

Duranton, G. & M. A. Turner (2016). Urban Form and Driving. Working paper, the Wharton School.

Duranton, G., Morrow, P. M., & M. A. Turner (2014). Roads and Trade: Evidence from the US. *The Review of Economic Studies*, 81(2), 681-724.

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

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

Inci, E., van Ommeren, J.N. & M. Kobus (2017). The external cruising costs of parking. *Journal of Economic Geography*, 47, 333–355.

Keeler, T. E., & Small, K. A. (1977). Optimal peak-load pricing, investment, and service levels on urban expressways. *Journal of Political Economy*, 85(1), 1-25.

Kobus, M.B., Gutiérrez-i-Puigarnau, E., Rietveld, P. & J.N. van Ommeren (2013). The on-street parking premium and car drivers' choice between street and garage parking. *Regional Science and Urban Economics*, 43, 395–403.

Martens, K., Benenson, I. & N. Levy (2010). The dilemma of on-street parking policy: exploring cruising for parking using an agent-based model, *Geospatial Analysis and Modelling of Urban Structure and Dynamics* eds B. Jiang and X. Yao, 121–138. Dordrecht: Springer Netherlands.

Millard-Ball, A., Weinberger, R.R. & R.C. Hampshire (2014). Is the curb 80% full or 20% empty? Assessing the impacts of San Francisco’s parking pricing experiment. *Transportation Research Part A*, 63, 76–92.

San Francisco Municipal Transportation Agency (2011). SFpark Rate Adjustment Policy: OnStreet Parking: Circle less, live more. (Revision 1, June 8 2011).

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

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

Small, K.A. (1999). Economies of scale and self-financing rules with non-competitive factor markets, *Journal of Public Economics*, 62, 351-82.

Small, K. A. & Verhoef, E. T. (2007). *The Economics of Urban Transportation*. London, Routledge.

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

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

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

Verhoef, E., P. Nijkamp &P. Rietveld (1995). The economics of regulatory parking policies: the (im)possibilities of parking policies in traffic regulation, *Transportation Research Part A*, 29, 141-156.

Vickrey, W.S. (1969). Congestion theory and transportation investment, *American Economic Review*, 59, 251-261.

Zakharenko, R. (2016). Time dimension of parking economics. *Transportation Research Part B: Methodological*, 91, 211–228.

Appendix A1 A Rational Search Strategy

A rational driver chooses to search a units of time before their destination to minimise expected travel time . The expected search time, Z, is then a function of a:

$$Z = \int_0^a (2\theta - 1)(a-\tau)\, rve^{-\tau rv} d\tau + \int_a^\infty (2\theta + 1)(a-\tau)\, rve^{-\tau rv} d\tau$$
$$= \frac{1 - arv + 2\theta\,(-1 + 2e^{-arv} + arv)}{rv}. \quad \text{(A1)}$$

The driver chooses a to minimise expected travel time. The first-order condition implies then an expected search time Z^* defined as follows:

$$Z^* = \frac{(2\theta - 1)}{rv} \ln\left(\frac{4\theta}{2\theta - 1}\right). \quad \text{(A2)}$$

Appendix A2 A Rational Search Strategy Allowing a Circling

Now we derive the total expected travel time, Z, as a function of a, when we allow for circling. Note that when $t = \left(\frac{N}{2r} + a\right)$, the driver has gone past their destination for a driving time that is equivalent to the walking limit, and expected walking time is capped. Hence, total expected travel time can be written as follows:

$$Z = \int_0^a (2\theta - 1)(a-\tau)\, \mathrm{rv} \cdot \mathrm{e}^{-\tau \mathrm{rv}} d\tau + \int_a^{\frac{N}{2r}+a} (2\theta + 1)(a-\tau)\, \mathrm{rv} \cdot \mathrm{e}^{-\tau \cdot \mathrm{r} \cdot \mathrm{v}} d\tau$$
$$+ \int_{\frac{N}{2r}+a}^{\infty} \left(t - a + 0.5\frac{N \cdot 2\theta}{r}\right) \mathrm{rv} \cdot \mathrm{e}^{-\tau \cdot \mathrm{r} \cdot \mathrm{v}} d\tau$$
$$= \frac{e^{-\frac{1}{2}(N+4ar)v}\left(-2\theta e^{a \cdot r \cdot v} + 4\theta e^{\frac{1}{2}(N+2 \cdot a \cdot r) \cdot v} + (2\theta - 1) \cdot (arv - 1) \cdot e^{\frac{1}{2}(N+4a \cdot r) \cdot v}\right)}{rv}. \quad \text{(A3)}$$

The first-order condition implies then a search time Z^* defined as follows:

$$Z^* = \frac{(2\theta - 1)}{rv} \ln\left(\frac{4\theta - 2\theta e^{-\frac{Nv}{2}}}{2\theta - 1}\right). \quad \text{(A4)}$$

Appendix B: Descriptive Information

Figure B1: Map of Melbourne

The nodes show the individual bays. Lighter borders show the blocks.

Heavy borders show the eight areas.

Figure B2: The distribution of the number of bays per block

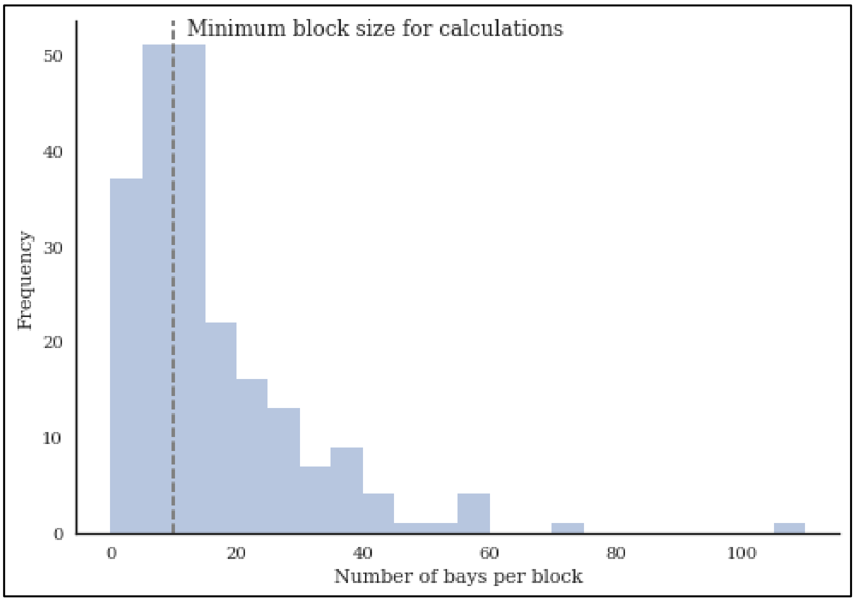

Figure B3: The distribution of the occupancy rate

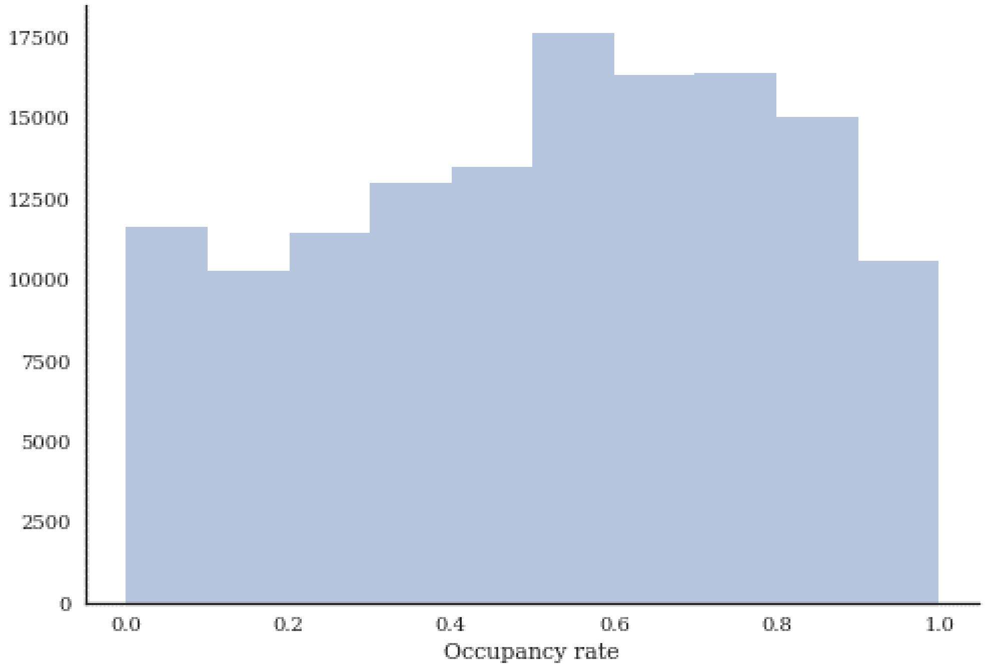

Figure B4: The distribution of the arrival rate (ratio of number of arrivals per hour to number of bays)

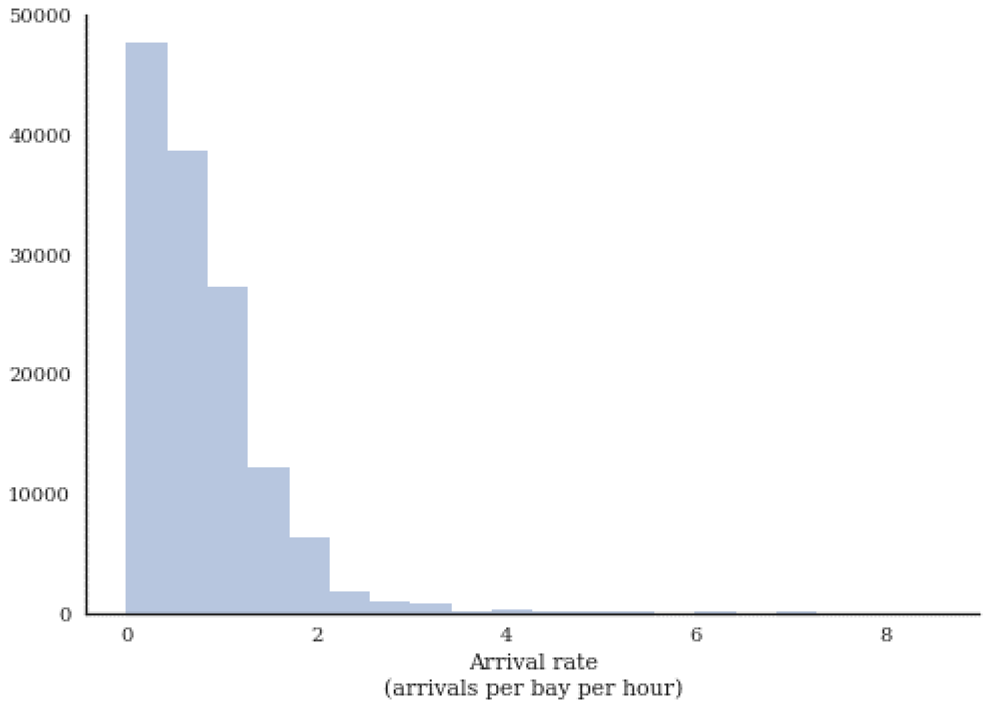

Figure B5: The distribution of the sampling rate

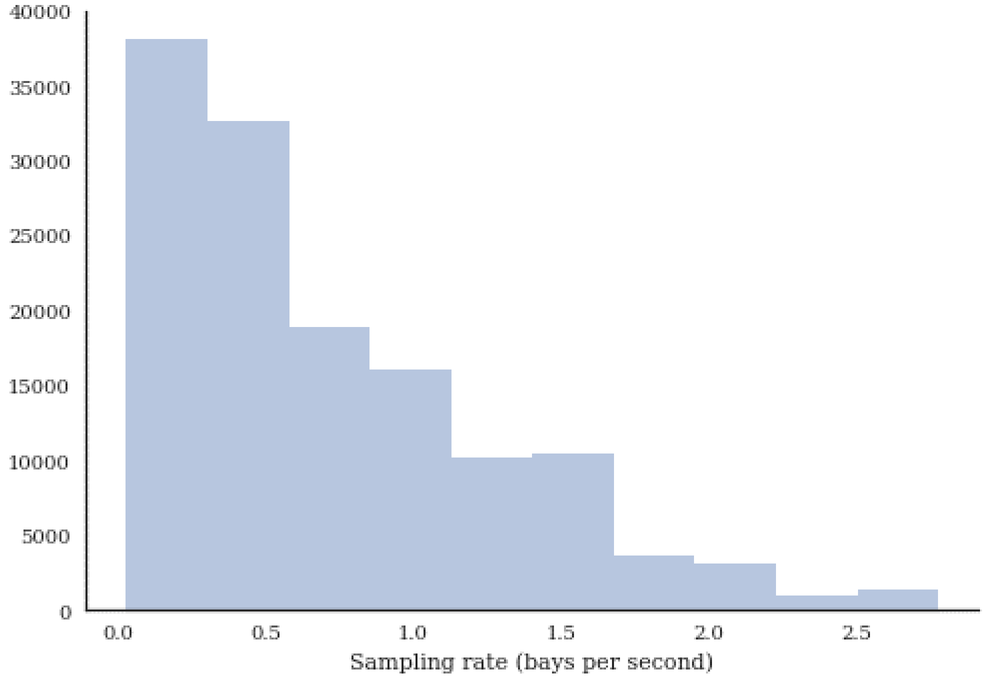

Figure B6: The average occupancy across areas of the central city.