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A novel methodology to estimate cruising for parking and related external costs

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Abstract

Practitioners need to know the level of cruising for parking when designing parking policies. Existing methodologies, such as counting, experiments, and survey, are either too expensive or infeasible to be undertaken on a large scale. Inci et al. (2017) introduce an instrumental-variables-based econometric methodology using administrative data to estimate the average level of cruising when parking is close to full occupancy. This paper introduces a novel methodology to estimate the marginal external cruising time (and thus cost) across time and space. Our methodology is easier to implement, requires even less data, estimates the whole distribution rather than the average, and does not require parking to be near full occupancy. It also allows for welfare evaluations of parking fees and supply. To illustrate all these, we apply our methodology to Melbourne, which generates rich policy insights. We also apply it to the same dataset that Inci et al. (2017) use for Istanbul and find consistent results, rendering confidence to both methodologies.

Keywords: marginal external cost of parking, parking externalities, parking fee, parking supply, parking time limits.

JEL codes: H23, H76, R41.

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1 Introduction

A long strand of literature shows that cities must limit excessive cruising for parking to be able to successfully manage traffic congestion (Vickrey, 1954; Roth, 1965; Arnott et al., 1991; Verhoef et al., 1995; Arnott and Rowse, 1999; Arnott and Inci, 2006; Martens et al., 2010; Arnott, 2014; Arnott et al., 2015; Zakharenko, 2016; Arnott and Williams, 2017). In practice, enacting such urban policies requires knowing the level of cruising for parking at different times and locations in the city. But how? As Shoup (2005, 2006) explains in detail, there are three common ways of measuring or estimating cruising for parking. Some cities undertake manual or automatic counting of cars cruising for parking. For instance, they use videotaping technologies to capture various activities of cars. Other cities undertake experiments in which drivers are asked to park at certain locations at certain times and then cruising is measured out of these experiments. The third method is undertaking surveys in which drivers are asked to report their (perceived) level of cruising (see, e.g., van Ommeren et al., 2012). Moreover, Hampshire and Shoup (2018) measure the share of traffic that is cruising for parking by counting how many cars pass a newly vacated space before a driver parks there. All these methods are fine except they are too expensive, if not infeasible, to be undertaken on a large scale.

A better alternative is to try to estimate cruising by using administrative parking data. This alternative is better for at least two reasons. First, once the methodology is developed, it is easy to continue making such estimations for different periods or with data of other cities. Second, such data is readily available for many cities around the world. Inci et al. (2017) present such a methodology. They use only two key variables (parking arrivals and vacancies) that can easily be extracted from administrative parking data. Using fixed effects, they wash out all other impacts and then estimate the causal impact of parking occupancy on the arrival rate into parking. Their crucial observation is that the arrival rate tends to be constant when parking is relatively far from full occupancy, then it starts to decrease sharply as the occupancy approaches the parking capacity. They use this sharp decrease to estimate the level of cruising induced by a marginal car parking at the location. For example, in their illustration with data of a parking location in Istanbul, they find that a marginal car parking for an hour induces on average 3.6 cars to cruise for parking in that hour, which translates into an external cruising cost that is in the same order of magnitude with the external traffic congestion cost of the same trip. It is important to note that the methodology presented in Inci et al. (2017) yields only an average to represent all time periods. Their identification strategy relies on two key points. First, they need to employ an instrumental variable approach to obtain causality. They use the number of drivers who face a discrete fee increase in a previous period to instrument for the occupancy level at the current time. Second, the identification is established only for occupancy levels just below the parking capacity.

This paper presents a new methodology to estimate cruising based on the theoretical framework introduced by Zakharenko (2016). In particular, we estimate the external cost of marginally increasing parking duration, which we call the *marginal external cost of (on-street) parking* (MECP hereafter). The MECP is an external cost because, while deciding their parking durations, drivers ignore cruising for parking by other drivers who aim to park at the same location (Zakharenko, 2016; Inci et al., 2017). A longer parking duration increases the occupancy rate of parking, and therefore other drivers' cruising costs, which includes not just in-vehicle search costs but also walking-time costs.

We improve on Inci et al. (2017) in four dimensions. First, our methodology is non-parametric and thus obtains cruising from the structural equations developed in the theory part.[1] The estimates are time varying rather than time invariant. Second, our methodology does not require causal inference based on instrumental variables, which means that it is easier to implement and requires fewer data. Third, our methodology estimates the whole distribution of cruising over time and space rather than just an average. Fourth, our methodology is generally applicable and does not require high occupancy rates. Our method also has disadvantages. As we will discuss at length, we will assume a Poisson process of arrivals, which may not hold if parking is extremely saturated (i.e., vacancies are close to 0) and if motorists are not rational or not well informed (e.g. they will search for parking even if the chances of finding a spot is extremely low). Fortunately, even if the Poisson process assumption does not hold, then it appears that we have underestimates of the marginal external costs of parking, so our approach is conservative.

Because our methodology estimates the whole distribution of the MECP due to cruising for any occupancy rate, it allows for welfare analysis of parking pricing and supply policies. We show that the distribution of the MECP can be used to calculate the marginal benefit of on-street parking supply. We also show that using the information about where and when cars park combined with information on parking supply, one can calculate the time-varying and location-specific marginal external time cost of parking, as well as the marginal benefit of increasing parking supply. On the side, we also show that the supply of on-street parking is self-financing provided that an optimal parking policy is in charge. That is, the parking revenue is sufficient to finance the (optimal level of) parking supply costs.

As an illustration, we apply our methodology to the city of Melbourne in Australia.

[1]With non-parametric, we mean that the estimates are not obtained from estimates that rely on parametric assumptions.

Similar to many North American cities, Melbourne has a policy of low on-street parking fees and restrictive parking time limits during day time. We estimate the MECP in Melbourne at the block level for half-hour intervals, and obtain time-varying and spatially detailed information. We demonstrate that during most hours of the week, the MECP in Melbourne is low (i.e., less than the parking fee), which means that there is little cruising for parking. Hence, relaxing parking time limits would increase welfare. There are, however, exceptions. In the evening, just before the parking time limits end and parking becomes free, we observe that the MECP far exceeds the parking fee, causing high levels of cruising. Therefore, extending paid parking further into the evening would substantially increase welfare. On Sundays, during which parking is free, the MECP is substantial for a significant part of the day. We also show that decreasing parking supply in several suburban areas around the city center is welfare improving.[2]

To provide a comparison of our methodology with that of Inci et al. (2017), we also apply our methodology to the same data they used, which contains a parking location on a busy street in Istanbul. They show that the MECP is extremely high during weekdays, which calls for higher parking fees for improving efficiency. Our methodology finds almost identical results for the *average* MECP on weekdays, which render confidence in both methodologies. We further show that there is quite some variation in the MECP across hours, which Inci et al. (2017) cannot estimate. While their methodology could not be applied to Sundays, using our methodology, we show that the MECP is much lower on Sundays.

The remainder of the paper is organized as follows. Section 2 describes the theoretical model that guides our empirical methodology. Section 3 extends the model by allowing drivers to have different parking search strategies by also taking into account their impact on drivers' walking time. Section 4 describes the institutional context and provides descriptive statistics about Melbourne data. Section 5 explains our concerns about our empirical methodology. Section 6 presents the main results. Section 7 makes a sensitivity analysis. Section 8 applies our methodology to the dataset used in Inci et al. (2017) to provide comparison. Section 9 concludes. An appendix contains additional derivations about parking search strategies and further details about our data.

[2] Our welfare analysis is partial for at least two reasons. First, we consider changes in only one parking policy parameter (e.g., the hourly parking fee), conditional on other policy parameters (e.g., current parking supply and time limits). Second, we ignore traffic congestion externalities.

2 Theoretical Framework

This section describes the theoretical framework that we use. We first introduce the basic model (in Section 2.1) and derive the optimal parking fee (in Section 2.2) following Zakharenko (2016). We then extend Zakharenko (2016) by deriving the optimally chosen parking supply by parking authorities (Section 2.3). In the final two subsections, we discuss how parking time limits impact on the results and explain the implications of our Poisson assumption, respectively.

2.1 The model

Our methodology builds up on the model developed by Zakharenko (2016), which makes clear how to calculate the MECP. To simplify notation, we shall present a version of the model with identical drivers who aim to park, although all our results hold also in the more general model with heterogeneous drivers.

The model operates under continuous-time, denoted by t. Space is homogeneous. Each car is occupied by only one driver. Hence, we use the words "car" and "driver" interchangeably. Drivers search in a block with a given number of parking spots with an endogenous rate of $I(t)A(t)$, where $A(t)$ is the *exogenous* rate of entry into the model and $I(t)$ denotes the *endogenous* decision to search. $I(t)$ is the probability that a driver, who appeared at time t, chooses to search for parking. Motorists incur the search cost to park in this block. Parked motorists leave at time t' after a (self-chosen) duration $\tau(t')$. Each driver has the same value of (search) time of c. A car that continues to park at time t during a certain day (from $t = 0$ to T) imposes a marginal search externality on arriving drivers.

We assume that a driver's walking time to his final destination is proportional to his in-vehicle search time with an exogenous walking-time multiplier of $\psi \geq 1$. One may argue that drivers search more to be able to find a parking spot closer to their destination so that they walk less. Our point here is that after controlling for everything else, if a driver ends up searching more, he will probably need to walk more, given the parking conditions at that time. If he is lucky, he may still find a vacant parking spot near his destination, but, in expectation, the walking time still is long. In the absence of walking, $\psi = 1$. We shall later allow for endogenous walking multipliers.

We denote the number of parked drivers by $n(t)$, where $n(t) = \int_0^{\tau(t)} [I(t-\tau)A(t-\tau)]\, d\tau$, and the total number of parking spots per block by N. The vacancy rate is, therefore, $v(t) = 1 - n(t)/N$. A driver randomly samples the parking spots at a rate of r (e.g., one parking spot per second) from a block with a vacancy rate of $v(t)$. Once he finds a vacant parking spot he parks his car and the search ends. The success of the parking search follows a

Poisson distribution with a rate of $rv(t)$. Therefore, the expected search time for an arriving driver at time t, $Z(t)$, is

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

which includes walking time as well as in-vehicle search time. The assumption of a Poisson process means that the parking search can be described independently of time and space, which is obviously a simplification and can be criticized (see, Arnott and Williams, 2017). We come back to this crucial assumption in Subsection 2.6 and investigate the relevance of spatial variation of occupancy within blocks.

We ignore any changes over time in the search environment while a driver is searching. This is a reasonable assumption because the search time for parking is typically relatively short. There are two implications of this assumption. First, the occupancy rate, denoted by $q(t) = n(t)/N$, and hence the vacancy rate, $v(t) = 1 - q(t)$, remains constant throughout the search process. Second, when drivers arrive at a block and decide to search, they also park in that block. Hence, the number of drivers parking in a given block at time t is equal to the number of drivers initiating search for parking in that block at time t. We come back to this assumption as well in Subsection 2.6.

Equation (1) can be used to estimate the whole 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 of all drivers who arrive at time t, $C(t)$, can be written as

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

We are interested in the MECP created by a parked driver who decides whether to extend his parking duration τ at time t. If the driver decides to increase this duration, the number of parked drivers increases marginally, which decreases the vacancy rate and marginally increases the search time of newly arriving drivers. Note that the marginal effect of an increase in duration τ by all parked drivers at time t on $n(t)$ is equal to $[I(t-\tau)A(t-\tau)]$. Here, however, we are interested in the marginal effect of increasing the duration by a single driver i (conditional on the other parked drivers), which we denote by τ^i. The marginal effect of an increase in duration τ^i (i.e. by *one* parker driver) on $n(t)$ is identical to one.

The MECP imposed by one additionally parked car during time t on searching drivers is then equal to

$$MECP = \frac{\partial C(t)}{\partial \tau^i(t)} = \frac{\partial C(t)}{\partial n(t)} = \frac{\partial C(t)}{\partial v(n(t))}\frac{\partial v(n(t))}{\partial n(t)} = \frac{c\psi}{r}\frac{I(t)A(t)}{Nv(t)^2}. \tag{3}$$

The latter expression, which has been derived by Zakharenko (2016), describes the key relationship that we use in the empirical section to non-parametrically estimate the MECP for each time and block.

The MECP is a function of the arrival rate of drivers per parking spot in the block, $I(t)A(t)/N$, and the vacancy rate, $v(t)$, both of which vary across blocks and over time. Administrative parking data typically includes information about both. The MECP also depends on the sampling rate, r. In our empirical section, we estimate a block-specific sampling rate using the spatial density of parking spots combined with assumptions on driving speed. We derive the walking multiplier ψ given assumptions regarding the search strategy. The value-of-time parameter c is unobservable, which we borrow from existing studies.

Given all these, the MECP can be calculated per block for any moment in time. Here is an example for a block with 20 parking spots, so $N = 20$. Suppose that at a certain moment the vacancy rate, v, is 0.10, and the hourly arrival rate, $I \times A$, is 30. The estimated sampling rate of a parking spot for this block is 1 per second, so $r = 3600$ per hour. Assume also that there is no walking, so $\psi = 1$ (which should result in a conservative estimate) and the hourly value of time, c, is \$25. The MECP for one hour of parking is then about \$1 dollar ($(25/3600) \times 30/(20 \times 0.01) \approx \$1.04$).

2.2 The optimal parking fee and entry fine

We first derive the welfare-optimal parking fee. The total cost of parking is equal to the sum of the search cost of parking $C(t)$, defined by equation (2), and the (time-invariant) capital costs of parking supply, denoted by $K(N)$, which increases in the number of parking spots N. The capital cost include the opportunity cost for competing uses, such as cafe seating, transport lanes or green space. 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:

$$W = \int_0^T \int_0^{\tau(t)} I(t-\tau)A(t-\tau)u(\tau)d\tau dt - \int_0^T C(t)dt + \int_0^T (1-I(t))A(t)u_0 dt - K(N), \quad (4)$$

where $\tau(t)$ is the parking duration of a driver who ends her parking at time t and $u(\tau)$ is the (indirect) utility of parking session which depends on duration τ, and u_0 is the (indirect) utility of no searching/parking (the outside option).[3]

Maximizing welfare with respect to duration, the optimal parking fee can be written as

[3]The above equation is identical to the one defined by Zakharenko (2016), except for the last term which refers to the capital costs.

(for details see (Zakharenko, 2016)):

$$p^*(t) = \frac{c\psi}{r}\frac{I(t)A(t)}{Nv(t)^2} = MECP. \tag{5}$$

Hence, the optimal parking fee is equal to the MECP, defined above. There are two important features of this pricing expression. First, the optimal fee, $p^*(t)$, is inversely proportional to the square of the vacancy rate, $v(t)$. Given a few vacancies, the marginal increase in parking search time caused by longer parking duration increases steeply. Having a higher parking fee when vacancy is low is a key argument of Shoup (2005). Second, the optimal parking fee is proportional to the number of searching motorists, $I(t)A(t)$. When there is a low number of searching motorists (such as overnight), the MECP is low, and so it is desirable to ask for a low price.

The optimal parking fee per unit of time is effectively a Pigovian tax which internalizes the external search cost. Note that we ignore here the externalities due to the travel congestion costs associated with each trip, which can be partially internalized by taxing parking independent of the duration of parking rather than taxing it per unit of time (Glazer and Niskanen, 1992). Equation (5) is essential in the welfare interpretations of our empirical results. It states that, in the social optimum, the parking authority should set the parking fee equal to the MECP. We have undesirable cruising if the actual parking fee is less than the MECP. We should, thus, increase the parking fee to increase welfare. Conversely, if the parking fee exceeds the MECP, the parking spaces are not being effectively utilized, and thus welfare can be increased by decreasing the parking fee. Hence, our estimates of the MECP, combined with the parking fees, can be used to undertake a welfare analysis.

Now that we have derived the optimal parking fee, the natural next question is if an additional entry fee (independent of the duration of parking) increases welfare. It is straightforward to show that a motorist will park if the following condition holds:

$$\int_0^{\tau^*(t)} [u(\tau) - p(t+\tau)]d\tau - \frac{c\psi}{r}\frac{1}{v(t)} - F \geq u_0, \tag{6}$$

where τ^* is the duration of parking of a driver who parks at entry time t and F is the entry fee. Here, the first term on the left-hand side denotes the gains of parking, whereas the second term denotes the private search costs. Zakharenko (2016) continues to show that maximizing the welfare function W with respect to the endogenous decision to search at time t, $I(t)$, implies that in the optimum, we have

$$\int_0^{\tau^*(t)}[u(\tau) - \frac{c\psi}{r}\frac{I(t+\tau)A(t+\tau)}{Nv(t+\tau)^2}]d\tau - \frac{c\psi}{r}\frac{1}{v(t)} = \int_0^{\tau^*(t)}[u(\tau) - p^*(t+\tau)]d\tau - \frac{c\psi}{r}\frac{1}{v(t)} \geq u_0. \tag{7}$$

Consequently, it follows from equations (6) and (7), and in line with intuition, that conditional on the optimal parking fee per unit time, $p^*(t)$, the optimal entry fee F is equal to 0.

In what follows, in line with what we observe for most cities around the world, we assume that the entry fee, F, is set to 0. Furthermore, in order to investigate the role of the endogenous search decision, we focus on the search decision of a "marginal" motorist (i.e., the motorist who is indifferent between searching and not searching) for whom $I(t)$ is strictly between 0 and 1, and (6) and (7) hold with equality. It then follows that if the parking fee, $p(t)$, is below $MECP(t)$, then the entry rate $I(t)A(t)$ exceeds the optimal entry rate, and any increase in the entry rate would decrease welfare. Conversely, if the parking fee, $p(t)$, exceeds $MECP(t)$, then the entry rate $I(t)A(t)$ is less than the optimal entry rate, and an increase in the entry rate would increase welfare.

2.3 Optimal parking supply

We now derive the marginal benefit of parking supply in order to obtain the optimal parking supply. To find the socially optimal parking supply, we maximize the social welfare function, given in equation (4), with respect to N. It follows that

$$\frac{dW}{dN} = \int_0^T \frac{\partial W}{\partial \tau(t)}\frac{\partial \tau(t)}{\partial N}dt + \int_0^T \frac{\partial W}{\partial I(t)}\frac{\partial I(t)}{\partial N}dt + \frac{\partial W}{\partial N} - \frac{\partial K}{\partial N} = \int_0^T \frac{\partial W}{\partial I(t)}\frac{\partial I(t)}{\partial N}dt + \frac{\partial W}{\partial N} - \frac{\partial K}{\partial N}, \tag{8}$$

where we use that $\partial\tau(t)/\partial N = 0$, because the decision to continue parking does not depend directly on supply.

In order to derive $\partial W/\partial N$, that shows up as the second term in equation (8), it is useful to first derive the marginal benefit of a parking spot *at time t* by calculating the reduction in search costs at that time due to an increase in the number of parking spots, N. Using equation (2) and the definition of the vacancy rate, we obtain

$$\frac{\partial C(t)}{\partial N} = \frac{\partial C(t)}{\partial v(t)}\frac{\partial v(t)}{\partial N} = -q(t)MECP(t). \tag{9}$$

Consequently, in line with intuition, the decrease in search costs at time t in response to adding one more parking spot is equal to the occupancy rate times the marginal increase in search cost due to one more parked car.

The marginal benefit of parking supply, $\partial W/\partial N$, (i.e., the total reduction in parking search costs by increasing supply) is obtained by integrating equation (9) over time t:

$$\frac{\partial W}{\partial N} = \int_0^T \frac{\partial C(t)}{\partial N} dt = -\int_0^T q(t) MECP(t) dt. \tag{10}$$

In our empirical application, we estimate $\partial C(t)/\partial n(t)$ using equation (3), and we are therefore able to calculate the marginal benefit of parking supply during the day by aggregating the daily marginal benefits over all time periods using equation (10). Note that (10) implies that when the occupancy rate is low (during the entire day), then the marginal search cost of one parked car is also low, and therefore the marginal benefit of parking supply is low.

Now assume that the parking fee is optimally set (i.e., $p(t) = MECP(t)$ for all t) which allows us to use the envelope theorem, implying that we can ignore the effect of N on welfare through its impact on $I(t)$. The first-order condition of optimal supply, $\frac{dW}{dN} = 0$, reads then as follows:

$$\frac{dW}{dN} = \frac{\partial W}{\partial N} - \frac{\partial K}{\partial N} = \int_0^T q(t) MECP(t) dt - \frac{\partial K}{\partial N} = 0. \tag{11}$$

Hence, in the social optimum, given the optimal fee, the marginal benefit of a parking spot due to the reduction in the search cost must be equal to the marginal capital costs.

Now suppose that $p(t) \neq MECP$. This implies that the search rate is not optimal, hence a change in supply will also change welfare through changes in the search rate. Then,

$$\int_0^T q(t) MECP(t) dt - \frac{\partial K}{\partial N} \begin{cases} > 0 & \text{if } p(t) > MECP(t) \\ < 0 & \text{if } p(t) < MECP(t) \end{cases}. \tag{12}$$

The last two equations are useful in empirical studies to evaluate the optimality of parking supply. Given estimates of the marginal benefit of a parking spot and information about the marginal capital cost of on-street parking, combined with estimates of the sign of $p(t) - MECP(t)$, one can determine whether parking supply should be increased or decreased from a welfare perspective. Hence, the optimal *direction* of the change in parking supply can be determined. For example, if $p(t) > MECP(t)$, then the marginal benefit of a parking spot due to the reduction in the search cost must exceed the marginal capital costs. If the latter is not the case, then this implies that the optimal parking supply is less than the current parking supply. For the special case that $p(t) = MECP(t)$, the exact optimal supply can be determined using equation (11).

In the empirical analysis, we derive the marginal capital cost of on-street parking using information about close substitutes in the private car-park rental market, for which we observe rents. An estimate of the marginal benefit of a parking spot net of the marginal capital cost can then be used to determine whether to increase or decrease the current supply of on-street parking is welfare improving.

2.4 Self-financing of parking supply

Our paper is complementary to the theoretical literature on the optimal pricing and supply of congestible facilities, and particular highway capacity. An important theme in this literature is under which conditions the road price is self-financing (i.e., revenue suffices to pay for the capacity costs) (see e.g., Small, 1999). Self-financing of highway capacity is examined in many theoretical settings. Perfect divisibility of capacity is one of the critical underlying assumptions, which may not hold for road capacity as the number of lanes is discrete as Small and Verhoef (2007) argue. However, such an assumption is more natural for on-street parking spaces. Franco (2017) examines the self-financing property of parking supply in the context of optimal choice of parking supply in central business districts. Though, she does not study the time variation within a day.

Assume now the capital cost of parking is proportional to the number of parking spots, with proportionality factor of k (i.e., $K(N) = kN$). We continue to assume that the parking fee and supply is optimally set. Using equations (5) and (9), we get

$$\int_0^T \frac{\partial C(t)}{\partial N} dt = \int_0^T q(t)p^*(t)dt. \tag{13}$$

This equation basically says that, given the optimal parking fee, the marginal benefit of a parking spot is equal to the marginal revenue of a spot.

Using equations (11) and (9), we get

$$N \int_0^T q(t)p^*(t)dt = kN. \tag{14}$$

The left-hand side of this expression is the parking revenue per block while the right-hand side is the capital cost per block.

Consequently, assuming constant returns to scale in the supply of parking and given optimal parking policy (including a time-varying parking fee), total parking revenue is equal to the total cost of parking supply, including the cost of land. So, we have a self-financing result for parking (as in Franco (2017)). This finding is useful for at least two reasons. First, it means that when the self-financing property 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, since these authorities own on-street parking, but do not include the opportunity cost of land (which is the main cost of on-street parking) in their budget.

2.5 Parking time limits

In our empirical investigation, we shall focus on the Melbourne parking market, where paid parking is combined with maximum parking time limits (usually, one or two hours). As Zakharenko (2016) argues, an optimal policy using parking fees does not require time limits from a welfare perspective. There are at least two additional arguments against time limits. First, enforcement costs of time limits are higher since parked drivers need to be checked multiple times to determine if they are violating time limits. Second, they induce parked drivers to move their car to another location nearby when reaching the limit, which is costly. Nevertheless, the presence of time limits raises the question to what extent the above results still apply. Parking time limits induce an implicit parking fee on drivers in the situations in which they would like to park longer than the time limit. This increases the *full price* of parking, which includes not just the parking fee but also the implicit cost of the time limit constraint.[4]

Let us denote the time limit by $\bar{\tau}$. There are now two mechanisms how such a limit may affect behavior and welfare. The first mechanism, discussed in detail by Zakharenko (2016), is that motorists who park and who are constrained leave after duration $\bar{\tau}$. In that case, given $F = 0$, the entry decision (shown in equation (6)) for motorists for whom the limit is effective can be rewritten as

$$\int_0^{\bar{\tau}} [u(\tau) - p(t+\tau)]\, dt - \frac{c\psi}{r}\frac{1}{v(t)} \geq u_0. \tag{15}$$

Recall here that motorists search in a block with a given number of parking spots with an endogenous rate of $I(t)A(t)$, where $A(t)$ is the rate of entry into the model and $I(t)$ denotes the decision to search. Hence, the motorists who are constrained by $\bar{\tau}$ will search less for parking (as the benefit of parking has reduced). In our data, however, we observe only few motorists for whom $\tau(t) = \bar{\tau}$ holds. This suggests the presence of an additional cost $Q(\bar{\tau})$.

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

For example, this cost may arise because motorists do not like to remove their cars to park somewhere else. If we assume that the latter cost is infinite, then equation (6) still holds, but we have the additional constraint that motorists will not park if $\tau^*(t) > \bar{\tau}$. Consequently, again it follows that the use of time limits induces motorists to search less for parking.

There are now two cases to consider in order to understand the effect of the presence of time limits on previous welfare results. The first case is when the parking fee exceeds the MECP. We show that this is by and large the dominant case in Melbourne. In this case, the presence of time limits does not change the conclusion that the full price is too high. Hence, the full price should be decreased from a welfare perspective, which can be achieved either by decreasing the parking fee or by relaxing the time limit (e.g., by extending it from 60 minutes to 120 minutes) or by combining both. The second case is the case in which the parking fee is lower than the MECP, which occurs on Sundays (when parking is free). It is then ambiguous whether the full price is higher or lower for arriving drivers, who intend to park longer than the time limit. Consequently, it is impossible to make a clear welfare comparison in terms of either parking fees or time limits.

The presence of time limits makes it also harder to decide whether the observed parking supply is optimal (again, since it is not clear whether the full price is too high or too low compared to the MECP). Nevertheless, when the MECP is less than the parking fee – which, as has been emphasized above, is the dominant case in Melbourne – welfare can be increased by decreasing parking supply.

2.6 Poisson assumption, spatio-temporal variation in occupancy

The assumption of a Poisson process (i.e., the binomial approximation) is obviously a simplification. Arnott and Williams (2017) investigate the performance of this assumption by undertaking simulations and find that this assumption results in an underestimation of the mean search time, especially when the average vacancy rate is very low (i.e., below 0.1). In our Melbourne data, the average vacancy rate is high (about 0.50) and the vacancy rate is below 0.1 in only 7 percent of the 30-minute intervals of observations, suggesting that our estimates for lower vacancy rates are slightly on the conservative side. If we do not focus on blocks but on more aggregated areas, it appears that the average vacancy rate is at least 0.14 (measured for a period of three hours), far above levels at which the results of Arnott and Williams (2017) suggest any bias. In other words, on theoretical grounds, we do not expect any bias.

Nevertheless, we have investigated this issue in several ways. First, the study by Arnott and Williams (2017) implies that our results might be biased because the occupancy rate varies over time within each block. We are able to test for this. Our results appear to be completely insensitive to the length of the time interval. When we use a 30-minute interval, or a 5-minute interval, we get almost identical results.

Second, the study by Arnott and Williams (2017) implies that our results might be biased because the occupancy rate varies spatially *within* each block. We do not observe such variation, so it is useful to investigate to what extent the results will differ when we allow for heterogeneity in occupancy rates within blocks. Suppose, therefore, that a block with a vacancy rate v is spatially heterogeneous such that for half of the bays, the vacancy rate is less than v and equal to αv, where $0 < \alpha \leq 1$, and hence the other half has a higher rate with a rate of $(2 - \alpha)v$. The expected search time for an arriving driver $Z(t)$ who randomly searches in one half and then in the other half is then increased by a factor $(1 - \alpha)^2/(\alpha(2 - \alpha))$.[5]

Now suppose that $\alpha = 1/2$ and hence the vacancy rate is 3 times larger in one half of the bays than the other half, which refers to a case of rather extreme spatial within-block variation in occupancy rates. In this case, the expected search time increases by only 33 percent, which is a very moderate increase. Hence, within-block variation in occupancy rate is unlikely to affect our conclusion.

Third, we are able to investigate spatial variation *outside* blocks. This is relevant if motorists first search in one block and then park in another block. If the occupancy rate strongly varies between those blocks our estimates might be overestimated. We examine this by focusing on spatial variation in occupancy rates between larger areas. It appears that spatial variation in occupancy rates between areas is rather small, see Figure 3. For example, the vacancy rate on Sunday afternoon varies between 0.15 and 0.28.

3 Search Strategies Allowing for Walking and Circling

There is an extensive literature on cruising for parking (see e.g., Arnott et al., 1991; Arnott and Rowse, 1999; Arnott and Inci, 2006; Martens et al., 2010; Arnott, 2014; Arnott et al., 2015; Zakharenko, 2016; Arnott and Williams, 2017). Walking is not featured much in this literature, although it is shown to be relevant for defining the marginal search externalities and interpreting the empirical results. In this section, we explain how we treat parking search in terms of both in-vehicle search and walking time in between the parking spot and driver's destination. We consider not only linear search strategies but also circling around blocks.

[5] Suppose $v_1 = \alpha v$ and $v_2 = (2-\alpha)v$ where $0 < \alpha \leq 1$. Search time increases then with a proportion equal to $(1/\alpha)(1/2) + 1/(2 - \alpha)(1/2) = 1/(\alpha(2 - \alpha))$. The relative increase is then equal to $(1 - \alpha)^2/(\alpha(2 - \alpha))$.

To be able to implement the theoretical framework we describe in the previous section in our estimation, we need to identify the walking multiplier ψ. This requires evaluating parking search strategies so that ψ can be identified for each of them.[6] In general, we show that ψ depends on the ratio between the speed of driving (while searching) and the speed of walking. We denote this ratio by θ, where $\theta \geq 1$. We provide 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 along a road. A naive linear search strategy is to first drive to the destination and then start searching. In this case, the driver first drives through the distance between his destination and parking spot and then needs to walk the same distance twice, right after parking and right before departing. As a result, we get $\psi = 2\theta + 1$. Then, if $\theta = 4$, we get $\psi = 9$. Remember that $\psi = 1$ when there is no walking. With linear search, however, it is a lot larger than 1. 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.

The naive strategy overestimates the walking time because a rational driver starts searching even before reaching his destination. A rational strategy is that the driver optimally chooses where to start searching before reaching the destination by minimizing expected travel time (i.e., the sum of in-vehicle driving and walking time). In Appendix A, we show that

$$\psi = (2\theta - 1) \ln \left(\frac{4\theta}{2\theta - 1} \right), \tag{16}$$

which is less than $2\theta + 1$. For example, if $\theta = 4$, we get $\psi = 5.8$, which is about 35 percent lower than the walking multiplier derived from the naive search strategy. Zakharenko (2016) minimizes the expected in-vehicle driving time only, and therefore obtains a larger multiplier.

3.2 Circling search strategy

A linear search strategy overestimates ψ since a driver can circle around the blocks to reduce walking time after reaching the destination, which is more consistent with empirical findings (Inci, 2015). To capture this effect, we assume that drivers search only within a block and

[6] In general, it is believed that drivers have a strong dislike of walking and typically aim to park very close to their 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 parking occupancy rate, which supports our assumptions about walking in the text.

that the destination is at one end of that block. Hence, a driver who obtains a random spot expects 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, spots, and spatial spot density, then the expected walking distance will be two blocks. We show that

$$\psi = (2\theta - 1)\ln\left(\frac{4\theta - 2\theta e^{-0.5vN}}{2\theta - 1}\right) \tag{17}$$

in Appendix A. 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 equation (16) from below, as the driver searches on a straight line. In contrast, when vN approaches zero (i.e., when the vacancy rate or the block is small), drivers circle around to reduce walking time, and ψ approaches 1 from above.[7] For $\theta = 4$, ψ remains between 1.0 and 5.8.

Since we find the circling search strategy to be more realistic, we use it in our 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 (e.g., Shoup, 2005). Hence, the multiplier level only matters for vacancy rates below 0.1. Assume now that $\theta = 4$ and block size is 20. Given a vacancy rate of 0.1, we get $\psi = 4.4$. With a vacancy rate of 0.01, ψ drops to 2.5.

4 Data and Descriptive Statistics

The data we use to estimate the MECP is collected by the local council in Melbourne and is publicly available (City of Melbourne, 2015). Central Melbourne has 4,245 on-street parking spots. Parking prices and supply have long been in practice, and hence drivers are fairly knowledgeable of them. We concentrate on March 2014 and use information on 3,609 parking spots that are open to the public after excluding residential parking and parking obstructed due to construction. We select parking spots that allow drivers to park for at least 15 minutes. These parking spots are distributed over 218 blocks. Figure 1 shows the blocks on a map. We further restrict our analysis to blocks that have at least 10 parking spots. In the end, we are left with 3,159 parking spots belonging to 135 blocks. Appendix B provides further details on data.

Information about whether a parking spot is occupied is obtained from in-ground sensors. There are as many parking sensors as parking spots that are active between 07:30 and 20:30 (parking spots do not have restrictions outside these hours). In the weekends, there are

[7]Note that $(2\theta-1)ln(2\theta/(2\theta-1)) = (2\theta-1)ln(1+1/(2\theta-1)) \approx (2\theta-1)/(2\theta-1) = 1$ for θ much larger than one.

Figure 1: Map of parking blocks in Melbourne

Note: The nodes show the individual parking spots, lighter borders show the blocks, heavy borders show the eight areas of the city center.

fewer time restrictions; hence not all parking spots are monitored. We know that 90 percent are monitored on Saturday mornings, 65 percent Saturday afternoons, and 45 percent on Sundays. Blocks without time restrictions are likely to have a higher MECP. Thus, we probably underestimate somewhat for Saturdays and particularly for Sundays.

We have information about the occupancy rate and the number of arrivals for 5-minutes intervals. We aggregate the data to 30-minute intervals, which is our unit of measurement. This introduces a small measurement error for the occupancy rate, as it is averaged over time. In total, we have 81,535 observations. We use information about the (time-averaged) occupancy rate, the ratio of the number of arrivals to the number of parking spots and the parking fee per block for each 30-minutes interval. Table B.3 in the Appendix B shows summary statistics at the block level. On average, the occupancy rate is 0.51 and the arrival rate in a block is 0.71 arrivals per parking spot per hour. The sampling rate, r, is derived from an assumed search driving speed of 20 km/h combined with information about the spatial density of parking spots within blocks. The average sampling rate is about 0.75 parking spots per second.

Figure 2 provides information about the distributions of (a) the number of parking spots per block, (b) the occupancy rate, (c) the arrival rate, and (d) the sampling rate. These figures show that there is a lot of variation in occupancy levels. Occupancy is generally (for

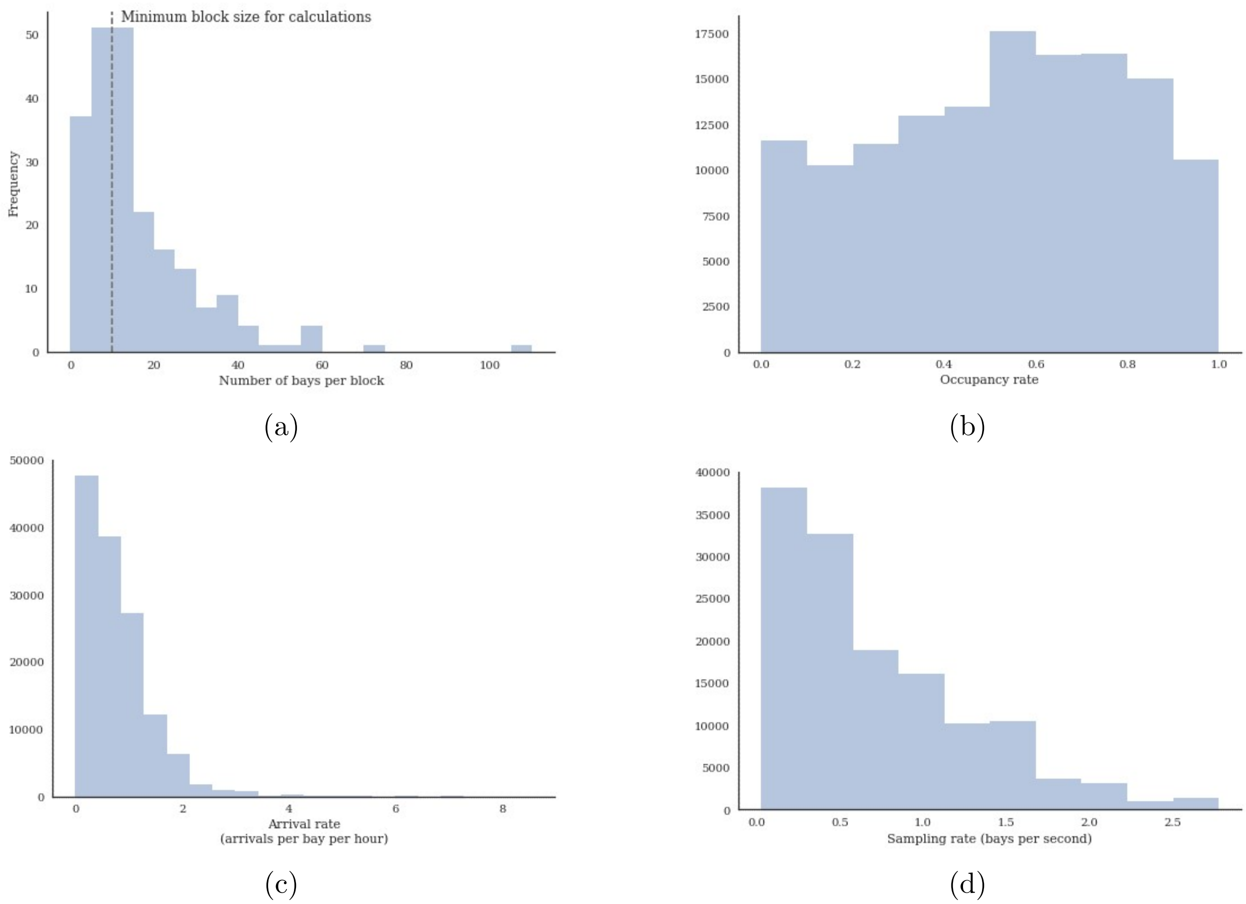

Figure 2: The distribution of (a) the number of parking spots per block, (b) the occupancy rate, (c) the arrival rate, (d) the sampling rate

95 percent of the observations) lower than 90 percent. These distributions mask a lot of heterogeneity over time and space. We, therefore, group blocks into eight areas and provide information about the average occupancy for these areas for different periods of the day in Figure 3, which shows, for example, that occupancy in the South-East city center tends to be higher and particularly so in the evening.

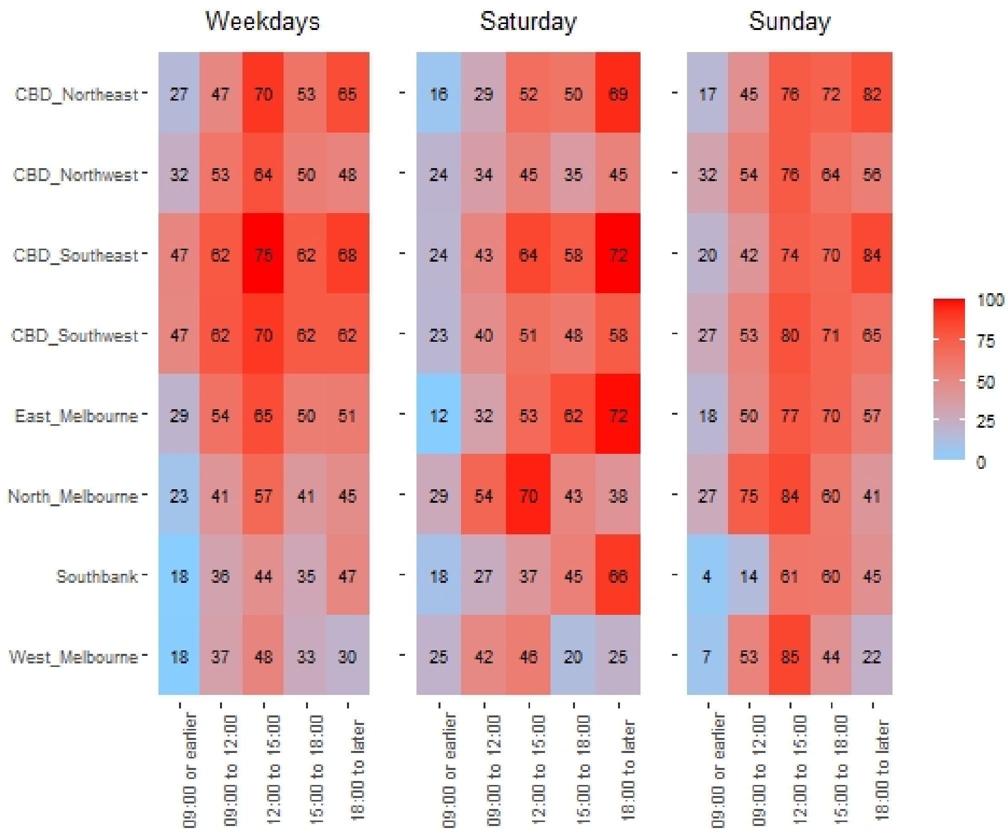

Figure 3: The average occupancy rate across areas of the city center
Note: CBD refers to central business district

The on-street parking fees in 2014 are the same for all days of the week but vary slightly over space, with higher fees closer to the city center, see Table B.2 in the Appendix B.1. In the city center, the parking fee is $5.50 per hour. In the inner suburbs, parking fees are usually around $1.70 or around $3.20 per hour, or free (but with time limits). On Sundays, parking is free everywhere.

The council sets time limits using a target occupancy range (City of Melbourne, 2008). The limits vary from five minutes to four hours (see Table B.1 in the Appendix B.1). They also vary throughout the week, or even within a day. They also frequently vary between parking spots that are spatially close to each other, sometimes even within the same block. Time limits are used when the parking fee is positive, but not always when parking is free.

We do not have any information when parking is free and there are no time limits.

Finally, we allow for circular in-vehicle search, as discussed in Section 3. We assume that the ratio of driving to walking speed is 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 & Regional Development, 2016). We use travel time values that are specific with trip purpose and occupancy and then calculate an average value. We ignore that drivers may have a higher willingness to pay to avoid cruising than traveling. Appendix B.3 summarizes the calibration procedure of the main model parameters.

5 Concerns about Estimation

We aim to estimate the MECP defined in equation (3) using information about blocks for 30-minute intervals. We discuss here five important concerns that arise in estimation.

First, our estimation is based on the assumption that drivers search for parking within one block and end up parking in that block. This assumption allows us to approximate the unobserved number of searching drivers by the number of drivers who park on a block within a given time interval, which we 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 focus on blocks with at least 10 parking spots, which reduces –but does not completely eliminate– the possibility that drivers also search in blocks with different vacancy levels. Our sensitivity analysis suggests that we end up with conservative estimates because of this minimum block-size selection.

Second, we assume that the number of arrivals and the vacancy rate are constant within a 30-minute interval. In our sensitivity analysis using 5-minute intervals, we show that our results are insensitive to this assumption. The simulation outcomes in Arnott and Williams (2017) reveal that one gets underestimates if the time interval is too long since the vacancy rate varies within the time interval. A 30-minute interval is apparently short enough to avoid this bias.

Third, we assume that parking is homogeneous in time limits within each block. This assumption does not hold. For about a quarter of blocks, parking spots differ in their parking time limits within blocks. Some parking blocks even contain extremely short-term parking spots (which allow for parking durations of 15 minutes or less), or other restrictions, such as loading parking spots for commercial use or disabled parking spots for eligible drivers.

Such parking spots are excluded from our analysis. However, we obtain only slightly higher estimates of the MECP in our sensitivity analysis, in which we distinguish between different time limits within blocks.

Fourth, equation (3) does not describe the MECP of a block when there are no vacancies in that block during a time interval. This, however, turns out to be an unimportant issue since observations without vacancies occur seldom given the chosen interval length of 30 minutes. One alternative is to exclude these observations, but we include them in our analysis by making a number of assumptions.[8] In particular, we assume that $MECP = 0$ when the number of arrivals is zero. This slightly underestimates the MECP. The underestimation becomes more severe for shorter time intervals because the share of observations with zero vacancies increases. Nevertheless, the estimated value of the MECP decreases only slightly even when we decrease the interval length to 5 minutes. When the arrival rate is positive, we use equation (3) while at the same time assuming that the vacancy rate is small but positive, and equal to $0.1/N$.

Fifth, the search process assumes that drivers sample parking spots with replacement (that is, drivers can possibly check out the same parking spot again while searching). This would result in overestimation of the MECP if drivers in reality sample without replacement. We investigated this issue further with numerical simulations. We find that the results are quite different for small blocks, but 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 departure rate is high, both methods converge to each other. For example, for a block of 20 parking spots, and a parking time limit of an 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. We assume that drivers arrive randomly with a constant inflow rate for the last hour and each driver parks for exactly 60 minutes. One can then calculate the expected level of the vacancy rate. Consequently, when vacancy rates are below 0.20, it is reasonable to assume that drivers search with replacement because they consider the same parking spots again hoping that one has been vacated since they last searched.

6 Main Results

We now discuss our main results. On a broader perspective, we contribute to the empirical urban economics literature on the welfare evaluation of parking policies. In this small (but

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

growing) literature, van Ommeren et al. (2011) show that residents' cruising for parking capitalizes into lower housing prices; 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) analyze the welfare consequences of San Francisco's adaptive parking pricing policy; Bakis et al. (2019) show that free on-street parking makes housing more expensive.

Our paper also relates to an empirical literature on traffic externalities, such as accident, congestion and environmental externalities (Keeler and Small, 1977; Chay and Greenstone, 2005; Davis, 2008; Anderson and Auffhammer, 2013) as well as the empirical literature on the effects of highway expansion (Baum-Snow, 2010; Duranton and Turner, 2011, 2012, 2016; Duranton et al., 2014). These two lines of literature give little or no attention to parking externalities and optimal pricing and supply of parking. This may be justified for highway travel, but not for busy urban areas, where the parking supply costs tend to be substantial and parking policies are economically and politically relevant (see e.g., Brueckner and Franco, 2017, 2018; Russo, 2013; De Borger and Russo, 2017, 2018; Inan et al., 2019).

The next subsection concentrates on the parking search time. The subsection following next reports our estimation of the MECP. A final subsection derives the marginal benefit of parking supply.

6.1 Parking search time

Figure 4 portrays the cumulative distribution of drivers' search time $Z(t)$, which is the sum of cruising and walking time. This figure reflects that search time is short for a large majority of drivers. 80 percent of them search less than 30 seconds, of which less than one third is in-vehicle. Very few drivers search for more than 2 minutes. This result is consistent with our descriptive finding that the occupancy rate is below 0.90 for most of the time.

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 5 shows the whole distribution of the occupancy rates between 0.90 and 0.95. It appears that a substantial proportion of drivers search for more than 1.5 minutes. One important point to note here is that the MECP is extremely convex in the vacancy rate, see Figure 6. For example, search time becomes 25 times larger if we move from 95 percent occupancy rate to 99 percent.

We should note here that the spatial and time resolution of occupancy is very important. For example, if the average occupancy rate is 0.95 in an area that contains, say, eight blocks, and the occupancy rate is measured during a period of, say, three hours (as in SFpark), then the MECP is expected to be very high since the occupancy rate is unlikely homogeneous

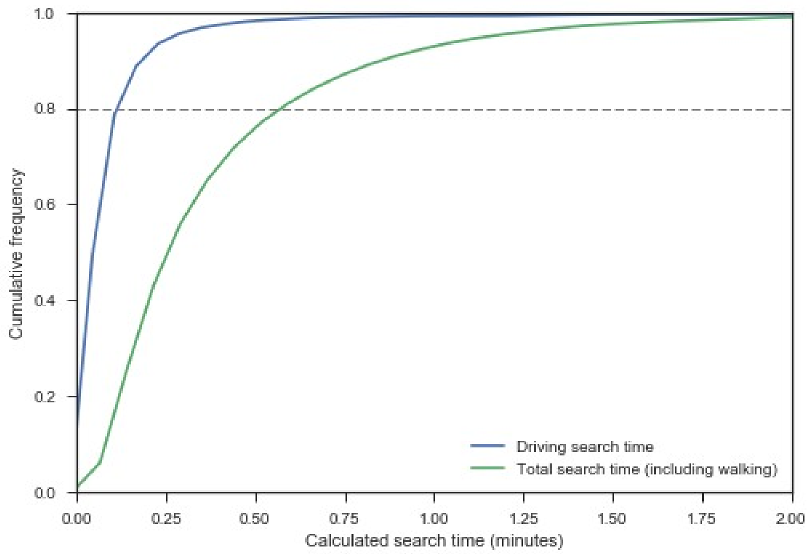

Figure 4: The cumulative distribution of search time

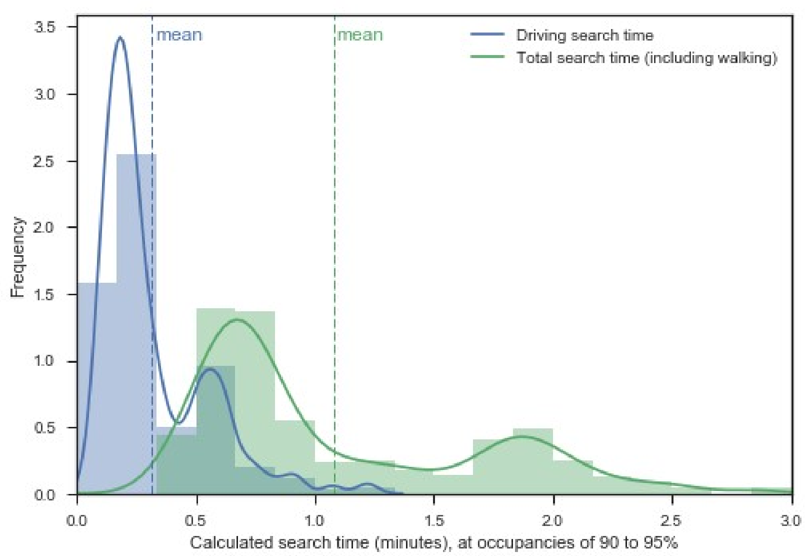

Figure 5: The distribution of search time for blocks with an occupancy rate of 90 to 95 percent

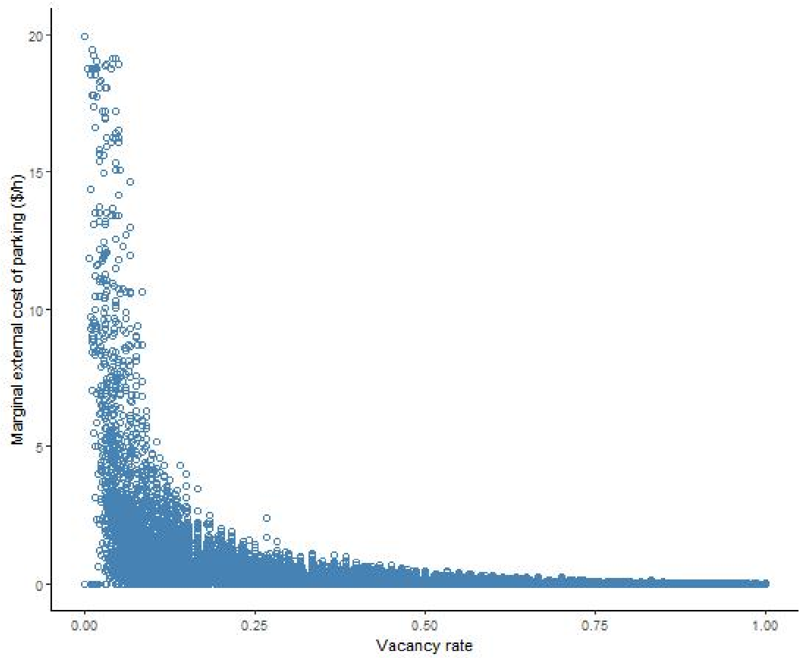

Figure 6: The MECP as a function of vacancy rate

across time and space. So, at some time periods and on some blocks, the MECP can still be extremely high.

6.2 The MECP

We now focus on the MECP. Remember that we have observations for 30-minute intervals. In order to facilitate comparisons with hourly parking fees, we shall provide this metric for an hour of parking. We are particularly interested in whether the uninternalized MECP (i.e., the MECP minus the marginal parking fee) is positive or negative. This is basically a measure of to what extent the MECP has been internalized by the parking fee.

We find that the uninternalized MECP is negative in 97 percent of the observations. Remember that parking time limits impose an implicit cost so that the full price exceeds the parking fee. Hence, in general, the full price of parking is too high. Since the on-street parking fee is far below the off-street parking fee, the parking time limit restrictions are almost always far too strict from a welfare perspective.

In 98.5 percent of observations, the uninternalized MECP is less than $1.00, so the parking fee is (approximately) equal to the MECP. In the remaining 1.5 percent of the sample, the uninternalized MECP exceeds $1.00 such that the MECP exceeds the parking fee. In this case, it is not clear whether the full price is too high or too low for arriving drivers who intend to park longer than the time limit. Arriving drivers will either end up not parking or park up to the maximum time limit. We observe that only 22 percent of parked drivers depart with less than 15 minutes remaining before the time limit expires. The departure rate hardly increases just before or after the time limit, which also suggests that most parked drivers with parking durations close to the time limit are not really constrained. As a result, it is, in principle, not immediately clear whether it would be welfare improving to increase or decrease the full price of parking in this case. We later show that high levels of the MECP are sometimes also caused by the parking time limits: high levels of uninternalized MECP frequently occur just before time limits expire and parking becomes free. Arrival rates strongly increase just before time limits expire, indicating that increasing the parking fee *after* the time limits expire would be welfare improving.

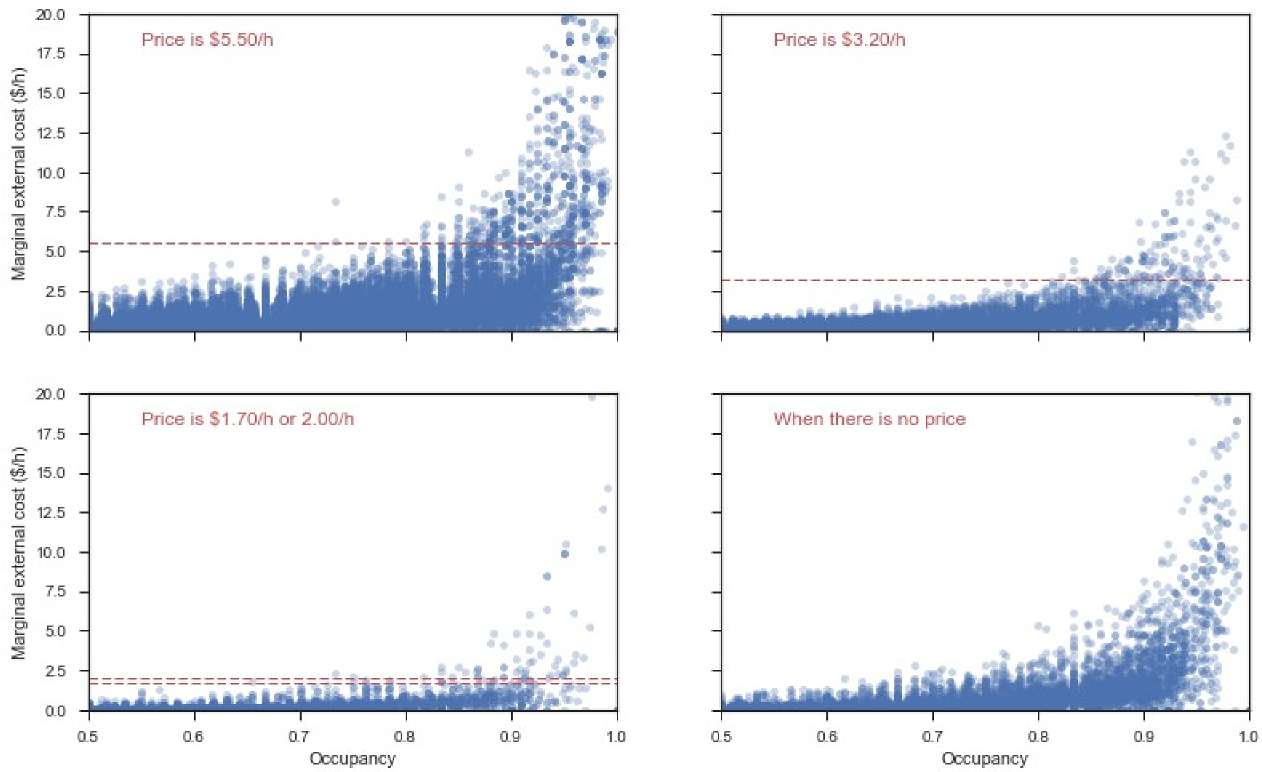

Figure 7: The MECP as a function of occupancy rate

It is insightful to examine the MECP when we distinguish between different parking fees. Figure 7 shows the results as a function of the occupancy rate. It reveals that in the absence of paid parking (lower right panel), the MECP is less than $1.00 (so rather small) in about 75 percent of the time, but it exceeds $1.00 in about 25 percent of the time so that MECP is non-negligible. The figure also reveals that when the parking fee is $1.70 (lower left panel) or $3.20 (upper right panel), the uninternalized MECP is almost always negative indicating that the parking time limits are too restrictive. The same holds in the city center areas with the highest parking fee of \$5.50 (upper left panel). However, for a non-negligible share of the sample (about 2 percent), the MECP exceeds the parking fee by at least \$1.00, of which for 1 percent, the MECP exceeds the parking fee by at least \$5.00.

We have also analyzed the temporal-spatial distribution of the MECP, which varies across hours of the day and days of the weeks, and there are strong patterns in the data. Figure 8 shows that the MECP fluctuates around \$4 per hour between 10:00 and 15:00 on Sundays.[9] It is substantial in the morning around the Queen Victoria Market in the north of the city center (a popular market area with relatively few private car parks).

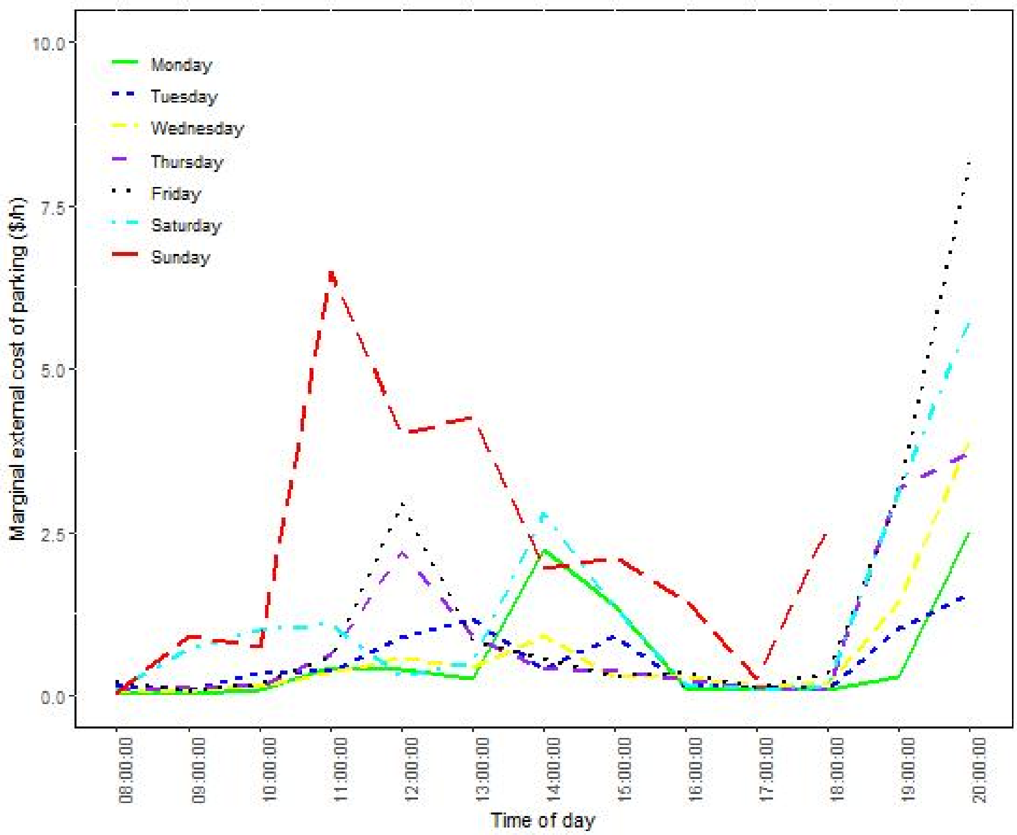

Figure 8: Daily profiles of the MECP

Figure 8 also shows that the MECP has 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

[9]The model predicts the worst cruising on Sunday afternoons. We made field observations on identified high cruising areas in the city center on Sunday, June 04, 2017 (i.e., more than three years after the data period) and found very strong evidence of cruising on this day. Occupancy was near 100 percent with substantial turnover (at least two departures per five minutes) and with vacant parking spots becoming almost immediately filled. Self-reported average cruising time was about 15 to 20 minutes. The percentage of drivers driving past a vacant parking spot was only 20 percent, suggesting that 80 percent of traveling drivers were cruising. The worst cruising 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 MECP of \$65.

the parking time limits end (because parking is free after the restrictions). For example, drivers who arrive 50 minutes before a one-hour time limit ends, pay only for 50 minutes and then park for free. Particularly, Fridays and Saturdays have a very large second peak because parking demand is high in the evenings. This is especially so in the South-East of the city center, a busy entertainment area with restaurants, bars, and nightclubs, see Figure 9. This implies that the extension of paid parking further into the evening would strongly increase welfare. In the city center, these costs are negligible early in the morning –just after restrictions start– implying that removing parking time limit restrictions in the morning would increase welfare.

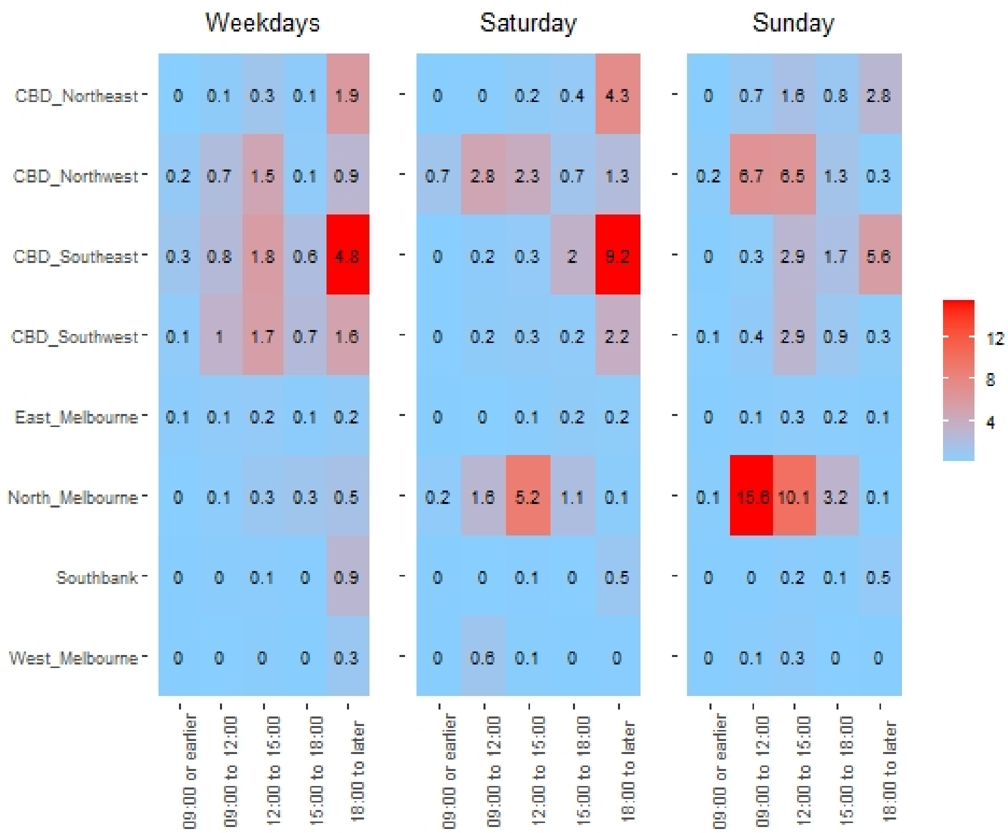

Figure 9: The MECP ($/h) across areas of the city center

6.3 The marginal benefits of parking supply

We now obtain the estimates of the marginal benefit of one month of parking supply using equation (10), for which we have to aggregate all marginal benefits during all time periods within the month. The comparison of the marginal benefit of supply with the capital cost of parking allows us to find out whether the parking is under or oversupplied, conditional on the current parking policy. We derive the capital cost of parking from the rental asking price for *monthly* off-street parking, which is typically around \$400 per month in the city center and \$200 in the inner suburbs surrounding the city center. We focus on monthly prices, as this market is most likely competitive. We find that the marginal benefits of a parking spot tend to be high in the city center, and that they strongly decrease as we move further away from the city center.

We emphasize that we calculate the benefits only for time intervals for which we have sensor data. Hence, we ignore the evenings and overnight. Consequently, we underestimate the marginal benefit of supply because cruising occurs outside observed hours. We expect the degree of underestimation to be small (likely to be negligible) in three of the eight suburban areas examined, namely East Melbourne, West Melbourne, and Southbank, because in these areas the marginal benefit is small during the observed hours and we do not observe a peak in the MECP just before the time restrictions end. Consequently, we focus on those three suburban areas and ignore the other areas. For these three suburbs, we find that the marginal benefit of supply is only about 20 to 30 percent of the capital costs. Hence, decreasing parking supply in the suburbs of Melbourne should increase welfare.

7 Sensitivity Analysis

There are several simplifications and assumptions in our methodology that are worthy of further discussion.

First, we ignore vehicle operating costs and travel congestion costs, 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, the total external costs increase by 30 percent for parking occupancy levels between 85 to 95 percent.

Second, we use a minimum block size of 10 parking spots in the main results. We also examined the minimum block sizes of 15 and 20 parking spots. Such specifications tend to give similar results except for areas with extensive cruising, for which the costs are somewhat lower with higher minimum block sizes. This suggests that we tend to underestimate the MECP (and therefore the marginal benefit of supply) for the whole area by selecting the minimum block size of 10 parking spots, potentially due to higher levels of cruising on smaller blocks.

Third, we assume that parking spots within a block are identical (after excluding short-term parking spots, loading zones, etc.). This assumption neglects that parking spots within blocks frequently differ with respect to parking time limits. We underestimate cruising if arriving drivers with longer intended parking duration disregard parking spots with shorter parking time limits. Because on-street parking fees are substantially lower than off-street parking fees, this difficulty is hardly relevant for our estimation procedure.

In our data, 25 percent of the blocks have multiple parking time limits. We, therefore, calculate the MECP allowing for multiple time limits. We achieve it 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 spots which allow to park for more than two hours). We, then, calculate the time-limit specific MECP (e.g., the MECP of a driver who parks at a parking spot with a time limit of two hours). For the parking spots belonging to blocks with multiple time limits, the MECP is higher than our original estimate, with a (trimmed) mean increase of 33 percent. 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. On average, the MECP is then about 8 percent higher (0.25 times 33 percent). Hence, using this alternative measure does not fundamentally change our conclusions.

8 Istanbul

Our methodology improves on Inci et al. (2017), which introduces an alternative way to derive the *mean* MECP. Inci et al. (2017) estimates the *causal* effect of the occupancy rate on the inflow rate during busy shopping hours. They show that, when the occupancy rate is close to 100 percent, the inflow rate into parking sharply falls, which is indicative of cruising.

Compared to Inci et al. (2017), our methodology has four key advantages: i) it requires fewer data (since the methodology in Inci et al. (2017) requires an instrument to establish causality), ii) it avoids the estimation of a causal effect, iii) it is non-parametric and allows the estimates of the MECP to be time-varying rather than time-invariant. (Inci et al., 2017, estimates only a mean effect), and iv) it is generally applicable (methodology in Inci et al., 2017, applies only for high occupancy rates).

One important question is whether the two methodologies generate similar outcomes. To compare our methodology with that of Inci et al. (2017), we now apply our methodology to the Tesvikiye Street in Istanbul that Inci et al. (2017) used. Appendix B.2 provides some details about the sample. They show that when occupancy rates are high, the marginal external cruising time is somewhere between 3.1 and 5.6 search minutes per hour parked (excluding walking time), which implies that substantial increases in parking fees would increase welfare. However, their approach could not be applied to Sundays. In that street, the average occupancy rate is high and equal to 0.91, but on Sundays it is, however, substantially lower and equal to only 0.76.

We find that the mean parking search time is very similar to the one reported by Inci et al. (2017). The sampling rate r is derived from an assumed search driving speed of 20 km/h combined with information about the spatial density of parking spots. The mean search time is 5.4 minutes, of which 1.5 minutes is in-vehicle. In contrast to Inci et al. (2017), we can also examine the distribution. It appears that very few drivers search for less than two minutes (a result which is in sharp contrast to our findings for Melbourne). This result is consistent with our descriptive finding that the occupancy rate is over 0.90 for most of the time (see Table B.5 in Appendix B.2). Figure 10 shows the cumulative distributions of drivers' search time $Z(t)$ for cruising and walking time, respectively.

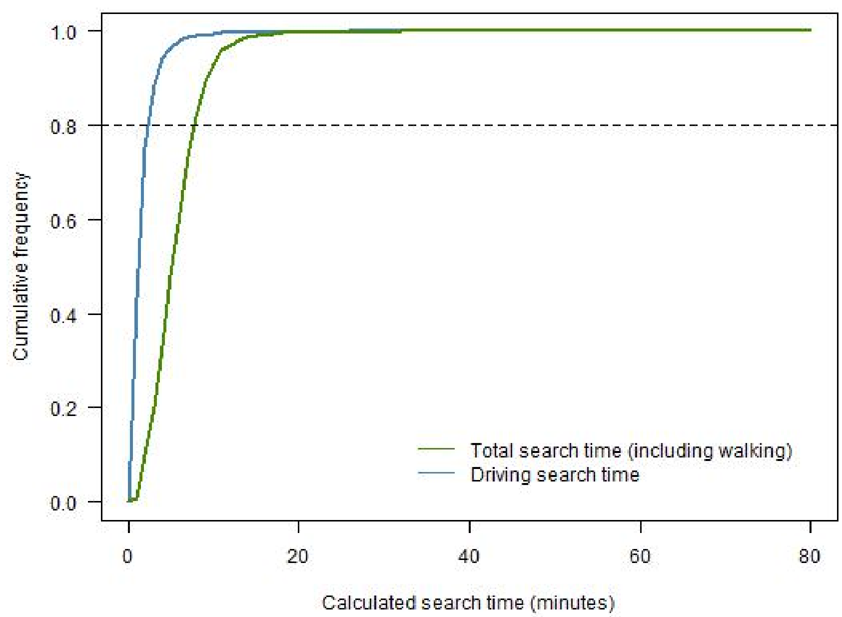

Figure 10: The cumulative distribution of parking search time in Istanbul

Our methodology provides estimates of the marginal external cruising time (from which one can calculate the MECP) that may differ across hours of the day and days of the weeks. Table 1 reveals that, on Sundays, the marginal external cruising time is substantially lower compared with the other weekdays. It also shows that the marginal external cruising time is also considerably higher on Saturdays. The table also implies that the marginal external cruising time does not vary a lot within the day (in sharp contrast to the results for Melbourne). This makes sense, as Inci et al. (2017) choose the location and the hours in order to get high occupancy rate since their methodology relies on that. The marginal external cruising times that include walking time costs tend to be a lot higher since the time spent walking is substantial.

We now transform the marginal external cruising time (measured in search minutes per hour parked) to monetary values by multiplying the figures with a value of time estimate, which is the counterpart of the MECP in our setting. We follow Inci et al. (2017) and assume that i) the hourly value of time while driving is equal to the average hourly wage in Istanbul (8.4 liras/person-hour ≈ \$4.2/person-hour), ii) the value of time while searching for parking is 38 percent higher than the value of time while driving, and iii) the car occupancy is 1.5 persons/car. In the end, we find that, due to an additional car parked for an hour, other drivers will be incurring a MECP of 6.2 liras/hour on average. This is substantial. For example, for 68 percent of drivers, the MECP is higher than 2 liras (about \$1), which is the parking fee per hour that drivers face after parking for an additional hour. This happens for only 30 percent of drivers on Sundays.

Table 1: Mean marginal external cruising time across hours of the day and days of the weeks

	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00
Search minutes per hour parked (in-vehicle + walking)										
Monday	20.7	21.1	20.9	20.5	20.6	20.1	20.3	20.2	19.9	18.9
Tuesday	22.2	21.9	22.3	22.1	22.0	21.1	21.2	21.5	22.0	21.2
Wednesday	20.7	21.2	21.3	21.3	20.6	20.0	20.1	20.7	20.3	19.9
Thursday	25.0	24.8	25.4	25.5	24.7	23.7	24.1	24.7	25.0	24.0
Friday	21.2	21.4	21.9	21.9	21.2	20.7	20.8	20.8	21.2	21.1
Saturday	34.3	35.5	36.0	35.4	35.1	34.2	34.8	33.6	34.7	34.4
Sunday	7.3	7.3	7.6	7.5	7.4	7.3	7.1	7.1	7.0	6.7
Search minutes per hour parked (only in-vehicle)										
Monday	6.5	6.6	6.5	6.4	6.5	6.3	6.4	6.3	6.1	5.7
Tuesday	6.9	6.8	6.9	6.9	6.9	6.5	6.5	6.6	6.8	6.5
Wednesday	6.4	6.5	6.5	6.6	6.3	6.1	6.2	6.3	6.2	6.0
Thursday	8.1	8.0	8.3	8.3	8.0	7.7	7.8	8.1	8.2	7.7
Friday	6.6	6.7	6.9	6.9	6.6	6.5	6.5	6.4	6.7	6.6
Saturday	12.0	12.6	12.9	12.7	12.5	12.2	12.3	11.8	12.3	12.2
Sunday	1.8	1.8	1.9	1.9	1.9	1.8	1.8	1.8	1.7	1.6

Notes: These figures can be transformed to monetary values by multiplying them with the value of time of 17.3 liras/car (car occupancy is 1.5 persons/car). For more details see Inci et al. (2017). 2 liras ≈ \$1 (in 2013).

In sum, our methodology finds very similar results for the *mean* MECP on weekdays, but we are also able to show that there is quite some variation between hours. Furthermore, we show that the MECP is much lower on Sundays.

9 Conclusion

In this paper, building on the theoretical framework developed in Zakharenko (2016), we provide a methodology to estimate the whole distribution of the marginal external cruising time and therefore the MECP over time and space. Our methodology makes it easy for cities to evaluate the optimality of their current parking fees and parking supply from a welfare perspective. We further show that if a parking authority introduces an optimal parking policy, then the cost of the parking supply is self-financing.

We apply our methodology to estimate the MECP for the city center of Melbourne, where on-street parking fees are far below off-street parking fees and cruising for parking is controlled with strict limits on the maximum parking duration (typically one or two hours). We estimate that, in general, the MECP in Melbourne is low and far below the (actual) parking fee. Relaxing parking time limits are likely to increase welfare for almost all blocks and time periods. Conversely, we show that there are substantial welfare losses towards the end of the day when the parking time limits expire, particularly on Friday and Saturday evening, which results in high levels of cruising. We argue that this problem can be solved by extending paid parking further into the evening. We also show that removing on-street parking spots in several suburban areas surrounding the city is welfare improving.

Inci et al. (2017) also provide a new methodology to estimate cruising. Our methodology is based on completely different assumptions. However, it yields similar results when we use the same dataset they use in their study. This renders confidence to both methodologies. Moreover, our methodology has several advantages over theirs. Our methodology is easier to implement, requires less data, estimates the whole distribution rather than an average and is not restricted to situations where the occupancy level is very high.

No methodology to estimate cruising for parking is magically perfect, and ours is not an exception. Our approach relies on the underlying assumption that the search process of drivers can be approximated using a Poisson distribution. Simulations by Arnott and Williams (2017) suggest that our estimates of the MECP are underestimates when vacancy rates are very low. In several parts of the paper, we also argue why we might be underestimating for various other reasons. Hence, our estimates can be considered conservative and parking search might be even more important than we estimate here. Future work should delve into improving our methodology.

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A Appendix: Search Strategies

A.1 A rational search strategy

To minimize his expected travel time (summation of the in-vehicle search time and walking time), a rational driver chooses to search for parking a units of time before their destination. The expected travel time time, Z, is then a function of a:

$$\begin{aligned} Z &= \int_0^a (2\theta - 1)(a-\tau) rve^{-\tau rv} d\tau + \int_a^\infty (2\theta + 1)(a-\tau) rve^{-\tau rv} d\tau \\ &= \frac{1 - arv - 2\theta(-1 + 2e^{-arv} + arv)}{rv}. \end{aligned} \tag{A.1}$$

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

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

A.2 A rational search strategy allowing for circling

We now derive the total expected travel time, Z, as a function of a, when we allow for circling. Note that, when $t = (N/2r + a)$, the driver has gone past his destination for a driving time that is equivalent to the walking limit, and expected walking time is capped. Hence, the total expected travel time can be written as

$$\begin{aligned} Z &= \int_0^a (2\theta - 1)(a - \tau) rve^{-\tau rv} d\tau + \int_a^{\frac{N}{2r}+a} (2\theta + 1)(a - \tau) rve^{-\tau rv} d\tau \\ &\quad + \int_{\frac{N}{2r}+a}^{\infty} (t - a + \frac{1}{2}\frac{N2\theta}{r}) rve^{-\tau rv} d\tau \\ &= \frac{e^{-\frac{1}{2}(N+4ar)v}\left(-2\theta e^{arv} + 4\theta e^{\frac{1}{2}(N+2ar)v} + (2\theta - 1)e^{\frac{1}{2}(N+4ar)v}\right)}{rv}. \end{aligned} \tag{A.3}$$

Then, the first-order condition implies an expected travel time Z^* defined as follows:

$$Z^* = \frac{2\theta - 1}{rv} \ln\left(\frac{4\theta - 2\theta e^{-\frac{NV}{2}}}{2\theta - 1}\right). \tag{A.4}$$

B Appendix: Data

This Appendix describes the data we use to estimate the MECP. We use data for Melbourne and Istanbul. The following two subsections describe the study areas and parking policies and provides descriptive statistics for each city. The last section describes the model variables and their computation.

B.1 Melbourne

Melbourne is located in the state of Victoria, Australia and has a population of about 4.5 million. Its city center – the City of Melbourne – contains 140,000 residents and 450,000 workers. In 2018, there was 33.9 million sqm built floor space in the Melbourne municipality, with residential accommodation being the largest space use, followed by office space and then by parking space (CLUE, 2018). The picture is similar for the Melbourne CBD. Moreover, the office employment is concentrated in Melbourne (CBD), while the majority of new dwellings over the past 10 years were built in the Melbourne CBD. On an average weekday, around 900,000 people are present in the city center (City of Melbourne, 2017). 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). Around 40 percent of on-street parkers come to the central Melbourne to work, 20 percent for personal business, 20 percent for delivery or servicing, and the remaining 20 percent come for shopping or other activities (City of Melbourne, 2008). 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).

The local council in Melbourne generally sets parking prices annually across broad areas and then uses a target occupancy range to guide time limits on individual parks and blocks. For example, on a block with time limits of two hours, when on-street parking occupancy rates are less than 50 percent in the peak period, the time limits are relaxed to three or four hours (City of Melbourne, 2008). As Table B.1 shows, the majority of parking spots have a time limit of 1 or 2 hours. The time limits differ significantly between individual bays, sometimes even if they are on the same block. In central Melbourne, on-street parking prices are typically below (short-term) off-street parking prices.

Table B.1: Parking time limits for Melbourne, share of parking spots

Time limit	Weekdays	Saturdays	Sundays
30 minutes	0.05	0.06	
60 minutes	0.30	0.33	
1 hours	0.44	0.48	0.45
2 hours	0.44	0.48	0.51
3 hours	0.07	0.06	0.04
4 hours	0.13	0.07	

The on-street parking fees in 2014 varied slightly over space, with higher fees closer to the city center. Parking fees are the same for all days of the week. On Sundays, parking is free everywhere. Table B.2 shows the parking fees for 2014. Commercial off-street parking fees vary a lot over space and time, and they are substantially larger than on-street parking fees. For example, in the city center, a typical garage charges at least \$20 per hour during the workday and at least \$10 per hour in the weekend and evenings.

Information about whether a parking spot is occupied is obtained from in-ground sensors (City of Melbourne, 2015). 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. The sensors are reliable for at least two reasons. First, they are continuously monitored because they are used to determine potential fines drivers have to pay. For the same reason, drivers have incentive to complain about malfunctioning sensors. In contrast, when sensors are not used for financial purposes,

Table B.2: The on-street parking fees ($ per hour) in 2014 for Melbourne

Area	Parking fee on weekdays	Parking fee on Sundays
City center	5.50	0
Inner suburbs	1.70 – 3.20	0

Notes: In the inner suburbs on weekdays, parking fees are usually around $1.70 or around $3.20 per hour, or free but with time limits.

as in SFpark,[10] authorities and drivers have less incentive to ensure that sensors are reliable.

We focus on March 2014, which has 4245 unique parking spots monitored. We discard parking spots that have disabled restrictions (103), that have residential restrictions or permit requirements (270), that have loading zone restrictions (86), parking spots that only have time restrictions of 15 minutes or less (effectively 'short stay' parking spots) (62), and parking spots that have obvious sensor or data errors (36). We also discard 79 blocks that have significant construction activities occurring during the month. Finally, we discard all observations outside of 7:30am to 8:30pm (as the vast majority of sensors are off overnight, and there is no pricing) and observations on a public holiday that occurs during the month. On average each parking spot has sensors working for 10 hours per day through the month.

We sample all parking spots at every 5 minutes for occupancy and an arrival or departure event, giving 12,857,040 parking spot-5 min time period observations. We then aggregate the data per block per 30 minutes, leaving 135,700 block-30 minute time period observations. Lastly we discard all blocks with less than 10 parking spots - leaving 81,535 block-30 minute time period observations. The final sample then includes 3,159 parking spots belonging to 135 blocks. Table B.3 shows the descriptive statistics.

Table B.3: Means and standard deviations for the occupancy rate and the arrival rate (arrivals per parking spot per hour) for Melbourne by day type

	Occupancy rate q		Arrival rate A	
	mean	std.dev.	mean	std.dev
Weekdays	0.52	0.25	0.73	0.53
Saturday	0.44	0.27	0.62	0.46
Sunday	0.60	0.28	0.63	0.43
All days	0.51	0.26	0.71	0.51

Notes: Number of observations is 81,535.

[10]SFpark uses new technologies and policies to improve parking in San Francisco.

B.2 Istanbul

Istanbul is the economic and cultural center and the most populated city in Turkey. It has in its metropolitan area around 15 million residents and 2.5 million vehicles of which 90 percent park on-street.[11] We have information derived from parking transactions for Tesvikiye Street in the central Istanbul. This one-way street is located in a busy and congested shopping district Nisantasi, which typically have high occupancy rates. For a more detailed description of the sample and the parking market in Istanbul, see Inci et al. (2017).

Table B.4: Parking fees in liras for 2013 (Tesvikiye Street, district Nisantasi)

Parking duration (h)	<1/4	1/4-1	1-2	2-3	3-4	4-5	5-6	7-8	7-24
Parking fee	0	6	8	10	13	15	17	19	20

Notes: Adapted from Inci et al. (2017); 2 liras ≈ $1 (in 2013).

[11]See `https://www.eltis.org/discover/case-studies/ispark-parking-turkey`, accessed April 1. 2020.

Table B.5: Means and standard deviations for the occupancy rate and the arrival rate (arrivals per parking spot per hour) for Istanbul across hours of the day and days of the weeks

	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00
	Mean occupancy rate q (std. dev. in parenthesis)									
Monday	0.90	0.90	0.91	0.89	0.87	0.79	0.84	0.86	0.86	0.81
	(0.15)	(0.15)	(0.13)	(0.15)	(0.18)	(0.23)	(0.18)	(0.17)	(0.17)	(0.18)
Tuesday	0.91	0.92	0.92	0.89	0.86	0.78	0.85	0.89	0.89	0.87
	(0.13)	(0.12)	(0.12)	(0.14)	(0.18)	(0.23)	(0.16)	(0.15)	(0.14)	(0.16)
Wednesday	0.91	0.91	0.92	0.90	0.85	0.77	0.85	0.89	0.89	0.86
	(0.13)	(0.13)	(0.12)	(0.14)	(0.20)	(0.24)	(0.16)	(0.14)	(0.14)	(0.15)
Thursday	0.91	0.91	0.92	0.90	0.88	0.79	0.87	0.91	0.91	0.87
	(0.14)	(0.13)	(0.11)	(0.13)	(0.16)	(0.22)	(0.13)	(0.10)	(0.10)	(0.15)
Friday	0.89	0.88	0.89	0.89	0.86	0.77	0.84	0.88	0.89	0.88
	(0.17)	(0.17)	(0.16)	(0.15)	(0.18)	(0.22)	(0.17)	(0.16)	(0.16)	(0.18)
Saturday	0.92	0.92	0.94	0.94	0.91	0.82	0.89	0.91	0.92	0.92
	(0.12)	(0.12)	(0.10)	(0.10)	(0.14)	(0.22)	(0.13)	(0.09)	(0.11)	(0.13)
Sunday	0.77	0.79	0.81	0.81	0.76	0.71	0.75	0.75	0.74	0.67
	(0.19)	(0.17)	(0.17)	(0.19)	(0.25)	(0.26)	(0.20)	(0.19)	(0.20)	(0.20)
	Mean arrival rate A (std. dev. in parenthesis)									
Monday	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44
	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.21)
Tuesday	0.45	0.44	0.44	0.44	0.45	0.45	0.44	0.44	0.45	0.44
	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)
Wednesday	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44
	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)
Thursday	0.44	0.44	0.44	0.45	0.45	0.44	0.44	0.44	0.44	0.44
	(0.20)	(0.20)	(0.20)	(0.21)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.21)
Friday	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.43	0.43
	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)
Saturday	0.43	0.44	0.43	0.43	0.44	0.44	0.44	0.43	0.44	0.43
	(0.20)	(0.21)	(0.20)	(0.20)	(0.20)	(0.20)	(0.21)	(0.20)	(0.20)	(0.20)
Sunday	0.46	0.46	0.46	0.45	0.45	0.46	0.45	0.46	0.46	0.45
	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)

Notes: Number of observations is 665,400.

Curbside parking is managed by the public operator ISPARK. Parking fees are collected by parking attendants, who record the transactions so we observe precise records of inflow and outflow times. The regular parking fee jumps discretely at the 15th min, then every hour up to 7 h of parking, and finally, a daily fee applies. Table B.4 shows the parking fees.

Our dataset includes 191,771 parking transactions covering the period between 1 January 2010 and 31 March 2013. The transaction data are extremely accurate. Inci et al. (2017) found very limited evidence of miscoded parking transactions. We follow Inci et al. (2017) and exclude observations on Sundays, 9 days during which the parking location was almost completely empty, 55 days with extreme overcapacity (likely caused by severe double parking), and only include observations for a time interval of 10 h during the day between 12:00 and 22:00. In the end, our sample includes parking transactions for 946 days. We observe exact times of arrival and departure and parking fee payments. There are 23 parking spaces on this street. We compute the parking durations and the occupancy rate using these variables. Table B.5 shows the descriptive statistics.

B.3 Calibration of the model parameters

We now explain step by step how the MECP is estimated. The parking facilities – streets or blocks – are the point of departure in our empirical analysis. The main information required for the econometric analysis is the parking transaction data and the information on parking supply.

1. Using the transaction data, we first calculate the number of arriving cars per unit of time (e.g., 30-minute intervals), $A(t)$, and the number of departing cars per unit of time, $L(t)$. The number of parked cars in an area at time t, $n(t)$, is calculated as the sum of the difference between the number transactions and the number of parking tickets expiring in each interval: $\int_0^t [A(x) - L(x)]\, dx$.

2. The occupancy rate, $q(t)$, is calculated using the data on the total number of parking spots in an area (e.g., a block), N, and the estimate of the number of parked cars in each period of the day, $n(t)$. The vacancy rate $v(t)$ is equal to $(1 - q(t))$.

3. Then, we estimate the expected search time of an arriving driver at time t, $Z(t)$, using equation (1), which we repeat here: $Z(t) = \psi/(rv(t))$. We use estimates of the walking time multiplier ψ divided with the product of the sampling rate r and the vacancy rate $v(t)$ (see below for the definitions of these variables). The unit of driving search time is minutes per found parking spot.

4. Finally, the MECP is computed using equation (3), which we repeat here: $MECP = ((c\psi)/r) \times (I(t)A(t))/(Nv(t)^2)$. Now we also use the value of time c.

Coefficients and variables

$\boldsymbol{N}$ Total number of parking spots in an area (say, a block). This information is available in the administrative parking data.

$\boldsymbol{t}$ Time of day. This information is available in the administrative parking data.

$\boldsymbol{A(t)}$ Arrival rate. For Melbourne, information about whether a parking spot is occupied is obtained from in-ground sensors. We simply count the number of arrivals for 5-minutes intervals. We aggregate the data to 30-minute intervals, which is our unit of measurement.

$\boldsymbol{n(t)}$ Number of parked cars in an area at time t. We observe the exact times of all arrivals and departures. We aggregate the data to 30-minute intervals, which is our unit of measurement. Combining the information on parking supply with the number of arrivals and departures, we compute the number of parked cars in an area at time t.

$\boldsymbol{q(t)}$ Occupancy rate. The occupancy rate at time t is computed as $q(t) = n(t)/N$, so the number of parked cars in an area at time t divided with the total number of parking spots in that area.

$\boldsymbol{v(t)}$ Vacancy rate. Vacancy rate is equal to $1 - q(t)$.

$\boldsymbol{r}$ Sampling rate. The sampling rate is the number of parking spots a driver is able to check per unit time (e.g., one parking spot per second). The sampling rate, for each block, is estimated from the spatial density of parking spots combined with the assumed driving speed as $r = 2 \times (\textit{driving speed } \times N)/\textit{length of block}$. Notice here that with parking on both sides of the road, the sampling rate is twice what would be found if there were parking on only one side. We assume that parking on either side of the road is equivalent. We use a search speed of 20 km/h.

$\boldsymbol{c}$ Value of time (VOT). We use the VOT from existing studies. For Melbourne, we use the VOT that is specific with trip purpose and occupancy and then calculate an average value. For Melbourne, the hourly VOT is \$25.

$\boldsymbol{\theta}$ Ratio of driving speed to walking speed. We assume a ratio of 4, which corresponds to a walking speed of 5 km/h and a driving speed of 20 km/h. This parameter is doubled to allow for return walking journeys.

$\boldsymbol{\psi}$ Walking time multiplier. This parameter depends on the ratio between driving and walking speed θ. The walking multiplier can take values between 1 and 5.8 (when $\theta = 4$).

$\boldsymbol{Z(t)}$ Expected search time of an arriving driver. The total search time per car (including walking time) at time t can be computed using equation (1), which we repeat here $Z(t) = \psi/(rv(t))$, so the walking time multiplier divided with the product of the sampling rate and the vacancy rate.

$\boldsymbol{C(t)}$ Total search cost per unit of time t. The total search cost per unit of time t can be computed using equation (2), which we repeat here $C(t) = (c/\psi r) \times ((I(t)A(t))/v(t))$. It is equal to the expected search time of an arriving driver multiplied with the product of the VOT, c, and the exogenous rate of entry into the model $A(t)$ and the endogenous decision to search $I(t)$. We observe in the data only the drivers that entered the model, so $I(t) = 1$. Consequently, we compute $C(t)$ as $cA(t)Z(t)$.

$\boldsymbol{MECP}$ Marginal external cost of parking. The MECP imposed by one additionally parked car during time t on searching drivers is computed using equation (3), which we repeat here $MECP = ((c\psi)/r) \times (I(t)A(t))/(Nv(t)^2)$. Using the already computed measures we can estimate non-parametrically $MECP$ as $C(t)/(Nv(t))$. For an example see Subsection 2.1.

$\boldsymbol{p(t)}$ Hourly price of parking. This information is observed in the data. Recall here that the optimal parking price equals the marginal external cost of parking, $p^*(t) = MECP$.

$\boldsymbol{K}$ Capital costs of parking supply. We use the capital cost of parking per parking spot from existing studies. We assume that the capital cost of parking is proportional to the number of parking spots, with proportionality factor of k (i.e., $K(N) = kN$), where k is the capital costs per parking spot.