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A model for estimation of the demand for on-street parking

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Abstract

This paper presents a stylised econometric model for the demand for on-street parking with focus on the estimation of the elasticity of demand concerning the full cost of parking. The full cost of parking consists of a parking fee and the cost of searching for a vacant parking space (cruising). The cost of cruising is usually unobserved. Ignoring this issue implies a downward bias of the elasticity of demand for the total cost of parking since the cost of cruising depends on the number of cars parked. We demonstrate that, even when the cost of cruising is unobserved, the demand elasticity can be identified by extending the econometric model to include the spatial interaction between the parking facilities. We illustrate the model with on-street parking data from Copenhagen and find indications of a somewhat greater parking demand elasticity than is usually reported in the literature.
Keywords: on-street parking, demand estimation, cruising-for-parking.
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1 Introduction

Cities around the world use parking policies to regulate the demand for on-street parking and, to some extent, the level of urban congestion. It is therefore relevant to estimate the sensitivity of the demand for on-street parking to cost.[1] The full cost of parking (the generalised cost of parking) consists of a parking fee and the cost of searching for a vacant parking space (cruising). The cost of cruising is typically unobserved,[2] but ignoring it biases the estimate of the demand elasticity because the cost of searching for a vacant parking space depends on the number of cars parked, i.e. the demand for parking (Inci et al., 2017; Zakharenko, 2016). This paper proposes a solution to this problem. We formulate an econometric model with both parking fees and cruising for parking as arguments for the demand elasticity for parking. We show how this demand elasticity can be identified, even in situations where cruising for parking is unobserved, when the model is extended to include spatial interaction between the parking facilities.

The economic literature has shown a growing interest in regulatory parking policies and provides a comprehensive treatment of parking pricing (Inci, 2015). Verhoef et al. (1995) analyse different parking policies as a substitute to road pricing and find that the use of parking fees is superior to physical restrictions on parking space supply. Fosgerau and De Palma (2013) show that workplace parking charging schemes can be used as a substitute for the time-varying toll to reduce urban congestion. Moreover, it is typically argued that parking should be priced at its opportunity cost, just like any other commodity. Arnott et al. (2005) identify a potential triple dividend from optimal parking pricing: reduced cruising for parking, reduced congestion (travel time savings), and the use of parking revenues to lower other taxes (reduced deadweight loss caused by tax distortions). However, in real life parking facilities are often underpriced (Small and Verhoef, 2007). This underpricing leads to cruising for parking, which is a pure loss from a social welfare

[1]This paper is based on a working paper by Madsen et. al. (2013) but uses an updated dataset allowing us to improve the empirical analyses and to achieve robust empirical results.

[2]The exceptions are van Ommeren et al. (2012), Inci et al. (2017) and van Ommeren et al. (2021). van Ommeren et al. (2012) examine cruising for parking, but in this study information on parking fees is not available. Inci et al. (2017) show that the mean cruising time can be computed by using parking data about arrival rates and vacancy rates. van Ommeren et al. (2021) extend the methodology developed by Inci et al. (2017) and propose a novel methodology to estimate the marginal external cruising costs across time and space.

perspective (Shoup, 2005; Calthrop and Proost, 2006). Arnott and Inci (2006) argue that parking pricing (especially hourly parking fees) has the downside that it can increase congestion by implying shorter parking durations and thus increase traffic congestion by increasing parking turnover. Arnott et al. (2015) examine the optimal level of curbside parking capacity when both urban transport and curbside parking are underpriced and consider the situation where garage parking is an alternative to the curbside.

Our paper adds new insights to the empirical literature that attempts to estimate the price elasticity of parking (see e.g. Feeney 1989; Concas and Nayak 2012; Lehner and Peer 2019). This small but growing literature suggests that the price elasticity of parking demand varies depending on many factors (e.g. local context, time of day, trip purpose, income and competing transport options) and lies in the range between -0.6 and -0.1; depending on the specification of parking demand (occupancy, dwell time and volume) as shown in Lehner and Peer (2019). Moreover, several studies estimate the price elasticity of demand for parking ignoring the cost of cruising (see e.g. Kelly and Clinch 2009; Hensher and King 2001). There is, however, a rather surprising absence of accurate empirical estimates of the effect of the total cost of parking on the demand for parking. This effect is important, as it is required for rigorous welfare analysis of a parking policy.

In this paper, we propose a new stylised econometric model to identify the elasticity of parking demand to total parking cost, using the usually available data collected by cities (parking occupancy rates and parking fees). We illustrate this model using parking data available for Copenhagen. We show that the effect of the parking fee is always less than the effect of the cost of parking in absolute value. We also show that the effect of total cost of parking can be identified, even if the cost of cruising is unobserved, by extending the econometric model to include the spatial interaction between the parking facilities (streets). Our empirical findings suggest that a significant cruising bias is likely to be present in the parking price elasticity measures in the literature (when interpreted as elasticities to the total parking cost).

The next section introduces an econometric model for the demand for on-street parking; Section 3 presents the empirical illustration, and Section 4 concludes.

2 An econometric model of the demand for parking

In this section, we specify an econometric model for the demand for on-street parking. First, in Section 2.1, we describe a standard model without spatial interactions. Then, in Section 2.2, we consider an extension of the model that takes the spatial interaction into account.

For both models, the demand for on-street parking is described in terms of the occupancy rate, i.e. the number of parked cars relative to the number of legal parking lots. The supply of parking lots is assumed to be constant, and the occupancy rate thus reflects the demand for on-street parking.[3] We ignore external factors affecting the demand for parking by affecting the overall traffic demand. In this way, the model proposes a partial description without interactions with other sectors. We simplify by ignoring the effect on the demand for on-street parking of other parking alternatives (e.g. private parking garages). We suggest that this effect is small and thus of little importance; see also Section 3.4, where we discuss possible difficulties caused by the unobserved off-street parking.

We use parking data from the City of Copenhagen to test the model and estimate demand elasticity of parking with respect to its full cost. The sample covers the years 2008-2019 with semi-annual counts (in April and September) and each count includes three daily measurements (at 12:00, 17:00 and 22:00). At the street level we observe the number of legal parking spaces and the number of occupied spaces, for each of the three daily counts. For the main empirical analysis, we focus on the noon count (12:00 am), while the other two counts are used for the sensitivity analyses.

2.1 A standard model for the demand for on-street parking

Let the demand for parking in street i at period t in terms of the occupancy rate, O_{it} (the number of cars parked divided by the number of parking spaces), be given

[3] We show in Section 3.2 that the supply of on-street parking in Copenhagen was constant in the period 2008-2019.

by

$$
\begin{aligned}
O_{it} &= \alpha_i + \beta c_{it} + \varepsilon_{it} && (1) \\
c_{it} &= p_{it} + S\left(O_{it}\right) && (2)
\end{aligned}
$$

where c_{it} is the total cost of parking in street i at period t, α_i is a street-specific fixed effect, and ε_{it} is an idiosyncratic error term. The cost c_{it} consists of a direct cost p_{it} (a parking fee) and an indirect cost, $S\left(O_{it}\right)$ that reflects the searching costs (cruising) and depends on the occupancy rate O_{it}. In line with the literature we assume that the searching cost function $S\left(\cdot\right)$ is increasing in the occupancy rate, see e.g. Anderson and De Palma (2004), Inci et al. (2017) and van Ommeren et al. (2021). Altogether, the equations (1)-(2) express that an increase in the parking fee reduces O_{it} and thus increases the number of vacant parking spaces; this in turn implies a lower cruising time and a lower cost of searching. The specification highlights the fact that the cost of searching, and the cost c_{it}, is an endogenous variable in the parking demand equation.

In our dataset, we do not have any information on searching in terms of time and costs and will therefore specify the functional relationship between the searching costs and the occupancy rate in order to arrive at a reduced form equation for O_{it} (see below). If we did have information on searching, then the total cost of parking c_{it} could be calculated and a valid instrument for c_{it} would be the parking fee p_{it}. Consequently, the parameter β could be estimated by IV estimation.

The street-specific fixed effects capture all time-invariant differences in the demand for parking between streets, such as the distance to the location of shopping and leisure activities and the number of residential parking permits.[4] Very importantly, the inclusion of street-specific fixed effects controls for endogeneity of the average parking fee level in a street. It is typically the case that the fees are higher in the city centre, where the demand is also high, and the reverse is true in the areas further away from the city centre. The street-specific fixed effects allow for this type of endogeneity but exclude the case where a change in the parking fee over time is a response to a change in demand. We find that this assumption is reasonable in most empirical applications to on-street parking. Typically, these

[4]Residents pay an annual fee and in return gain the right to park on-street in a specific area.

adjustments are a result of political decisions rather than demand reactions.[5]

In order to obtain a reduced form equation for the parking demand in terms of the occupancy rate O_{it} we need to specify how the searching costs depend on the occupancy rate. We assume that the costs of searching are linear in the occupancy rate:

$$S(O_{it}) = a + bO_{it} \quad \textit{where} \;\; b > 0. \tag{3}$$

Using eq. (3) it is straightforward to show that the reduced form equation implied by equations (1)-(2) is

$$O_{it} = \tilde{\alpha}_i + \tilde{\beta} p_{it} + \tilde{\varepsilon}_{it} \tag{4}$$

where $\tilde{\alpha}_i = (\alpha_i + a\beta)/(1 - b\beta)$, $\tilde{\beta} = \beta/(1 - b\beta)$ and $\tilde{\varepsilon}_{it} = \varepsilon_{it}/(1 - b\beta)$. For $\beta < 0$ then $\tilde{\beta} \in]\beta, 0]$ since $b > 0$ such that the parameter corresponding to p_{it} in the reduced form equation is less than β in absolute value. The parameter describes the total effect of increasing the parking fee. The direct effect is that this will decrease the demand for parking, and the indirect effect is that it will in turn decrease the searching cost, which will increase the demand for parking. The larger the value of b, the smaller the absolute value of the total effect, i.e. the more biased is the elasticity of demand for parking with respect to the total cost of parking. From this reduced form equation it is not possible to identify the parameter β in the demand equation and the parameters a and b in the searching cost function separately.

2.2 Spatial interaction between the parking facilities

The framework in Section 2.1 assumes that the demand for parking in a specific street is independent of the cost of parking in all other streets. This assumption is obviously not likely to hold in practice since the demand for parking in a specific street expectedly will also depend on the cost of parking in neighbouring streets. We now extend the model to allow for this. More formally, we assume that the demand for parking in street i depends on both the cost of parking in street i and on the cost of parking in neighbouring streets $j \neq i$. As before, the cost of parking consists of a parking fee and a searching cost which is increasing in the occupancy

[5] This is the case in our illustrative example from the City of Copenhagen; see Section 3.1.

rate. The demand for parking in street i at time t is now given by:

$$
\begin{aligned}
O_{it} &= \alpha_i + \beta c_{it} + \gamma \sum_{j \neq i} w_{ij} c_{jt} + \varepsilon_{it} \qquad (5)\\
c_{jt} &= p_{jt} + S\left(O_{jt}\right). \qquad (6)
\end{aligned}
$$

The parameter γ corresponding to the term $\sum_{j \neq i} w_{ij} c_{jt}$ in eq. (5) describes how the demand for parking in a specific street is affected by the costs of parking in neighbouring streets. The spatial weights w_{ij} for $j \neq i$ are pre-specified and each weight defines the exact neighbouring effect of a specific street. We use the following geographically derived weights:

$$
w_{ij} = \exp\left(-\theta d_{ij}\right) \qquad (7)
$$

where d_{ij} is the shortest route between streets i and j, and $\theta > 0$ is a specified constant. The weights are exponentially decreasing in the distance and approach zero as the distance increases. For a more extensive discussion of spatial weights, see e.g. Upton et al. (1985) and Anselin (2013).

The model defined by equations (5)-(6) allows for substitution between the demand for parking in different streets as given by the spatial weights and the model parameters. The model implies the following own and cross elasticities with respect to the total parking cost:

$$
\begin{aligned}
e_{ii} &= \frac{\partial O_{it}}{\partial c_{it}} / \frac{O_{it}}{c_{it}} = \beta \frac{c_{it}}{O_{it}} \qquad (8)\\
e_{ij} &= \frac{\partial O_{it}}{\partial c_{jt}} / \frac{O_{it}}{c_{jt}} = \gamma w_{ij} \frac{c_{jt}}{O_{it}}. \qquad (9)
\end{aligned}
$$

Intuitively, we would expect $\gamma > 0$ such that all other streets are substitutes for parking in one particular street. Everything else equal, the closer two streets are located to each other the higher the substitution effect is, i.e. $e_{ij} > e_{ik}$ for $d_{ij} < d_{ik}$ since $w_{ij} > w_{ik}$. It is important to note that the difference in substitution effect between two different streets is determined by the parameter θ, which is pre-specified and not estimated. In this study, the parameter θ is set at 0.25. This implies that spatial weights are close to zero (< 0.1) for streets more than ten kilometre away. The need to specify the spatial structure a priori is a limitation in all spatial models; see Gibbons and Overman (2012) for a discussion of this. We have also estimated the SDM for a range of different values of the decay parameter as a robustness check.

As our dataset does not contain information on searching time or searching cost, equations (5)-(6) cannot be used directly in estimation. Instead, our approach is to impose assumptions on the relationship between the searching cost and the occupancy rate and use that to reach a reduced form equation that can be estimated. As eq. (3) in Section 2.1 we assume that the costs of searching are linear in the occupancy rate, i.e. $S(O) = a + bO$. Using this, equations (5)-(6) can be written as (in matrix notation):

$$O_{nt} = \tilde{\alpha}_n + \tilde{\beta} p_{nt} + \tilde{\gamma} W_n p_{nt} + \lambda W_n O_{nt} + \tilde{\varepsilon}_{nt} \tag{10}$$

where the n-vector $\tilde{\alpha}_n$ have elements $(\alpha_i + a\beta + a\gamma \sum_{j \neq i} w_{ij}) / (1 - b\beta)$, parameters are defined as $\tilde{\beta} = \beta/(1 - b\beta)$, $\tilde{\gamma} = \gamma/(1 - b\beta)$ and $\lambda = b\tilde{\gamma}$, the weight matrix W_n has elements w_{ij} and zeros in the diagonal, and the error term $\tilde{\varepsilon}_{nt}$ is i.i.d. $N(0, \tilde{\sigma}^2 I_n)$ with $\tilde{\sigma}^2 = \sigma^2/(1 - b\beta)^2$ across $t = 1, ..., T$. This is the standard Spatial Durbin Model (SDM) with fixed effects $\tilde{\alpha}_n$, exogenous regressors p_{nt} and $W_n p_{nt}$ and the spatially lagged endogenous regressor $W_n O_{nt}$; see e.g. LeSage and Pace (2009). Like in the simple framework of Section 2.1 the parameters of main interest, β and γ in eq. (5), do not appear as parameters in the SDM model, and as before we have that when $\beta < 0, \gamma > 0$ and $b > 0$ then $\tilde{\beta} \in]\beta, 0]$ and $\tilde{\gamma} \in [0, \gamma[$. Therefore estimates of $\tilde{\beta}$ and $\tilde{\gamma}$ will underestimate the marginal effects of increasing parking costs β and γ. However, the structural parameters β, γ and b in the demand for parking eq. (5) can be obtained as functions of the parameters $\tilde{\beta}, \tilde{\gamma}$ and λ, as follows:

$$\begin{aligned} b &= \frac{\lambda}{\tilde{\gamma}} \\ \beta &= \frac{\tilde{\beta}}{1 + \lambda/(\tilde{\beta}\tilde{\gamma})} \\ \gamma &= \tilde{\gamma} - \lambda\beta \end{aligned} \tag{11}$$

The identification of the SDM in eq. (10) is based on an assumption that the occupancy of parking in neighbouring streets $j \neq i$ has no effect on the demand for parking in street i except for cruising. This suggests that the coefficient λ is likely an overestimate, which implies that the estimates of the structural parameters β and γ in eq. (11) are conservative, while the identified cost of searching (and the coefficient b) is an upper-bound estimate of the cruising costs.

Estimation of eq. (10) is performed by maximum likelihood as described in Lee (2004). In addition, Lee (2004, 2007) investigate the sources of identification and various reasons for failure to identify the model parameters in different versions of spatial autoregressive (SAR) models. It is shown that when the exogenous regressors (in our case p_{nt} and $W_n p_{nt}$) and the spatially lagged regressor are collinear, the source of identification will be coming from the covariance structure of the error terms. This in turn implies that the covariance structure of the error term in eq. (10) must be correctly specified. In our case, we assume that the elements in the error term are independent across i, t with constant variance. Obviously, an identification that relies on variation in exogenous variables is more appealing, since assumptions imposed on the error term such as constant variance are somewhat arbitrary.[6] Lee and Yu (2010) show that the estimation of a spatial model with unit-specific fixed effects is straight forward. We follow Lee and Yu (2010) and estimate the SDM by using results from standard panel data models, i.e. maximisation of the conditional likelihood function gives consistent estimators of the model parameters where the conditioning is done with respect to unit-specific averages of the dependent variable as sufficient statistics for the unit-specific effects.

Finally, if the impact of the occupancy rate on cruising costs is negligible ($b = 0$), then the parameter corresponding to parking fee (p_{it}) in the reduced form demand eq. (4) will be unbiased, so $\beta = \tilde{\beta}$. The SDM in eq. (10) also reduces to the standard demand model (the reduced form demand eq. (4)) when the spatially lagged endogenous regressor $W_n O_{nt}$ has no impact on the demand for parking, i.e. $\lambda = 0$. In this case $b = 0$, $\gamma = \tilde{\gamma}$ and $\beta = \tilde{\beta}$. In the following section we will empirically investigate the existence and significance of the cruising bias on the estimate of the parking demand elasticity.

[6] The problem is discussed in a paper by Gibbons and Overman (2012) and is similar to the identification problem in models where the outcome variable depends on some expected value of the outcome variable, the reflection problem; see Manski (1993).

3 Empirical illustration

This section of the paper presents an illustration of the application of the econometric model. We use parking data from the City of Copenhagen, with which, it is possible to test the model and estimate demand elasticity of parking with respect to its full cost. In Section 3.1 we briefly describe the parking market and parking policies in the City of Copenhagen. This section includes a discussion of a several key assumptions that underlie the identification of the model and the interpretation of its parameters. The data set provided by the City of Copenhagen for the analysis is described in Section 3.2 and estimation results are discussed in Section 3.3. We conclude the section with sensitivity analyses.

3.1 Parking in the City of Copenhagen

About two-thirds of the parking spaces in the City of Copenhagen are on-street, so this is the dominating way of parking. Like many other cities, the City of Copenhagen has a long history of paid parking (for both publicly provided and privately provided parking places). In 1990 the City of Copenhagen initiated a new system for payments for parking, where the inner city was divided into different zones and then successively expanded until the regulation covered the whole city central area in 2007. Except for a minor extension of the central (red) parking zone in 2013, the regulatory area did not change significantly until the introduction of a new (yellow) parking zone in 2017, besides changes in the pricing scheme.[7] The purpose of the system was to reduce the traffic and the number of parked cars in the city, especially commuting in cars to workplaces in central Copenhagen.

In the zonal system, all on-street parking is charged a fee depending on the duration of the parking, the time of day and the location of the zone. The zones closest to the historical city centre are more expensive. See below for details. Many other European cities use similar systems, where payment for on-street parking varies across zones and time intervals.[8] At present, the zonal system covers six zones: red is the city centre with few residents and many shops, restaurants and

[7]Map A.1 in Appendix A shows the extension of the red parking zone in 2013.

[8]Special rules apply for residents in a parking zone, who can purchase parking permits that grant them unrestricted parking close to their home address (when available). The price of a residential parking permit is about €90 per year per car. The parking permit is connected to a specific car and there is no limit on the number of residence parking permits available.

offices; green, blue and yellow parking zones have more residents; seven smaller zones (Grønjord, Hellerup Station, Vanløse Station, Lergravsparken, Nordvest, Valby Syd and Havnestad) are parking zones with only time restrictions, and the remaining areas are free parking zones, see Figure 1 (a).

3.2 Data

The survey data used in the empirical analysis is provided by the City of Copenhagen. The sample covers the years 2008-2019 with semi-annual counts (in April and September, starting with September 2008) except for the years 2011 and 2012, for which we only observe one account per year.[9] Each count includes three daily measurements (at 12:00, 17:00 and 22:00). For all observed streets in central Copenhagen we know the number of legal parking spaces and the number of occupied spaces for each of the three daily counts. We do not have information about cruising costs or cruising time. Furthermore, we do not have information about alternative parking (e.g. private parking houses and workplace parking).[10] The final sample then includes 45,054 parking spots on 909 streets. Table 1 shows the descriptive statistics for each daily measurement. The mean number of parking spaces is, as expected, not different for the three daily measurements, while the mean number of occupied parking spaces increases for later daily measurements, when the parking fees are lower and when residents dominate (after work hours). In Denmark municipal parking requirements have been used to accommodate the demand for parking. More importantly for our study, the City of Copenhagen has chosen to fix the supply of on-street parking. Figure A.2 in Appendix A shows that the mean supply of on-street parking has been constant in the period 2008-2019. Consequently, the occupancy rate reflects the demand for on-street parking.

In the empirical analysis, we have reduced the dataset in several ways. First, the three different time counts represent different traffic situations. For example, in the Danish National Travel Survey, we see many shoppers and short-term parkers at noon while residents dominate after work hours. For the main empirical analysis, we choose to use the figures from the noon count (12:00 am). The other two counts

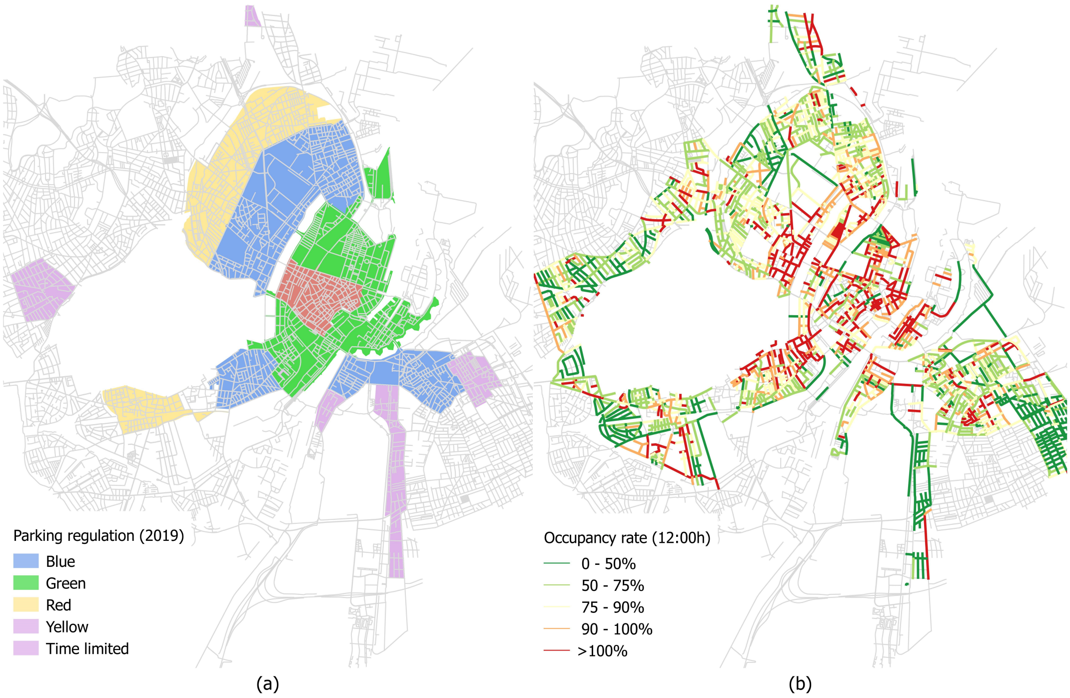
[9]Table A.1 in Appendix A shows the number of parking counts.

[10]This obviously represents a limitation for the econometric analysis and is further discussed in Section 3.4. If available, such information could be included in the model as additional parking lots.

Daily measurement	12:00		17:00		22:00	
	mean	std.dev.	mean	std.dev.	mean	std.dev.
No. of parking spaces	50	45	49	44	50	35
No. of occupied spaces	37	33	40	35	44	39
No. of streets	909		909		909	
No. of obs.	19,089		19,089		19,089	

Table 1: Means and standard deviations by daily measurement

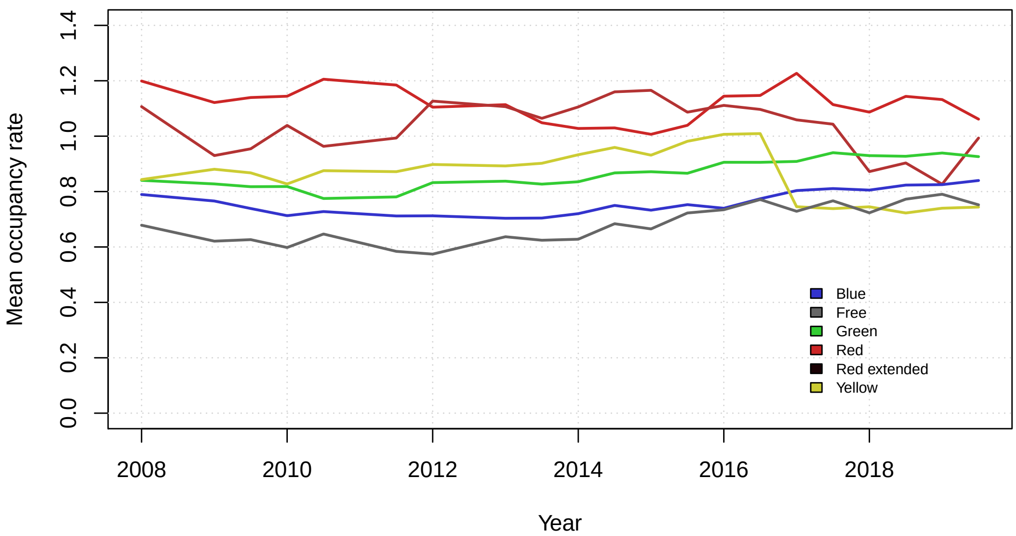
Figure 1: Map of Copenhagen's parking regulation (a) and occupancy rates at 12:00 am (b) in September 2019



(17:00 and 22:00) are only used for the sensitivity analyses. Second, the dataset provides the number of occupied spaces as well as the number of legal parking spaces for each street. With this information we can calculate the occupancy-rate for each street. Occupancy is generally (for 64% of the observations) lower than

90%.[11] Note that the occupancy rate can be above 100%. This is possible since the number of legal parking lots is rarely physically marked and thus it is possible to deviate from the estimated number, depending on the size of the cars and the density of the standard size of parked cars. Because of this, and because illegally parked cars are recorded as well, we accept an occupancy rate above 100% in our dataset but choose to censor the occupancy rates above 130%.[12] Given the uncertainty surrounding an appropriate censoring, in the empirical analysis we estimate models with alternative censoring rules as robustness checks. Figure 1 shows both the map of parking regulated zones and the occupancy rates measured at noon in September 2019. It shows, for example, that the occupancy rate in the city centre and in the north-east tends to be high. The occupancy rate is also high after work hours, in the afternoon and in the evening, when resident parking dominate; see Figure A.4 in Appendix A.

Figure 2: Mean occupancy rates by parking zone at 12:00

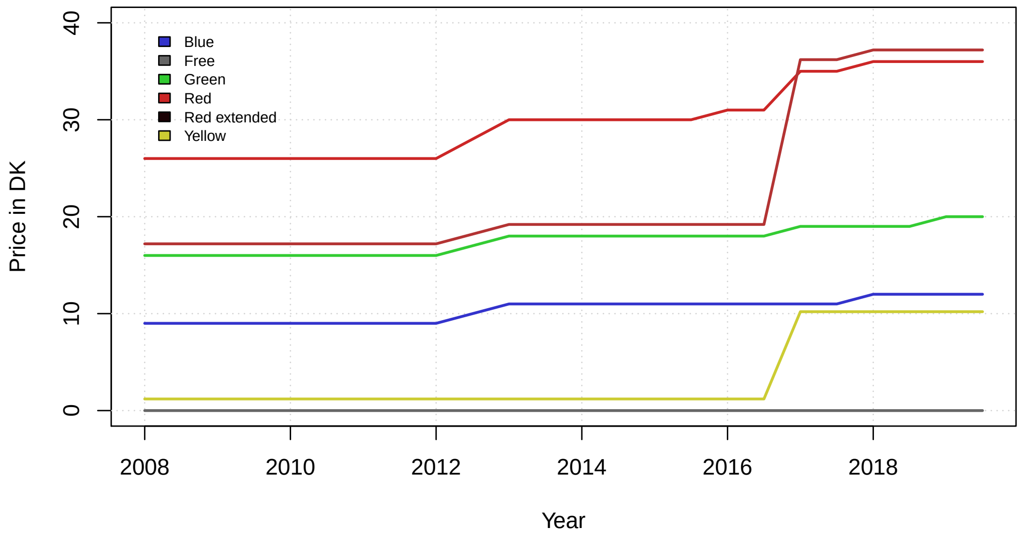


Note: Periods represents the semi-annual counts (in April and September) starting with September 2008.

[11]The histogram for the occupancy-rate is provided in Appendix A, Figure A.3.

[12]This rule of censoring occupancy rates above 130% is based on the technical analysis of the parking capacity in the City of Copenhagen.

Figure 3: Average nominal parking fees (DKK/h) by pariod and parking zone



Note: Period represents the semi-annual counts (in April and September) starting with September 2008.

Figure 2 shows that the mean occupancy rate for the red zone (central Copenhagen) has consistently stayed above 1, which indicates that there is generally no excess supply of parking places in the zone, i.e. empty spots will generally be filled immediately and thus cruising for parking is present. For the green and blue zones and for the outer zone we find very high occupancy rates, indicating little or no excess supply, and potentially, cruising for parking. The figure also shows that the occupancy rate for the yellow parking zone significantly dropped in 2017 when paying for parking in this parking zone was introduced. We also note that the occupancy rates are highest in the red zone at the 12:00 count. The temporal pattern of occupancy rates seems to hint at a potential substitution effect between contiguous zones coinciding with pricing changes.

The parking fees for the zones are shown in Figure 3. The parking fee for the red zone (the city centre) is almost three times as high as for the blue zone. Outside the three zones (the outer city) there are generally no fees for parking.

The nominal prices have been changed a few times during the years 2008-2019.[13] Finally, paying for parking in the yellow parking zone was introduced in 2017. Night parking rates are substantially lower or zero.[14]

3.2.1 Preliminary analyses of the effect of the parking fee on the occupancy rate

We now explore the effect of the parking fee on the occupancy rate using simple dif-in-dif (DiD) models. We estimate simple model specifications in which we hypothesise that the treatment area consists of parking zones for which parking fees changed. Formally, the specification is:

$$O_{it} = \theta T_{it} + \tau_t + \mu_i + \varepsilon_{i,t} \tag{12}$$

where O_{it} is the occupancy rate in street i in period t, T_{it} is a dichotomous variable that is 1 for the treated streets for the period after the parking fee raise and 0 otherwise, τ_t is period-fixed effect, μ_i denotes street-fixed effects, and $\varepsilon_{i,t}$ is a random error term. We estimate separate models for the two most important parking fee changes: i) the parking fee change in the red, blue, and green parking zones in the year 2013, and ii) the introduction of parking pricing in the yellow zone and the parking fee change in the red parking zone in the year 2017. For the first model, we restrict our sample to the years 2008-2016 and for the second model to the years 2014-2019.

Table 2 shows the results. The first two columns in Table 2 refer to a simple model based on eq. (12). The estimated coefficients suggest a reduction of the occupancy rates of 5.3 and 22.0 percentage points for the parking fee changes in 2013 and in 2017, respectively. These are sizeable effects. At the sample average of the occupancy rate in the red parking zone (1.12) they correspond to reductions in the occupancy rate of 4.9% and 19.6% for the parking fee changes in the years 2013 and 2017, respectively. The relatively large magnitude of the parking fee

[13]For the econometric analysis we correct the nominal parking fees for inflation based on the CPI provided by Statistics Denmark; see Table PRIS117 at https://www.statistikbanken.dk/pris117. The inflation rate from 2008 to 2019 was very low, so correcting for inflation does not significantly affect the estimation results.

[14]Parking is free during weekends from Saturday at 17:00 until Monday at 8:00 and on public holidays.

change in 2017 is likely driven by the introduction of parking pricing in the yellow parking zone and the extension of the red parking zone.[15]

Table 2: The impact of the parking fee raise on the occupancy rate

Parking fee change in year	2013	2017	2013	2017
Locally at distance			500m	500m
	[1]	[2]	[3]	[4]
Dummy indicating park. fee chg. (T_{it})	-0.053***	-0.220***	-0.072***	-0.256***
	(0.013)	(0.017)	(0.028)	(0.022)
Street fixed effects (μ_i)	Yes	Yes	Yes	Yes
Time fixed effect (τ_t)	Yes	Yes	Yes	Yes
R-squared	0.649	0.549	0.636	0.574
Number of obs.	9,810	4,732	3,345	2,170

Note: Dependent variable is the occupancy rate O (share). Censoring $O = 1.30$. Parking fee change in year 2013 corresponds to the parking fee change in red, blue, and green parking zones, and parking fee change in the year 2017 to the introduction of parking pricing in yellow zone and parking fee change in red zone. For the parking fee change in 2013 models we restrict sample to the years 2008-2016 and for the parking fee change in year 2017 model to the years 2014-2019. *** indicate that estimates are significantly different from zero at the 0.01 level; standard errors are in parentheses.

One possible econometric issue when estimating the effect of a parking fee change on the occupancy rate is that parking fee changes might be related to areas associated with higher occupancy rates. We can reduce this difficulty by comparing adjacent streets that differ in parking fee levels and then using a spatial regression discontinuity design (RDD) around the parking zone borders, which we combine with a (DiD) set-up from eq. (12). We now focus on changes in the occupancy rates, close to the borders of the parking zones – within approximately 500 m – that have experienced a raise in parking fees; see columns [3] and [4] in Table 2. Estimation results do not significantly change compared to the simple models. Finally, we have also estimated the number of different DiD models in which we consider two treatment timings (in the years 2013 and 2017) and different treated and control parking zones; see Appendix B. The estimation results from these additional DiD models confirm our findings in Table 2. In the next section we proceed to a more structural analysis.

[15] Notice here that the parking fee increased from 0 to 10 DKK in the yellow parking zone and from 18 to 35 DKK in the extended red parking zone.

3.3 Empirical results

We now describe the empirical results. We first present our results on the parking price elasticity based on the standard demand model. Next, we discuss the results obtained from the estimation of the Spatial Durbin Model (SDM).

Table 3 reports the estimation results. All estimated equations include street- and time-specific effects. The street-specific effects control for all the time-invariant systematic differences in the demand for parking at the street level,[16] while the time-specific effects account for unobserved parking demand shocks over time that affect all streets (e.g. business cycles). Column [1] shows the estimates for the standard demand model based on eq. (4). Since the supply of on-street parking was constant in the period of the observation, we interpret the effect of the parking fee on the occupancy rate as a demand effect. As we expected, an increase in the parking fee decreases the demand for on-street parking. The parameter associated with the parking fee ($\widetilde{\beta}$) in this standard model is estimated to -0.028; see column [1]. The parameter estimate is tight and indicates a plausible effect.

The estimation result allows us to derive parking fee elasticity.[17] The parking fee elasticity is different from the elasticity of demand with respect to total cost of parking since the total cost of parking consists of a parking fee and the cost of cruising. The parking fee elasticity in the red parking zone (the historical city centre) at the sample average of the occupancy rate in the red zone (1.12) and the parking fee of 30 DKK/hour is -0.76, i.e. raising the parking fee in the red zone by 1% reduces demand for on-street parking in the historical city centre by 0.76%. This estimate of the parking fee elasticity is consistent with those reported in the literature (see e.g. Lehner and Peer (2019)). However, the estimated elasticity is likely an underestimate of the parking demand elasticity because, as shown in Section 2.1, the parameter corresponding to the parking fee in the reduced form equation ($\widetilde{\beta}$) is less than the parameter corresponding to the total cost of parking (β) in absolute terms. The *cruising bias* is caused by the fact that while the cost of cruising is usually unobserved, ignoring it biases the estimation of the price elasticity of demand because of the dependence of the costs of cruising on the

[16] e.g. street attributes such as one-way traffic, the number of residential units, the distance to the location of shopping and leisure activities, the number of residential parking permits, the supply of public transport, etc.

[17] The parking fee elasticity is defined as $\varepsilon_{O,p} = \frac{\partial O}{\partial p}\frac{p}{O} = \widetilde{\beta}\frac{p}{O}$.

Table 3: Models for on-street parking in terms of the occupancy rate

	[1]	[2]	[3]
	Std. model	Std. model	SDM
Daily measurement	12:00	22:00	12:00
	Eq. (4)	Eq. (4)	Eq. (10)
Parking fee, ($\tilde{\beta}$)	-0.028***	-0.030***	-0.034***
	(0.001)	(0.008)	(0.001)
$W \cdot p$, ($\tilde{\gamma}$)			0.0002***
			(0.00001)
$W \cdot O$, (λ)			0.001***
			(0.0002)
Street fixed effects	yes	yes	yes
Period fixed effects	yes	yes	yes
R^2	0.263	0.231	
Log likelihood			-1,980.957
Number of observations	19,089	19,089	19,089

Note: Dependent variable is the occupancy rate O (share); censoring $O = 1.30$; parking fee is measured in DKK/hour; W is the spatial weights matrix; *** indicates that estimates are significantly different from zero at the 0.01 level; in the SDM $\theta = 0.25$; standard errors are in parentheses.

number of cars parked. Our findings indicate that due to the cruising bias, the parking demand elasticity (the car drivers' response to an increase in the total cost of parking) is most likely larger than proposed in the literature.

Cruising for parking is more or less absent at night and consequently, the bias caused by the unobserved cost of cruising on the parameter associated with the parking fee is lower. We, therefore, re-estimate the standard demand model based on eq. (4) using only observations from the night measurement (22:00). As expected, the parking fee parameter increases in absolute value by about 7%; see column [2].[18] This is likely because the bias caused by the unobserved cruising costs is smaller.[19]

Column [3] in Table 3 reports the estimated coefficients for the SDM based

[18]Recall here that the parameter associated with the parking fee ($\tilde{\beta}$) in the reduced form demand model is less than the parameter associated with the full cost of parking (β) in absolute value; see Section 2.1.

[19]When we estimate the standard demand model using only the observations from the afternoon measurement (17:00), then the parking fee parameter is similar to the coefficient estimated in model [1]; see Table B.2 in Appendix B.

on eq. (10). All the estimated coefficients are significant and have the expected signs. The $\tilde{\beta}$ is estimated to be -0.034; which, for the red parking zone, translates into a parking fee elasticity of -0.91, 16% larger (in absolute terms) than the elasticity computed from the standard demand model. The coefficients associated with the parking fees in the neighbouring streets ($\tilde{\gamma}$) and with the occupancy rates in the neighbouring streets (λ) are both significant and positive. This suggests that increasing parking fees and occupancy rates in the neighbouring streets of a street, raise the demand for parking in that street.

We can also use these estimates ($\tilde{\beta}$, $\tilde{\gamma}$ and λ) to recover the structural parameters (β, γ and b) and consequently to learn about the impact of the total cost of parking on the parking demand; see eq. (11). We find that the coefficient associated with the total cost of parking (β) is significantly negative and equal to -0.039 (std.err is 0.002), b is 3.433 (std.err is 1.038), and γ is 0.0002 (std.err is 0.00001). The total parking cost elasticity for the red parking zone is then -1.1, suggesting that a 1% increase in the parking costs will reduce the occupancy rate in the red zone by 1.1%. This elasticity is essential for a rigorous welfare analysis, and it should not be confused with the parking fee elasticity, as currently used in the literature due to the lack of better estimates. Our results imply that the introduction of paid parking (or changing parking fees) likely have larger welfare effects than previously suggested. Finally, higher parking fees do reduce cruising costs ($b = 3.433$).[20] Consequently, the impact of an increase in the parking fee on the demand for parking would be underestimated if the cruising costs are ignored.

3.4 Sensitivity analyses

We have performed a number of sensitivity analyses. Most of the robustness checks focus on critical data selection issues and model assumptions. It appears that the results are very robust for censoring of the occupancy rate and for correcting the nominal parking fees for inflation. The parameter associated with the parking fee in the standard model lies in the range $[-0.29, -0.24]$; see Table B.2 in Appendix B. We conclude that, despite the apparently plausible a priori arguments for censoring the occupancy rate, the empirical importance of the censoring appears to be limited.

[20] Recall from Section 2.2 that this is likely an upper bound estimate.

Table 4: Quantile regression estimates of the parking fee on the occupancy rate

	Quantile regression estimates					OLS
	0.10	0.25	0.50	0.75	0.90	
Parking fee, $(\tilde{\beta})$	-0.032***	-0.030***	-0.029***	-0.027***	-0.026***	-0.028***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Street fixed effect	yes	yes	yes	yes	yes	yes
Period fixed effect	yes	yes	yes	yes	yes	yes
Number of obs.	19,089					

Note: Dependent variable is the occupancy rate O (share); censoring $O = 1.30$; parking fee is measured in DKK/hour; *** indicates that estimates are significantly different from zero at the 0.01 level; standard errors are in parentheses.

It may be observed that the bias caused by the unobserved cost of cruising on the parameter associated with the parking fee is likely modest for lower levels of the occupancy rate. We have therefore also estimated a quantile regression model (see e.g. Machado and Silva, 2018). We find that, the absolute value of the parking fee coefficient decreases with the occupancy rate; see Table 4. Moreover, the estimated coefficient for the tenth percentile, so when the cruising for parking is absent, is in absolute terms about 20% higher compared with the estimate for the ninetieth percentile, and similar in magnitude to the estimated coefficient associated with the total cost of parking (β). This illustrates the importance of accounting for cruising costs.

Before we focus on the spatial interaction between the parking facilities (SDM), we address the importance of including the cost of parking in neighbouring streets. We now assume that the demand for parking in street i depends on both the parking fee in street i and on the parking fee in neighbouring streets:

$$O_{it} = \tilde{\alpha}_i + \tilde{\beta} p_{it} + \tilde{\gamma} \sum_{j \neq i} w_{ij} p_{jt} + \tilde{\varepsilon}_{it}$$

where the parameter $\tilde{\gamma}$ describes how the demand for parking in a specific street is affected by the parking fees in neighbouring streets. The spatial weights $w_{i,j} = exp(-\theta) d_{i,j}$ for $j \neq i$ are pre-specified; see Section 2.2. We expect $\tilde{\gamma} > 0$ such that all other streets are substitutes for parking in one particular street. Table 5 confirms our expectations. The substitution effect is positive and the estimated $\tilde{\gamma}$ coefficient is of similar magnitude as the substitution effect estimated in the SDM model; see Table 3. Moreover, the parameter associated with the parking fee in this extended standard model is slightly higher in absolute terms compared with the standard model ignoring the substitution effect. Although the estimated coefficients of this extended standard model are similar to the corresponding coefficients in the SDM model, they are not sufficient to recover the structural parameters (β, γ and b).

We have also estimated the SDM using observations for the afternoon measurement (17:00). This can be considered as a test of the importance of cruising bias, because cruising for parking is likely lower during the afternoon and therefore λ is expected to be low. We find that, when restricting our sample to the afternoon measurement, the coefficient λ is not statistically significant; see Model

Table 5: Models for on-street parking in terms of the occupancy rate at 12:00

	[1]
Parking fee, ($\tilde{\beta}$)	-0.035***
	(0.001)
$W \cdot p$, ($\tilde{\gamma}$)	0.0002***
	(0.00001)
Street fixed effects	yes
Period fixed effects	yes
R^2	0.275
Number of observations	19,089

Note: dependent variable is the occupancy rate O (share); censoring $O = 1.30$; parking fee is measured in DKK/hour; W is the spatial weights matrix; $\theta = 0.25$; *** indicates that estimates are significantly different from zero at the 0.01 level; standard errors are in parentheses.

[1] in Table 6. Moreover, it is more than three times lower compared with the corresponding coefficient estimated when cruising for parking is considerable (see Model [3] in table 3). Estimation results are also qualitatively similar when we restrict our sample to lower occupancy rates ($O \leq 100\%$), so when the cruising for parking is lower; see Model [2] in Table 6.[21]

The reported estimations results are based on a distance decay parameter that equals 0.25. This value is somewhat arbitrary, and we have therefore also estimated the main SDM model based on equation (10) for a range of other values ($\theta \in (0, 1]$). Figure 4 shows the estimates of the structural parameter β associated with the total cost of parking as a function of the decay parameter θ. This shows that the results are sensitive to the value of the decay parameter, i.e. the β coefficient increases in absolute terms with the decay parameter θ (when the impact of the distant streets is lower).[22] However, for all considered θ values the absolute value of the estimated structural parameter β is larger in absolute terms than the OLS estimate.[23]

Some issues deserve further discussion when estimating the parking demand

[21] Identification of the SDM was not possible for the lower thresholds of the occupancy rates because of the limited number of observations, and when using observations for the night measurement (22:00), most likely due to the limited variation of parking fees.

[22] We find the similar results when we focus on the 17:00 measurement; see Figure B.1 in Appendix B.

[23] $|\hat{\beta}_{SDM}| \geq |\hat{\beta}_{OLS}| = 0.03$ with $|\hat{\beta}_{SDM}| \in [0.03, 0.06]$.

Table 6: SDM for on-street parking in terms of the occupancy rate

	[1]	[2]
		$O \leq 100\%$
Daily measurement	17:00	12:00
Parking fee, ($\tilde{\beta}$)	-0.034***	-0.030***
	(0.002)	(0.002)
$W \cdot p$, ($\tilde{\gamma}$)	0.0002***	0.0002***
	(0.00001)	(0.00002)
$W \cdot O$, (λ)	0.0003	0.0003
	(0.0002)	(0.0004)
Street fixed effects	yes	yes
Period fixed effects	yes	yes
Log likelihood	-3165.16	-438.96
Number of observations	19,089	19,089

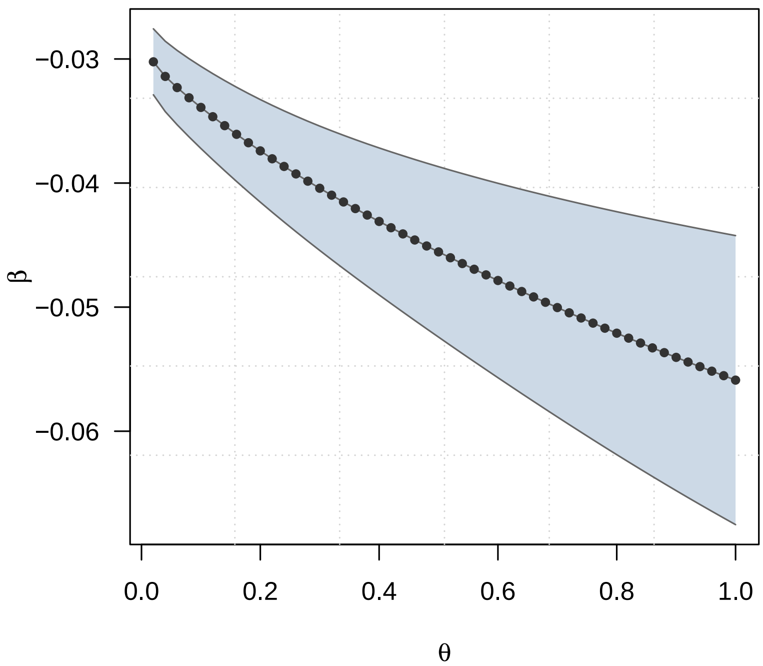
Note: dependent variable is the occupancy rate O (share); censoring $O = 1.30$; parking fee is measured in DKK/hour; W is the spatial weights matrix; $\theta = 0.25$; *** indicates that estimates are significantly different from zero at the 0.01 level; standard errors are in parentheses.

models and when interpreting the provided empirical results. The first issue is related to limited price variation posing a threat to identification. Being a contentious issue, parking price changes usually require cumbersome political agreement to deviate from simple updates based on the inflation index. This implies that many cities might need to rely on a single price change when estimating parking demand elasticity, making it potentially difficult to identify the impact of parking fee change on the demand for parking. In such a scenario, other identification strategies like event studies or regression discontinuity around the time of the policy change might be advisable. However, the temporal and spatial data requirements to perform them are unfeasible for many cities.[24] In any case, until full digitalisation of the parking market, administrative data collected is still a highly valuable resource to guide policy interventions.[25] In this regard, we believe that our method can help cities leverage its potential, given that even under limited

[24] An example of such a high level of requirements can be seen in Ostermeijer et al. (2021).

[25] Current digitalisation level in the parking market is still relatively low, although rapidly increasing. Many cities cannot even leverage parking transaction data to measure occupancy, as resident permit holders are not asked to register their parking events (not even when payment is fully managed through smartphone apps). Additionally, even when on-street parking occupancy sensors are available, their geographical coverage is limited.

Figure 4: β as a function of θ at 12:00



Note: The β coefficient is from the main SDM model based on equation (10) (see model [3] in Table 3) for a range of different decay parameter values ($\theta \in (0, 1]$). The shaded area represents the 95% confidence interval.

price variation (when we restrict our analysis to the single price change in 2013 or in 2017) we find fairly similar results to the ones including all price variations. The second issue is the fact that we do not have information about off-street parking occupancy and prices in our model, which might bias our results. As in many cities, parking garage prices in Copenhagen tend to be higher than curbside prices due to some degree of localised market power and the fact that drivers seem to confer curbside some premium (Kobus et al., 2013; Gragera and Albalate, 2016), helping them apply higher mark-ups. The direction of the bias is difficult to assess, as garage parking enters as an unobserved neighbouring facility for both occupancy and prices. The parking spatial competition literature does not offer a clear-cut answer about the sign of the adjustments that can be expected from garages as a response to curbside fee changes (Albalate and Gragera, 2017; Ostermeijer et al., 2021). This issue, however, is not particular to our methodological approach but a common fault affecting the majority of studies dealing with parking demand. Private operators will rarely share garage occupancy data and the public sector although a relevant player usually owns only a fraction of off-street capacity. As mentioned before, if such information is available it will simply enter into our estimation method as an additional parking facility.

4 Conclusion

This paper deals with estimation of the elasticity of the demand with respect to the full cost of parking. It proposes a new methodological framework to clarify the identification of the effect of the cost of parking, consisting of the costs of searching for parking (cruising) and a parking fee, on the demand when the cost of searching is unobserved. We take into account the data availability, i.e. (city) transport authorities collect parking data that include the occupancy rates and sporadically and if relevant, the parking fees, and illustrate the model using on-street data from the City of Copenhagen for the years 2008-2019. Our illustrations suggest that the parking demand elasticity is most likely larger than proposed in the literature.

Our findings have a number of implications. First, we demonstrate that parking fees can potentially be a useful policy instrument to organise the parking market and reduce the external costs of traffic such as congestion (cruising), air pollution, and other relevant local environmental externalities. We find that the introduction of paid parking (or changing parking fees) likely have larger welfare effects than previously suggested. Our empirical results suggest that parking demand elasticity should not be confused with the parking fee elasticity, as currently used in the literature due to the lack of better estimates. Second, the proposed empirical methodology can be useful for the estimation of other similar reduced form demand equation describing the demand with the constrained capacity. In particular, the reduced form demand equations resulting from a bottleneck model is a good example (see e.g. Arnott et al. 1993). Finally, the proposed methodology makes it possible to make a straightforward extension of the demand model to include spatial interactions. In this way many of the identification problems in applied spatial economics can be avoided.

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Appendices

A Data

Figure A.1: Map of extension of red parking zone in 2013

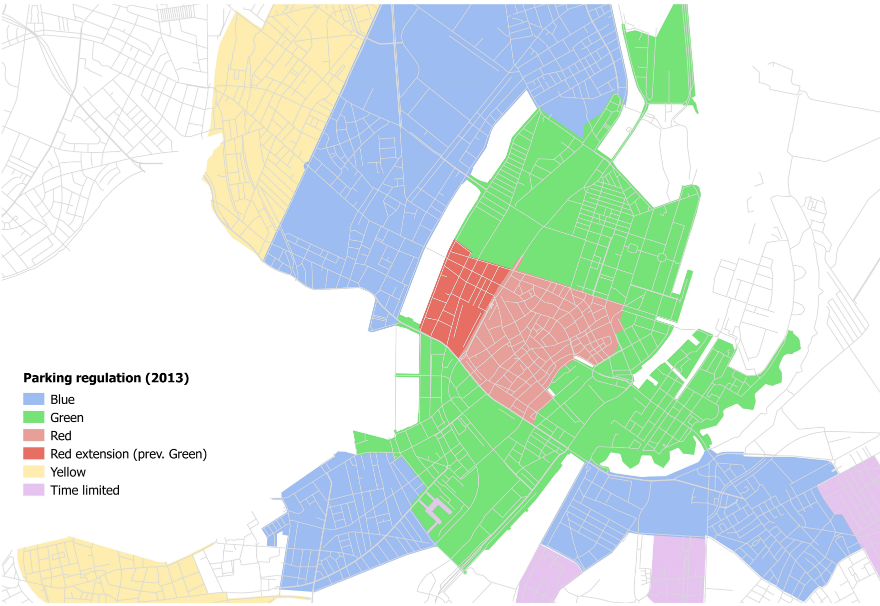
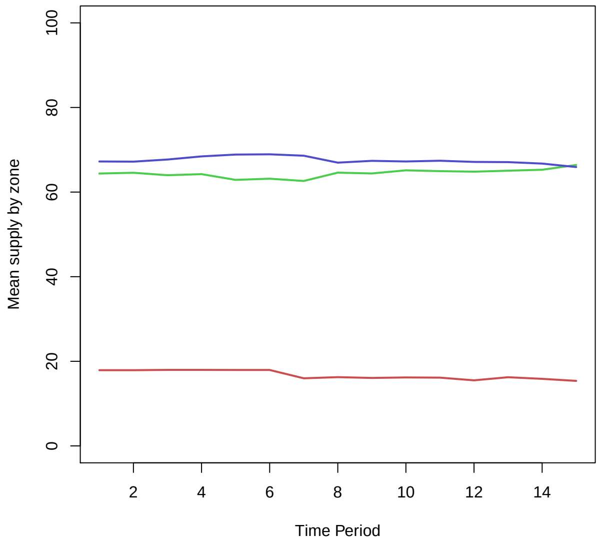


Table A.1: Number of parking counts

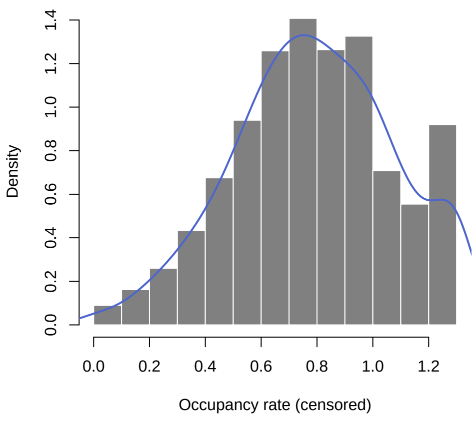
Year	Number of counts
2008	1
2009	2
2010	2
2011	1
2012	1
2013	2
2014	2
2015	2
2016	2
2017	2
2018	2
2019	2

Figure A.2: Mean supply of on-street parking by period and parking zone



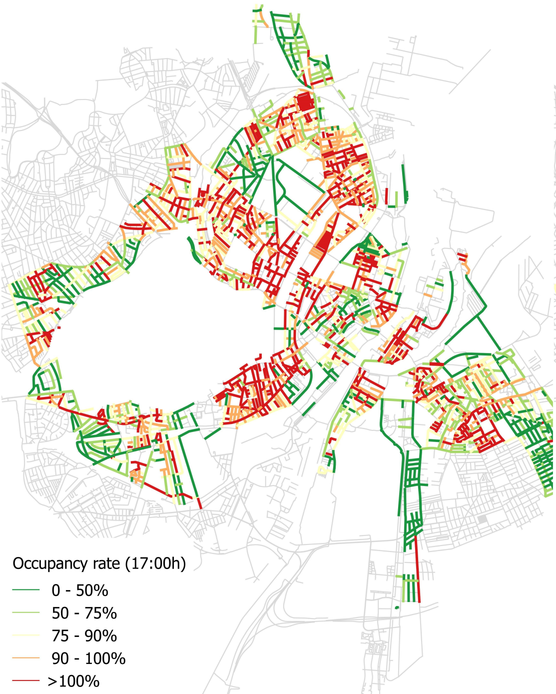
Note: Periods represent the semi-annual counts (in April and September) starting with September 2008.

Figure A.3: Histogram for the occupancy-rate

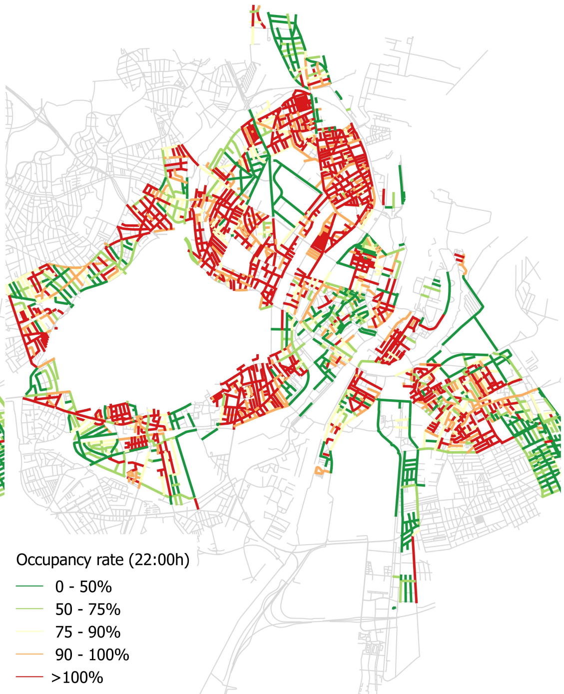


Note: Number of observations: 19,089. The occupancy rate is censored at 1.3%.

Figure A.4: Occupancy rates at (a) 17:00h and (b) 22:00h in September 2019



(a)



(b)

B Estimation results

B.1 Additional Difference-in-Difference models of the impact of the parking fee change on the occupancy rate

In this section we estimate 11 different DiD models in which we consider two treatment timings (in the years 2013 and 2017) and different treated and control parking zones. Table B.1 reports the results. The data window under consideration for each models is given by columns *period start* and *period stop*. Only data within the window is used for the estimation. The column *change in parking fee (DKK)* shows the associated change in parking fee for the *treated* parking zone. For the first treatment period (the year 2013) two parking zones - Free and Yellow - have no change in price during the window. One set of specifications is therefore estimated with these zones as control and one set of specifications with only Yellow parking zone. The estimation results confirm our findings in table 2. They suggest that larger parking fee changes imply larger reductions of the occupancy rates. For only 2 out of 11 models we do not find significant impact of parking fee change on the occupancy rate. This comes as no surprise because these two models are associated with relatively small parking fee adjustments.

Table B.1: Additional DiD models of an impact of the parking fee change on the occupancy rate

Control	Treated	Time of treatment	Period start	Period stop	Chg. in parking fee (DKK)	Park. fee chg. (T_{it})
Free	Red	April 2017	April 2013	September 2019	4	-0.021***
						(0.024)
Free	Red ext.	April 2017	April 2013	September 2019	17	-0.232***
						(0.038)
Free	Yellow	April 2017	April 2013	September 2019	9	-0.287***
						(0.014)
Free	Red	April 2013	April 2008	September 2016	4	-0.089***
						(0.023)
Free	Blue	April 2013	April 2008	September 2016	2	-0.062***
						(0.011)
Free	Green	April 2013	April 2008	September 2016	2	-0.014***
						(0.013)
Free	Red ext.	April 2013	April 2008	September 2016	2	0.032
						(0.030)
Yellow	Red	April 2013	April 2008	September 2016	4	-0.119***
						(0.018)
Yellow	Blue	April 2013	April 2008	September 2016	2	-0.092***
						(0.008)
Yellow	Green	April 2013	April 2008	September 2016	2	-0.044***
						(0.011)
Yellow	Red ext.	April 2013	April 2008	September 2016	2	0.002
						(0.033)

Note: Dependent variable is the occupancy rate O (share). Censoring $O = 1.30$. The model specification is $O_{it} = \theta T_{it} + \tau_t + \mu_i + \varepsilon_{i,t}$, where O_{it} is the occupancy rate in street i in period t, T_{it} is a dichotomous variable that is 1 for for the treated streets for the period after the parking fee raise and 0 otherwise, τ_t is period-fixed effect, μ_i denotes street-fixed effects, and $\varepsilon_{i,t}$ is a random error term. *** indicates that estimates are significantly different from zero at the 0.01 level; standard errors are in parentheses.

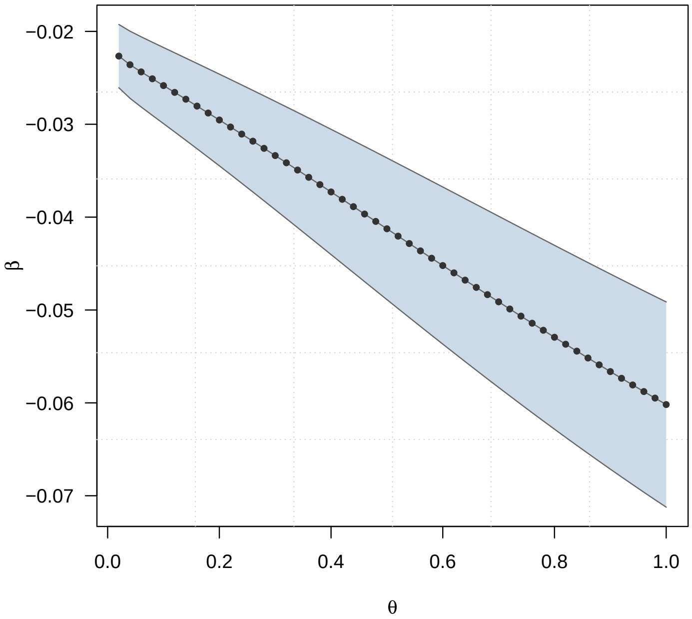
B.2 Additional parking demand models

Table B.2: Additional standard demand models for on-street parking in terms of the occupancy rate

	[1]	[2]	[3]	[4]	[5]
Daily measurement	17:00	12:00	12:00	12:00	12:00
Parking fee	deflated	deflated	deflated	nominal	nominal
Censured occ. rate	yes	no	yes	yes	no
Parking fee, ($\tilde{\beta}$)	-0.024***	-0.029***	-0.028***	-0.024***	-0.029***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Street fixed effects	yes	yes	yes	yes	yes
Period fixed effects	yes	yes	yes	yes	yes
R^2	0.260	0.236	0.206	0.206	0.236
Number of obs.	19,089	19,089	19,089	19,089	19,089

Note: dependent variable is the occupancy rate O (share); censoring $O = 1.30$; parking fee is measured in DKK/hour; *** indicates that estimates are significantly different from zero at the 0.01 level; in the SDM $\theta = 0.25$; standard errors are in parentheses.

Figure B.1: β as a function of θ at 17:00



Note: The β coefficient is from the main SDM model based on equation (10) (see model [3] in Table 3) for a range of different decay parameter values ($\theta \in (0, 1]$). The shaded area represents the 95% confidence interval.