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# The effect of paid parking and bicycle subsidies on employees' parking demand

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ABSTRACT

Employers usually offer free parking to employees, which may lead to welfare losses. Using exogenous variation in daily peak-hour parking tariffs, monthly subscription fees and bicycle subsidies faced by hospital employees, we demonstrate that employees' parking demand is reduced by about 5 percent for every euro per-day tariff increase, and that it is reduced by about 2 percent for every euro subscription fee increase. The introduction of higher parking prices particularly reduced demand during peak hours. We offer compelling evidence that bicycle subsidies reduce parking demand. Hospitals that offer free parking to employees, but then introduce a parking tariff equal to marginal parking costs, induce modest yearly welfare gains of € 60 per parking space, about 8 percent of parking resource costs. This is slightly less than previously found in the literature.

## 1. Introduction

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

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

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

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

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

To be more specific, we study an increase in parking prices for employer-provided parking at the Maastricht University Hospital (UMC+) in the Netherlands, which has over 7000 employees. This hospital has several parking areas, including parking garages for employees. The motivation to increase parking prices was that the space used for parking was needed to construct a new hospital building. Instead of building new underground parking space, the hospital opted to increase the price of parking to reduce peak-hour parking demand.

The new tariff structure has two important features: an increased peak-hour tariff on busy days and a monthly subscription fee. Both depend on the employees' residence location and fall with employees' commuting distance. Hence, employees who live closest to the hospital experienced the highest tariff increases and the highest subscription fees. We therefore expect the strongest decreases in parking demand for this group, especially as the bicycle is a good substitute for the car at short distances.[1]

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

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

In the literature, there is not much known about bicycle subsidies and their effect on bicycle usage by commuters. Wardman et al. (2007) find that a modest financial reward strongly increases bicycle usage in Great Britain. The literature is unclear whether the bicycle is a close substitute to the car and whether the substitutability differs for countries where bicycle use is more common, such as the Netherlands. Parkin et al. (2008), Stinson and Bhat (2004) and Wardman et al. (2007) claim that higher car ownership levels reduce bicycle usage, which indicates that car and bicycle are substitutes. However, Hu and Schneider (2015) suggest that the bicycle is more likely a substitute for the bus than for the car.[2]

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

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

The rest of our paper is organized as follows. In Section 2, we discuss the estimation methodology, followed by a section about the hospital parking policy and the data. In Section 4, we discuss the results. Section 5 is the welfare analysis and Section 6 concludes.

## 2. Data and descriptives

### 2.1. The hospital and its parking policy

The Maastricht University Hospital has about 7200 employees. In the period we investigate (September 2014 until December 2016), employees have the opportunity to park their cars at several hospital-owned parking lots. The hospital aimed to reduce parking capacity from 2100 to 1650 and therefore changed its parking policy in October 2015. We report some descriptives in Table 1. In the old regime, employees had to pay € 0.75 per day. In the new parking regime, daily parking tariffs increase during peak hours, defined from 6:00 till 14:00 on Monday till Thursday, and fall with commuting distance: employees closest to the hospital (within 2 km) have to pay € 3, while employees furthest away (over 7 km) have to pay € 1 for parking during the peak hours. Outside peak hours, the tariff was unchanged. On average, employees pay € 1.31 per day in the current regime.

Furthermore, bicycle use is subsidized in the new regime, which further increases the relative price of car parking. The reward for

[1] In the Netherlands, the bicycle is used in about 25 percent of all commuting trips (CBS, 2004).

[2] Furthermore, mode choice is affected by weather, which we take into account (Liu et al., 2015; Saneinejad et al., 2012).

**Table 1**
Parking tariffs (Monday to Thursday).

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

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

bicycle use is between € 0.50 and € 1.00, increasing with distance, between early October and the end of March, which we will label as "winter". Cycling seems to be an important transport mode, as the share of bicycling is at least half the demand of car users during winter.[3]

In the new regime, employees also have to buy a monthly subscription, which cost between € 1 and € 5, depending on commuting distance, see Table 1. Employees only have to pay for the subscription during a month when they actually make use of the hospital parking during that month. So, peak-hour parking tariffs increased by about € 0.56 per day (€ 1.31 − € 0.75) in the new regime. The monthly subscription fee is € 1.61 on average, whereas the average bicycle subsidy is € 0.94.

### 2.2. Data

We have employee parking transaction data from September 2014 to December 2016 (data from September 2015, the month before the tariff increase, is missing), which is over a year *before* the start of the new regime and over a year *after* the start of the new regime. For employees we know the commuting distance (and the exact employment period). For 6600 employees we were able to match parking transaction data to the commuting distance. We exclude employees that were not employed during the entire study period, which leaves us with 4718 employees. We also use daily weather data (temperature, sunshine, precipitation, wind speed) from the Royal Netherlands Meteorological Institute (KNMI) which will use as control variables to control for weather-induced variation in parking demand.

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

### 2.3. Descriptives

The average daily parking demand per employee in our sample is slightly above 0.27. As we exclude the employees who never park, the average parking demand will be even lower. The relatively low demand is a result of the inclusion of observations of all employees, including those who do not work on a certain day.[4] Daily parking demand during peak hours (between 6:00 and 14:00) is 0.24, so almost 86 percent of all parking transactions are during the peak hours.

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

There is a strong association between commuter distance and parking demand. Table 2 shows this relationship for the old regime (about 800,000 observations) as well as the new regime (about 1.1 million observations). We also give this information for parking during peak hours. These data show that parking demand is less in the new regime for distances up to 7 km. As one may expect, parking demand rises with commuting distance.

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

Table 3 shows monthly parking demand, the monthly *extensive margin* (the share of employees who park at least once during the month), and the monthly *intensive margin* (monthly parking demand given that an employee parks at least once during the month).

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

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

**Table 2**
Daily parking demand.

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

**Table 3**
Monthly parking demand during peak hours.

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

Employees park about four days per month during peak hours on average, which is consistent with the previous table, falls in the new regime.

The extensive margin is 0.62 in the old regime, but only 0.54 in the new regime. The intensive margin is, on average, about six in the old regime and seven in the new regime. Note that this suggests that the intensive margin increases in the new regime, but this is a spurious relationship, because, as we will show, this is entirely due to a selection effect of employees who park at least once.[5] Fig. A1 in the Appendix shows the distribution of the monthly parking frequency per employee conditional on parking at least once. In the new regime, infrequent parking (one to ten times per month) becomes less common, whereas frequent parking (over ten times per month) does not change.

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

Table A1 in the Appendix shows the descriptives of aggregated demand. On average, parking demand is about 1250 per day. In the new parking regime, demand is reduced by slightly over 50 parking transactions per day. Such a reduction is also suggested by the cumulative distribution of aggregated daily demand, which can be found in Fig. A2 in the Appendix.

## 3. Econometric methodology

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

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

We know the exact commuting distance for every employee at the beginning of the study period. Hence, commuting distance is time-invariant.[6] Prices for parking depend on the residence location, but differ only between four commuting-distance intervals (0–2,

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

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

2–5, 5–7, > 7 km) and change with the new parking regime. We include these intervals and the interaction of these intervals with the new parking regime. In essence, we aim to exploit variation over time in the parking probability of employees by controlling for day-of-the-week and month fixed effects.

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

$$\pi_{ikt} = \frac{\exp(\sum_{j=2}^{4} \beta_{j0} d_{ij} + \sum_{j=1}^{4} \gamma_{j0} p_t d_{ij} + \omega_{t0})}{1 + \sum_{k=1}^{2} \exp(\sum_{j=2}^{4} \beta_{jk} d_{ij} + \sum_{j=1}^{4} \gamma_{jk} p_t d_{ij} + \omega_{tk})}. \tag{1}$$

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

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

$$Q_{im} = \sum_{j=2}^{4} \bar{\beta}_j d_{ij} + \sum_{j=1}^{4} \bar{\gamma}_j p_m d_{ij} + \bar{\mu}_m + \bar{\epsilon}_{im}, \tag{2}$$

where $Q_{im}$ denotes the parking frequency of employee $i$ in month $m$, $\bar{\mu}_m$ are month fixed effects, $\bar{\beta}_j$and $\bar{\gamma}_j$ are other parameters to be estimated, and $\bar{\epsilon}_{im}$ is the error term.

Third, note that $Q_{im} = E_{im} \times I_{im}$, where $E_{im}$ is the monthly *extensive margin*, that is, the probability that an employee parks during a month, and $I_{im}$, the monthly *intensive margin*, that is, the parking probability for employees who park at least once per month. The extensive margin is estimated in the same way as in (2), so in another regression we replace $Q_{im}$ with $E_{im}$:

$$E_{im} = \sum_{j=2}^{4} \tilde{\beta}_j d_{ij} + \sum_{j=1}^{4} \tilde{\gamma}_j p_m d_{ij} + \tilde{\mu}_m + \tilde{\epsilon}_{im}, \tag{3}$$

Fourth, we estimate the effect of paid parking on the intensive margin. As we now make a selection of employees for which holds that $E_{im} = 1$, and do not have balanced panel, we include employee fixed effects $\sigma_i$.[7] Hence, we estimate:

$$I_{im} = \sum_{j=2}^{4} \check{\beta}_j d_{ij} + \sum_{j=1}^{4} \check{\gamma}_j p_m d_{ij} + \check{\mu}_m + \check{\sigma}_i + \check{\epsilon}_{im}, \text{if} E_{im} = 1. \tag{4}$$

In (2) and (3), rather than using commuting-distance intervals, we also estimate models using parking tariffs as continuous variable, $\tau_{it}$, so we replace $\sum_{j=1}^{4} \check{\gamma}_j p_t d_{ij}$ by $\check{\delta}\tau_{it}$.

Fifth, we are interested in the effect of the new regime on the *distribution* of parking demand at the level of the hospital. This enables us to investigate whether higher parking tariffs affect demand more on relatively calm or busy days. To estimate the effect of a variable on the distribution of a dependent variable, it is now standard to use quantile regressions (see Koenker and Bassett, 1978; Koenker and Hallock, 2000; Machado and Mata, 2005; Angrist and Pischke, 2008). Let $\theta$ be the $\theta$th quantile of the daily parking demand $Q_t$. For example, for the conditional median, $\theta = 0.5$. Recall that $p_t$ denotes the parking regime. Furthermore, we include day-of-the-week fixed effects $\omega_t$ and weather controls $w_t$ (sunshine share, precipitation, wind speed, summer or winter). Thus, we estimate equation (5):

$$\{\dot{\gamma}_\theta, \dot{\zeta}_\theta, \dot{\omega}_{\theta t}\} = \underset{\breve{\gamma},\breve{\zeta},\breve{\omega}_t}{\operatorname{argmin}} \mathrm{E}[\rho_\theta(Q_{im} - \breve{\gamma} p_t - w_t' \breve{\zeta} - \breve{\omega}_t)], \tag{5}$$

where $\rho_\theta(\bullet)$ is a 'check function', which based on an asymmetric weighting function (see Koenker, 2005; Angrist and Pischke, 2008, pp. 271), and $\dot{\gamma}_\theta$, $\dot{\zeta}_\theta$ and $\dot{\omega}_{\theta t}$ are vectors of parameters to be estimated.

Sixth, we estimate the effect of the bicycle subsidy, which was only given during winter months in the new regime. We introduce the dummy variable $s_t$, which equals one during summer months. We then explain the parking probability, $P_{it}$, of employee $i$ on day $t$ in the following equation:

$$P_{itm} = \sum_{j=2}^{4} \bar{\bar{\beta}}_j d_{ij} + \sum_{j=1}^{4} \bar{\bar{\delta}}_j s_m d_{ij} + \sum_{j=1}^{4} \bar{\bar{\eta}}_j (1 - s_m) d_{ij} + w_t' \bar{\bar{\zeta}} + \bar{\bar{\omega}}_t + \bar{\bar{\mu}}_m + \bar{\bar{\epsilon}}_{itm}, \tag{6}$$

where $\bar{\bar{\omega}}_t$ are day-of-the-week fixed effects and $\bar{\bar{\mu}}_m$ are calendar month fixed effects. $\bar{\bar{\beta}}_j$, $\bar{\bar{\delta}}_j$, $\bar{\bar{\eta}}$ and $\bar{\bar{\zeta}}$ are the other parameters to be estimated.

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

**Table 4**
**Daily peak and off-peak demand.** *(Dependent variable: parking frequency of an employee in off-peak hours or peak hours).*

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

*Notes:* We use a multinomial logit model on peak days (Monday to Thursday). Standard errors between brackets. Significance levels are indicated by asterisks. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Month-of-the-year fixed effects were excluded in order to calculate the marginal effects.

## 4. Main results

### 4.1. Daily parking demand

We estimate the effect of the parking regime on the employees' choice to park during peak hours, during off-peak hours or not to park at all, using a multinomial logit model as in (1). Table 4 reports the marginal effects of the new regime. The estimated coefficients can be found in Table A2.

The results show that demand for off-peak-hour parking is hardly affected by the introduction of the new parking regime. There is a small but statistically significant decrease in off-peak-hour parking demand by employees in the 2–5 and 5–7 km group, whereas there is a small increase in parking demand for people living further away than 7 km. Recall that only employees during peak hours are affected by the parking price. This suggests that for employees who live nearby, peak and off-peak-hour parking demand are complementary. This makes sense for example for employees who sell their car due to the peak period parking price increase, and as a result, will also stop using the car off-peak hours. For employees who live further away, peak hour and off-peak-hour parking demand are almost perfect substitutes (as the decrease in peak-hour demand is close to the increase in off-peak-hour demand). Hence, it seems that workers living close to the hospital have chosen alternative travel modes (e.g., the bicycle) without incurring rescheduling cost (from peak to off-peak); while long-distance commuter might not and thus rely on their private vehicle, but still shift their commute from peak to off-peak hours.

Clearly, the reduction in peak-hour parking demand is an order of magnitude higher than the reduction in off-peak-hour parking demand. Hence, the main effect of the new parking policy is an overall reduction in parking demand though a reduction in peak hour demand. The magnitude of the effect ranges from 0.2 percentage points for the employees living further away than 7 km to almost 5 percentage points for employees living closer than 2 km. Given an average parking demand of 0.27, the effects are substantial.

### 4.2. Monthly parking demand

We now focus on the effect of the new parking regime on the employee's monthly parking demand during peak hours using Eq. (2), as we have seen that demand for off-peak hours does not play an important role. In Table 5 we analyze the total effect, as well as the intensive and extensive margins per commuting distance category.[8] Consistent with the results of Table 4, as shown in column (1), demand of employees who live closest to the hospital are affected strongest by the new regime. On average, employees closer than 2 km reduce their demand by 1.1 days per month, whereas demand by the employees outside 7 km reduced by 0.36 days per month.

In columns (2) and (3) the dependent variable is a dummy variable indicating whether someone parked at least once a month, where we still use a specification as in (3). We see a decrease in the extensive margin particularly for those with a small commuting distance, which supports the hypothesis that the subscription fee discourages particularly employees living within a short distance from work. Using the monetary price increase for the first parking transaction (the combination of the tariff increase and the subscription fee), we show in column (3) that a one-euro tariff increase reduces the probability that an employee parks during a month by almost 3 percentage points. Given that the extensive margin is about 0.58 on average, this equals a 5 percent decrease. We assume here that the monthly subscription fee, including the tariff increase of one (i.e. the first) parking transaction, affects the extensive margin (which seems reasonable because the probability of parking at least once should theoretically only depend on the price of parking once), whereas the daily increase affects the intensive margin (the expense on the monthly subscription fee is a sunk cost and should not have any effect).

In column (4), which is based on Eq. (4), we also see a decrease in parking demand at the intensive margin in the new regime. Employees who live closer than 7 km reduce monthly parking demand by over one transaction per month, whereas it is half a

[8] We have also estimated the corresponding nonlinear models (Logit and Poisson models without employee fixed effects), which give very similar results. With employee fixed effects, the non-linear models are difficult to estimate, but the marginal effect of linear and nonlinear models tend to be identical. See also the discussion in Van Ommeren and Russo (2014) who estimate nonlinear models with fixed effects. In their paper, the marginal effects of linear and nonlinear models are nearly identical

**Table 5**
Monthly parking demand (during peak hours).

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

*Notes:* The extensive margin is the probability to park at least once and the intensive margin refer to monthly parking demand given that an employee parks at least once. Price increase refers to the combination of the price increase and the subscription fee for the extensive margin, whereas it refers to the daily tariff increase for the intensive margin Standard errors between brackets Significance levels are indicated by asterisks. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

transaction for employees outside 7 km. As the average intensive margin in the old regime ranges from 4.6 to 6.8 for these groups in the old regime, the derived price elasticities are around −0.3.[9]

Column (5), which also is based on Eq. (4), shows that a tariff increase of one euro decreases demand at the intensive margin by 0.75 days per month. As the average intensive margin is about 6, this is a 12 percent decrease. Hence, the effect on the intensive margin is stronger than on the extensive margin.

The results imply that, given that about 60 percent of the employees park at least once during a month, a one-euro daily tariff increase reduces aggregated parking demand by 2100 ($-0.75 \times 0.60 \times 4700$ employees) transactions per month, which is about 105 per day, or 8 percent of the original demand. This result indicates that the target of reducing parking demand by 450 transactions per day is not met at all.

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

### *4.3. Aggregate daily parking demand: Quantile regressions*

In this section we investigate the effect of the new parking regime on aggregate daily parking demand and specifically on the *distribution* of the number of parking transactions per day (during peak days) to check if higher parking tariffs affect demand more on relatively calm or busy days. We estimate quantile regressions, using Eq. (5), on different parts of the daily parking-transaction distribution. We control for day of the week and weather conditions. Table 6 gives the results of the 10th, 25th, 50th, 75th and 90th quantile.

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

It is also interesting to investigate whether the effect of the new regime depends on weather conditions. Observe that in Table 6, parking demand is strongly affected by sunshine. Therefore, we interact sunshine share with the new parking regime. The results are shown in Table 7.

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

**Table 6**
**Quantile regression daily parking demand** *(Dependent variable: total parking frequency per peak day)*.

| | 10% | 25% | 50% | 75% | 90% |
|---|---|---|---|---|---|
| New regime | −45.8** | −67.5*** | −64.9*** | −60.8*** | −76.2*** |
| | (21.6) | (24.2) | (11.2) | (9.1) | (13.2) |
| Sunshine share | −96.4** | −112.5*** | −91.5*** | −78.4*** | −78.8*** |
| | (38.4) | (43.0) | (20.0) | (16.1) | (23.5) |
| Precipitation | 2.13 | 2.06 | 2.89** | 2.65** | 4.46*** |
| | (2.51) | (2.80) | (1.30) | (1.05) | (1.53) |
| Maximum wind speed | 7.81 | 8.99 | 4.24 | 4.29** | 3.77 |
| | (5.04) | (5.64) | (2.62) | (2.12) | (3.09) |
| Day-of-the-week fixed effects | yes | yes | yes | yes | yes |
| Calendar month fixed effects | yes | yes | yes | yes | yes |
| Number of observations | 407 | 407 | 407 | 407 | 407 |
| Sum of deviations | 7956 | 14,413 | 15,338 | 10,475 | 5246 |

*Notes:* Standard errors between brackets. Significance levels are indicated by asterisks. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

**Table 7**
**Quantile regression daily parking demand** *(Dependent variable: total parking frequency per peak day)*.

| | 10% | 25% | 50% | 75% | 90% |
|---|---|---|---|---|---|
| New regime | −87.6*** | −62.8 | −79.8*** | −109.3*** | −118.3*** |
| | (34.0) | (40.5) | (19.6) | (11.8) | (21.1) |
| Sunshine share | −209.8*** | −101.8 | −128.4*** | −142.5*** | −127.2*** |
| | (57.2) | (68.0) | (32.9) | (19.9) | (35.4) |
| Sunshine share | 122.8* | −20.8 | 61.9 | 109.6*** | 92.3** |
| × New regime | (71.6) | (85.2) | (41.2) | (24.9) | (44.4) |
| Precipitation | 0.90 | 2.07 | 2.57* | 4.46*** | 5.29*** |
| | (2.40) | (2.86) | (1.38) | (0.84) | (1.49) |
| Maximum wind speed | 9.60** | 8.06 | 3.24 | 2.16 | 2.99 |
| | (4.84) | (5.76) | (2.78) | (1.68) | (3.00) |
| Day-of-the-week fixed effects | yes | yes | yes | yes | yes |
| Calendar month fixed effects | yes | yes | yes | yes | yes |
| Number of observations | 407 | 407 | 407 | 407 | 407 |
| Sum of deviations | 7909 | 14,409 | 15,273 | 10,246 | 5134 |

*Notes:* Standard errors between brackets. Significance levels are indicated by asterisks. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

It again appears that parking demand has decreased more at the higher end of the parking distribution.[10] Sunshine again reduces parking demand, but the effect is generally weaker in the new regime, as the sunshine share interaction term is usually positive. This means that the difference in parking demand between both regimes is stronger during fully overcast days than during sunny days. As parking demand is lower on sunny days, this suggests that in the new regime days with extremely high parking demand are less common.

### *4.4. Bicycle subsidy*

In the previous analyses, we ignored the effect of the bicycle subsidy on car parking demand.[11] As the bicycle subsidy increases the opportunity costs of car parking, it may further reduce car parking demand. The subsidy is only offered during the winter, so we distinguish between the effect of the parking tariff increase on parking demand during the summer months (when there was no bicycle subsidy) and the combined effect of the parking tariff increase and the bicycle parking subsidy during the winter months.[12]

Bicycle commuting depends on season and weather (see, for example, Nankervis, 1999; Bergström and Magnusson, 2003; Brandenburg, et al., 2004; Stinson and Bhat, 2004; Heinen, et al., 2010). In absence of a bicycle subsidy, one expects a stronger response to parking prices in summer, when it is generally more attractive to substitute to cycling. We can mitigate any bias by including calendar month fixed effects and weather controls, which allows us to more accurately estimate the effect of bicycle subsidies on car parking demand. Table 8 reports the results, which is based on the Eq. (6).

Column (1) shows the results when we do not include calendar month fixed effects and do not control for weather. Demand is reduced in the new regime during summer and winter and the decrease is slightly more pronounced during summer months for

[10] Sunshine generally reduces parking demand. For example, on a fully sunny day, total parking demand is reduced by about 100 to 210 cars in all quantiles in the old parking regime.
[11] This was included when estimating the effect of the new regime, but excluded when analyzing the effect of prices.
[12] Note that the latter effect is difficult to interpret, because the increase in opportunity costs of parking depends on the probability of using a bicycle.

**Table 8**
**Peak-parking demand in winter and summer** *(Dependent variable: dummy indicating if an employee parks at a certain peak day).*

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

*Notes:* Commuting distance, day of the week and month fixed effects are included. Standard errors between brackets. Significance levels are indicated by asterisks. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

employees who live further away. The inclusion of calendar month fixed effects makes the price effect less pronounced in summer, but more pronounced in winter, as shown in Column (2). The results now indicate that employees who live close to the hospital (within 5 km) are more affected by the new parking regime in the winter, which is an indication that they are affected by the bicycle subsidy. The results indicate that for employees residing within 2 km, the bicycle subsidy reduces parking demand by 0.016 (−0.053 + 0.037). The inclusion of weather controls in Column (3) does not change this result.[13]

In Column (4) we remove the calendar month fixed effects, but the results still do not change. The effect of the bicycle subsidy, that is, the difference in the effects of the new parking regime between summer and winter, as implied by Columns (2) to (4), is statistically significant for employees within 2 km of the hospital as well as those within 2 to 5 km at conventional significance levels according to a standard linear-restriction *F*-test.[14]

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

## 5. Welfare analysis

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

Welfare losses arise when the parking price is lower than the marginal resource costs. According to the hospital, the resource cost of all 2100 parking spaces is about € 1.4 million per year, which is about € 3.50 per parking space per peak day on average. We will use € 3.50 for the welfare calculation. Note that the *average* resource costs are likely less than the *marginal* resource costs, so our welfare calculations are conservative.[15] This resource cost is still higher than the highest peak tariff. The deadweight loss is a function

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

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

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

**Table 9**
Welfare losses per parking policy.

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

**Table 10**
Welfare losses per distance categories.

| Distance | $dQ_j/dp_j$ | Annual deadweight loss | | |
|---|---|---|---|---|
| | | Free parking | Low tariff | High tariff |
| < 2 km | −0.021 | 4260 | 2630 | 90 |
| 2–5 km | −0.030 | 29,010 | 17,910 | 5330 |
| 5–7 km | −0.045 | 37,320 | 23,040 | 12,190 |
| > 7 km | −0.012 | 45,630 | 28,170 | 23,280 |
| Total | | 116,220 | 71,750 | 40,890 |

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

of the slope of the demand curve $dQ/dp$ and the difference between parking price $p$ and resource costs $c$. We use the group-specific demand responses ($dQ$) estimated in Table 4, and we use parking tariff changes ($dp$) as reported in Table 1. We sum the welfare losses of employees in each distance category, based on 200 peak days per year (there are four peak days per week) and the number of employees in each group $N_j$. The deadweight loss (DWL) is given by:

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

We compute these welfare losses in case of free parking and those of the different price schemes, compared to the welfare-optimal marginal-cost pricing. The derived welfare losses are shown in Table 9.

If parking is free, a deadweight loss of about € 116 thousand arises, about 60 parking space, which is about 8 percent of the resource costs. If the parking tariff is € 0.75, as in the old regime, the deadweight loss decreases to € 72 thousand per year. In the new regime it is € 40 thousand or € 20 per parking space per year, which is 3 percent of the resource costs. Table 10 shows the computed welfare losses per distance category in the three pricing regimes.

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

We have ignored above the *external* cost of car travel. We assume here an external cost of € 0.08 as in Van Ommeren and Russo (2014). Note that the reduction in demand is entirely due to employees with a commuting distance of less than 7 km, about 30 percent of the full sample. Moreover, within this group, 11 percent have a distance of less than 2 km, 46 percent have a commuting distance from 2 to 5 km, and 43 percent have a commuting distance between 5 and 7 km. Hence, assuming a two-way commute, and that all car users switch to other modes, the daily welfare loss of free parking due increase in external cost *per employee* is equal € 0.015. On an annual basis, per parking space, is equal to € 12. This is about 20 percent of the welfare loss due to inefficient use of parking. The latter percentage is much lower than in Van Ommeren and Russo (2014), who are not able to distinguish between differences in marginal effects depending on distance.

## 6. Conclusion

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

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

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

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## Appendix A

See Figs. A1 and A2 and Tables A1 and A2.

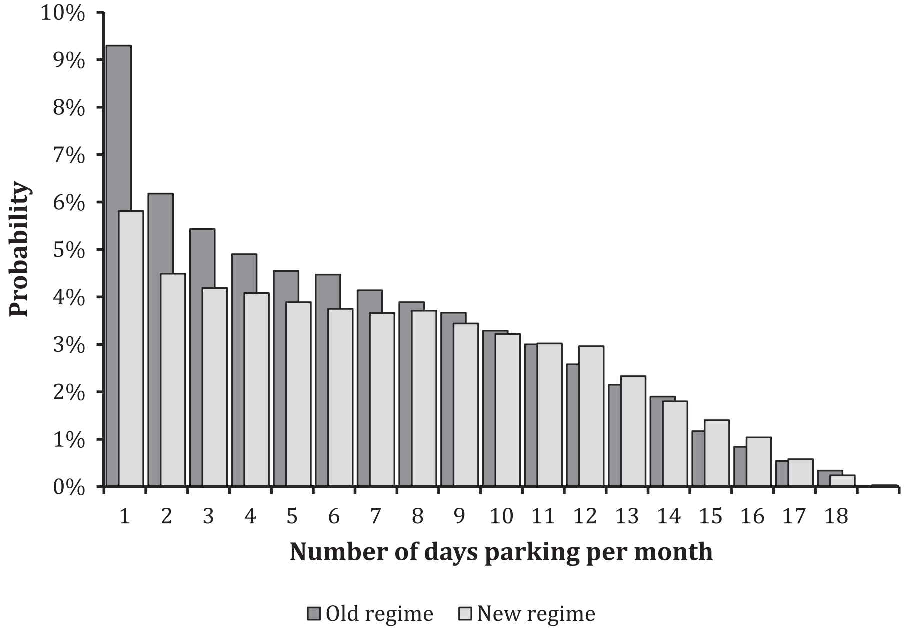


**Fig. A1.** Peak-hour parking frequency per employee per month.

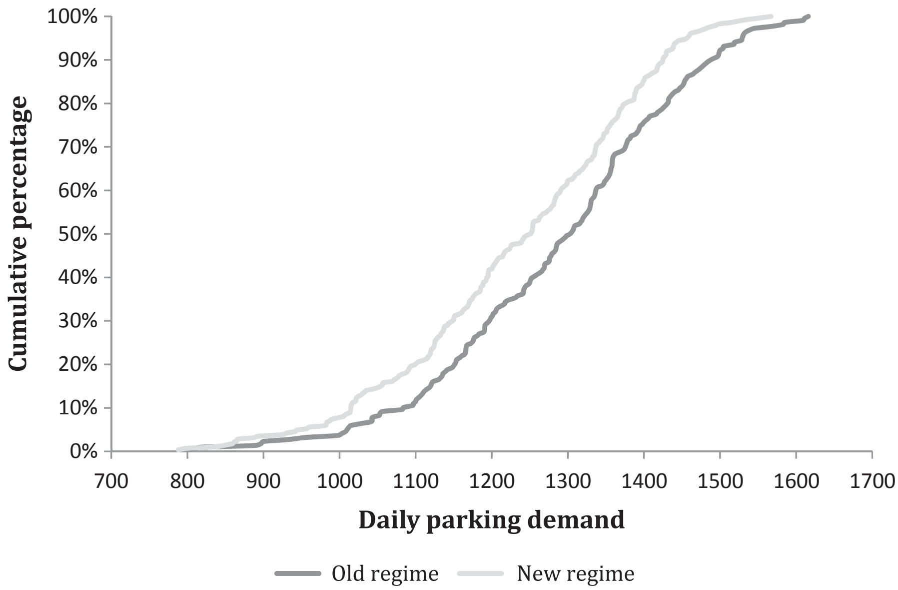


**Fig. A2.** Cumulative probability curve of aggregated daily parking demand.

**Table A1**
Aggregated daily parking demand.

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

**Table A2**
Daily peak and off-peak demand: estimated coefficients.

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

*Notes:* We use a multinomial logit model on peak days (Monday to Thursday). Standard errors between brackets. Significance levels are indicated by asterisks. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Month-of-the-year fixed effects were excluded in order to calculate the marginal effects.

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