DECIPHERING A (PARTIAL) MARKET: THE CASE OF OFF-STREET RESIDENTIAL PARKING IN ZURICH

Georgios Sarlas*
PhD Student
Institute for Transport Planning and Systems, ETH Zurich
HIL F 51.3, Stefano-Franscini-Platz 5, 8093, Zurich, Switzerland
Tel: +41 44 633 37 93; E-mail: georgios.sarlas@ivt.baug.ethz.ch

Uzeyr Sinan
BSc Student
Dept. of Civil, Environmental and Geomatic Engineering, ETH Zurich
8093, Zurich, Switzerland
E-mail: sinanu@student.ethz.ch

Kay W. Axhausen
Professor
Institute for Transport Planning and Systems, ETH Zurich
HIL F 31.3, Stefano-Franscini-Platz 5, 8093, Zurich, Switzerland
Phone: +41 44 633 39 43; E-mail: axhausen@ivt.baug.ethz.ch

* Corresponding author
ABSTRACT

Off-street residential parking market can be viewed as a case where the market-clearing price is the result of a set of characteristics, some of which have been the result of different policies. However, modelling of the pricing mechanism that governs such partial markets has received very low attention in the literature, mainly due to their unregulated nature. The current study aims to fill in that gap by employing a spatial hedonic modelling approach to model off-street parking rental prices for the city of Zurich. In addition, an overview of the various policies in place concerning the on- and off-street parking provision in Zurich is presented. The results highlight the existence of local partial market clearing conditions with rental prices being highly sensitive on the availability of on-street parking in the close vicinity of residences, while the identification of the influence zones of the employed variables brings forward interesting behavioral aspects concerning the decision to rent an off-street parking place. In conclusion, the current study shows that modelling of private off-street parking markets has the potential to shed some light on the underlying mechanisms and provide some useful quantified insights, and it can constitute a useful supplementary tool for policy-making.

Keywords: Residential parking, Off-street parking, Parking policies, Hedonic modeling, Spatial regression
INTRODUCTION

Undoubtedly one of the key elements of driving is the parking end of the trip that can end up adding considerate costs both to the driver and to the society. Parking scarcity, particularly present in urban cores, amplifies the overall implications of parking in various ways. Driven by this, different policies have emerged over the years to mitigate these implications and regulate parking provision. Following the categorization suggested by Barter (1), parking policies can be divided into three categories, the conventional supply-focused policies, the parking management policies, and the market-based policies, where regulation of parking is achieved in different ways. Conventional supply-focused policies aim at providing the required parking space on the basis of different associated demand needs per land use, through the enforcement of minimum and maximum requirements. In summary, parking management policies focus mainly on the demand side by introducing restrictions such as restraints, time limitations, and pricing. On the contrary, market-based policies assume that prices should be determined from the market itself in order to accomplish the efficiency goals and they can constitute a second-best pricing alternative after congestion pricing (2).

Shoup (3) has advocated extensively in favor of policies allowing the existence of market-based parking fees as a way to eliminate cruising and its external costs. As Arnott (4) states “the on-street parking fee is set inefficiently low (in Boston, the rate is $1.00 per hour), with the result that on-street parking spaces are rationed not only through the fee but also through cruising for parking”, pointing out that the existence of pricing cannot be a panacea on its own if the on-street parking remains underpriced. A thorough review of the economics of cruising and parking in general is provided by Inci (5).

In the spirit of Shoup, Millard-Ball et al. (6) evaluated San Francisco’s parking pricing experiment and concluded that market-based fees have helped reducing cruising by 50%. In the same context, a study was conducted for the case of Zurich (7) where a simulation-based approach showed that a policy as such would result to spatially differentiated pricing while city’s revenues would be overall increased. Interestingly, market-based fees seem to be the rule in Japan where the existing regulatory framework has enabled land owners to commercially exploit space in such a way, resulting to the minimization of externalities (8).

Residential Parking

Residential parking constitutes a relatively understudied, but nevertheless important aspect of parking provision. As residential parking we denote the provision of parking at the residence and it includes both public on-street and private off-street parking spaces. The impact of residential parking supply on car ownership has been examined (9, 10) and the main findings show that it has substantial influence on the car ownership levels. Furthermore, another study (11) showed that the provision of residential off-street parking affects the overall commuting behavior, in aspects such as car ownership, and mode choice.

In addition, provision of free residential parking can also have implications on the housing market where as Shoup (12) argues: “the cost of free parking is embedded in the prices of everything...especially in the property prices and rents”. Concerning the off-street parking case, in another study (13) a hedonic model was estimated in order isolate the impact of off-street parking on housing prices (when bundled together), and it was concluded that parking requirements can influence parking affordability. In a similar context, Manville (14) summarizes how off-street parking requirements act in the housing market.

In general, different policies are practiced concerning residential parking. For the case of on-street parking, the most common policy is to provide residents the right to park in restricted public zones through acquiring a residential parking permit (RPP), either freely available or for a nominal price (for a very low and spatially undifferentiated fee). Normally, the use of these restricted zones is unlimited for residents while non-residents can only park for a short time. However, this situation can give rise to a competition both within and between the two groups.

In (15), the authors investigate the possibility of charging residents for on-street parking in New York, a practice which is quite common in European countries. Their findings suggest that residents are
willing to pay for an average $408 per year. In the same spirit, the welfare losses accruing from the existence of an underpriced RPP were estimated in another study (16).

The economic aspects of this policy are discussed in (17) where they demonstrate that RPP programs are “unlikely to result in a first-best allocation of on-street parking spaces, if an efficient level of economic vitality is to be ensured at the same time”. Furthermore, in (18) the authors evaluate the existing RPP program in Berkeley, concluding that imposing short-term limitations to non-residents can be problematic and result to underused spaces.

However, the pricing mechanisms that govern the residential off-street parking has received very little attention in the literature, mainly due to their unregulated nature. Nevertheless, we believe that an analysis of the market of off-street parking has the prospect to offer some qualitative and quantitative insights, useful both for evaluating and shaping policies. To the best of our knowledge, there have been no studies of hedonic modelling of off-street residential parking. We select Zurich as a case study to estimate a hedonic model of parking rental prices in order to understand how underpriced the residential parking permits are. The results highlight the existence of local partial market clearing conditions with rental prices being highly sensitive to the availability of on-street parking in the close vicinity of residence, while the identification of the influence zones of the different employed variables brings forward interesting behavioral aspects concerning the decision to rent an off-street residential parking place. In addition, the results of the estimated spatial regression model provide further support to the argument of local partial markets.

ZURICH PARKING SCHEME

The existing parking provision in Zurich is the result of a combination of supply-focused and parking management policies put into practice over the last decades. As Garrick and McCahill state (19) “Since the late 1980s, Zurich has developed an alternative that's worth studying because it breaks all the rules of conventional transportation planning, and yet has been vitally important to the success of that city”.

Provision of Public Parking Spaces

Two are the main turning points of city’s overall parking policy concerning the provision of public parking. At first, in 1989 the city council decided to implement a parking restraint policy regarding the on-street parking in order to protect the residential areas from excessive traffic and emissions. In particular, on-street parking was divided into two categories, namely the blue and white zones (marked accordingly). Blue zones are designated on-street parking spaces reserved for residents who upon paying a yearly fee of 300 Swiss francs (CHF) gain the right to park without any time limitations inside them, whereas non-residents can remain parked at the same space for an hour during the day but without paying a fee (using a parking disc to indicate their arrival time). Extending the stay during the day is possible for a non-resident by acquiring a one day parking permit for the price of 15 CHF. From the afternoon till the next morning (6pm till 9am), and during Sundays and holidays, there is no limitation over the use of blue zones. This zone contains 70% of the total 50'000 (approximately 35'000) public parking on-street spaces available in the city (20).

The white zone is aimed for shorter stays (up to 2-4 hours), normally upon a fee which is paid at a parking meter adjacent to the location. The hourly price and the time limitation vary spatially, but not temporally, and they are announced on signs. In general, the pricing period is coordinated with the business opening hours, meaning that the majority of spaces are available for overnight parking free of charge (20). Apart from the on-street parking, there is also a number of parking garages scattered across the city (some owned and operated by the city) offering off-street parking possibilities. In total, their capacity is of about 20'000 off-street parking places. They are more expensive than the nearby on-street parking (1-5 CHF per hour) and the pricing is in force around the clock. In summary, pricing and time limitation have been exploited as tools for parking management policy making, aiming at altering the demand for parking, especially during the day.

The second turning point was in 1996, where the so-called historic compromise agreement was made (21). This agreement entailed the preservation of the number of visitor- and customer-oriented public parking spaces in the center of city (district 1) stable at the levels of 1990, on the basis of making
the city more pedestrian friendly and also to put an end to the long-standing dispute over the location and the number of public parking spaces. Gradually, surface parking places were replaced by underground parking garages, freeing up space that had an overall positive impact on city’s landscape and functionality (some interesting photos of the affected places before and after the agreement can be found at (21) along with detailed maps showing the yearly on-street parking removal until 2009).

Private Off-street Parking Spaces

Apart from the garages, private off-street parking spaces exist, normally on-site, and they are exploited commercially. Zurich’s policy concerning the off-street parking can be summarized as rather unconventional regarding the implementation date of the existing regulations. More specifically, the city of Zurich has a supply-focused policy where a regulatory framework including zoning parking ordinances where the minimum and maximum parking requirements per land-use are specified. In particular, as Garrick and McCahill discuss (19), the particularity of Zurich lies on the fact that they incorporated maximum parking regulation in their ordinances relatively early (1989) while in the following ordinances (1996) and amendment (2010) both the maximum and minimum parking requirements were decreased further. The existing regulations include zonal ordinances dividing the city into 5 zones. More specifically, for each 120 square metres of residential floor area the minimum required parking space varies from 0.1 (in the city centre) to 0.7 (in the suburbs) while the maximum from 0.1 to 1.15 (22). Essentially, the city council had decided to regulate the market in such a way to avoid giving rise to excessive parking supply, and thus to restrain car ownership and usage.

According to the parking directory of the city where all parking spaces (both public and private) are recorded, there are about 210’000 private off-street parking places. Moreover, there is no price regulation in place for private parking places, the vast majority of which are commercially exploited by the owners. It should be noted that in most of the cases in Zurich, off-street parking is not bundled with housing. Observational data suggest that in average their rental price is of about 150 CHF per month. It is worth pointing out the substantial price difference between the public and private public parking spaces when it comes to the residential parking case.

According to the official data from the city of Zurich, approximately 43’000 annual residential permits have been issued this year while at the same time about 140’000 vehicles in total are registered. Taking into account the quantity of blue zone parking spaces (35’000), it becomes apparent that the demand exceeds the on-street supply massively. The implication of this is that seeking for an on-street parking becomes a tedious process, given that drivers have to compete not only with other drivers with residential permit, but also with short-stayers during the day, and non-residents drivers after 6 pm. Official data regarding the occupancy rates of the on-street spaces are not available to the authors, however field observational data indicate high occupancy levels during the day (especially in areas close to the center and areas with mixed land use), and overall saturation in the evenings.

MODELLING OFF-STREET PARKING PRICES

Modelling off-street parking prices has the merit that it can provide some quantified insights on the impact of different determinants on market-clearing prices. The advantage of estimating such models can be viewed as twofold. First, among the involved determinants, the impact of different policies will be isolated and hence allow us to draw conclusions concerning their effectiveness. Secondly, to comprehend better the pricing mechanism and acquire knowledge useful for determining future policies. Essentially, the observed market price is the result of the interaction between two underlying mechanisms that leads to a local equilibrium. The demand mechanism is responsible for specifying the demand for parking at any given location while the supply mechanism specifies the available off-street and on-street parking capacity along with the restraints concerning their use. The interaction between the two mechanisms leads to market-clearing prices. Naturally, both mechanisms are of high interest concerning policy making issues. For instance, the decision to offer underpriced, or even free, on-street parking can be assumed to be giving drivers an incentive to cruise for an empty spot and can consequently lead to lower market-clearing prices. On the contrary, deciding to decrease the number of
both on-street and off-street parking places through regulation is expected to have an uplifting impact on the market prices, given certain demand.

**Modelling approach**

Economic theory suggests that the determination of the price of a particular good relies heavily on its characteristics. Based on this insight, employing the hedonic pricing approach allows to model a good’s price based on its characteristics bundle, making the assumption that the good itself is perceived from the market as a bundle of attributes, rather than a single commodity. Hedonic pricing as theory has been put forward by Lancaster and Ridker and Henning, and ever since it has found wide application in the area of modelling housing prices. Departing from the housing market case and in a similar vein, off-street parking market can be considered as a case where the market-clearing price is the result of a set of characteristics, some of which have been the result of different policies.

Following the categorization of characteristics as presented by Ridker and Henning, we distinguish the characteristics as specific to the property, to the location, and to the neighborhood. In general, the main amenity of off-street parking is that it provides a reserved place for parking. Given the problem at hand, in the first category amenities regarding the off-street parking space should be included. Garage parking is a characteristic of apparent value in comparison to the unsheltered option since it offers security, minimization of corrosion due to weather, and no exposure to acts of vandalism. Characteristics such as ease of access, sufficient lighting etc. can be considered as property characteristics as well, however obtaining such data is burdensome. Regarding the location characteristics, the accessibility of the location can be interpreted as such. Last, the majority of the characteristics correspond to neighborhood characteristics where the population density, the mixture of land uses, the availability of on-street parking alternatives, the income of the people living in the neighborhood (thus more or less willingness to pay) etc. are considered to belong to this category.

Ideally, a model formulation capable of accounting for the simultaneity and the interdependence of the two mechanisms determining the price should be employed (such as structural equation model). However, the choice of a simpler model has the advantage that it can incorporate directly supply-demand interaction variables in its specification, which in many cases is more meaningful from a policy making perspective. In addition, there is sufficient evidence in the literature that modelling of spatial variables, such as off-street parking, can involve spatial effects which need to be addressed accordingly. The incorporation of spatial effects into a structural equation system remains a methodological challenge which has not been addressed in the existing literature. Therefore, we consider the estimation of a single linear model, which we will extend accordingly to account for spatial effects and along the same line of thought as prevailing approaches for hedonic modeling, as the preferred alternative for the purposes of our study.

On the modelling front, an ordinary least squares (OLS) model is estimated to serve as the benchmark for our analysis. More specifically, the hedonic pricing model takes the following form:

\[ P = \beta X + \epsilon \]  

where \( P \) is the vector with the \( N \) off-street parking rent observations, \( X \) is a matrix with the bundle of \( k \) attributes per observation with dimensions \( Nxk \), \( \beta \) the estimated parameters, and \( \epsilon \) a vector with \( N \) error terms.

However, a drawback of modelling data of spatial nature is the potential existence of spatial effects that need to be taken into account within the model specification and estimation procedure in order to avoid giving rise to statistical problems such as unreliable statistical tests and biased and inconsistent estimated parameters. In particular, spatial effects correspond to the cases of spatial dependence and heterogeneity. "As spatial dependence, it can be considered to be the existence of a functional relationship between what happens at one point in space and what happens elsewhere. Spatial heterogeneity is considered to be the lack of structural stability of the various phenomena over space, and also the lack of homogeneity of the spatial units of the observations". More specifically,
spatial dependence pertains to the case of having spatially autocorrelated residuals, hence violating the assumption of independent and identically distributed (iid) error terms of the OLS model. Spatial simultaneous autoregressive (SAR) models constitute a modelling alternative that allows to account for the spatial dependence issues. The assumption of these models is that the response variable at each location is a combination of the explanatory variables at that location but also of the response of neighboring locations in different ways depending on the underlying process that gives rise to the autocorrelation issues. More specifically, in the case where a spatial variable has been omitted from the specification of the model, the error terms tend to be spatially autocorrelated and this should be accounted for in the error term (spatial error model). In the case where the price of neighboring locations has an indirect effect on the price of each location, then the inclusion of a spatially lagged price variable can resolve the spatial dependence issues and facilitates the estimation of explanatory variables’ direct effects on the price (spatial lag model). Both models are estimated in terms of maximum likelihood estimation (more information can be found at [27, 28]). Their formulation is presented below.

**Spatial error model:**

\[ P = \beta X + u, \quad u = \lambda W + \epsilon \]  

(2)

where \( u \) is the error term, \( \lambda \) the spatial autoregressive coefficient, \( W \) the spatial weight matrix with dimensions \( N \times N \), and \( \epsilon \) a vector of iid error terms.

**Spatial lag model:**

\[ P = pW + \beta X + u \]  

(3)

where \( p \) is a spatial autocorrelation parameter.

Spatial autocorrelation is normally measured in terms of the Moran’s I measure which shows the degree of autocorrelation (0 value indicates no autocorrelation, while 1 or -1 perfect autocorrelation) (28). The spatial weight matrix \( W \) specifies the neighborhood of each location. Its determination takes place experimentally by identifying up to what spatial extent there is statistically significant autocorrelation (a detailed discussion and illustration can be found at [29]).

On the front of spatial heterogeneity, geographically weighted regression (GWR) constitutes a technique which allows different relationships to exist in space, instead of a global relationship, and provides localized estimates of the coefficients (more information can be found at [30]). The formulation of the model is presented below.

\[ P_i = \beta_{i0} + \sum_{k=1}^{N} \beta_{ik} x_{ik} + \epsilon_i \]  

(4)

where \( P_i \) is the price at location \( i \), \( \beta_{i0} \) is the local regression intercept, \( \beta_{ik} \) is the local regression coefficient for \( k \)th explanatory variable at location \( i \), \( x_{ik} \) is the value of the \( k \)th explanatory variable at location \( i \), and \( \epsilon_i \) is the random error at location \( i \). Essentially, GWR fits a localized regression model by taking into account the observations within a bandwidth and weighing them based on a kernel distance function.

**OFF-STREET PARKING PRICES DATA**

We utilize off-street parking advertisement rental data that we obtained from web resources for the period of 2010-2014, where information about the monthly price, the location of the parking place, the advertisement date, and whether or not it corresponds to a garage is included. Due to the nature of the data and their utilization as a byproduct for our purposes, a high risk of incorrectly registered information and non-market-clearing prices is entailed, thus a data cleaning process is designed to ensure their validity. At first, we take as indication that the market fails to clear the price if an advertisement for the same location is reposted within a short time. For such cases, we keep the latest observation per year, given that a sufficient time exists (at least three months) until it is reposted in the subsequent year. Observations for the same location with extreme price differential, are excluded unless the differential can be justified on the basis of different characteristics (garage or not). Cases with unusually low or high...
prices, are checked individually to determine if they correspond to actual prices or they are the result of typing mistakes, by comparing them with neighboring locations rental prices. Last, only for a small subset of the locations we have more than one valid posting over the observation period, thus the alternative of panel data analysis is rejected. Instead, we choose to randomly pick an observation per location and hence perform pooled cross-sectional analysis with the subsequent inclusion of year dummy variables to capture structural changes over time. An overview of the rental prices along with their spatial distribution is given in Figure 1.

In order to obtain the required location and neighborhood characteristics of the off-street parking places, additional data sources are utilized. In particular, detailed spatial data for on- and off-street places were provided from the city of Zurich (more information at (7)). Concerning the built environment, buildings data including total floor area, land uses, and spatial location are obtained from cadastral information and the federal register of buildings (more information at (31)). Socio-economic data such as aggregated population and household statistics on a hectare level are acquired from the Swiss federal office of statistics. Household data correspond to the year 2012 since data for previous years are unavailable. Finally, the accessibility values refer to the accessibility to employment opportunities and they were calculated at the institute for the purposes of a different project (31).

To make a proper distinction for the hedonic model, public on-street parking spaces are divided into unlimited and limited on the basis of the time limitations in place. The unlimited category includes all parking spaces in the blue zone, parking spaces in the white zone but without a time limitation, and also the uncategorised parking spaces. The limited category includes the remaining white zone parking spaces. It should be mentioned that information pertinent to the pricing of the white zone parking spaces is not available to the authors, however we assume that spaces without time limitations are free of charge since in the majority of cases this aligns with the actual situation in Zurich. In the following table a description of the variables employed in the regression models along with their summary statistics are presented.
**TABLE 1 Definition and summary statistics for variables**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Mean</th>
<th>Std. dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>RentalPrice</td>
<td>Market-clearing price for off-street parking space (PS) [CHF]</td>
<td>151.99</td>
<td>78.8</td>
</tr>
<tr>
<td>log(PuTacc)</td>
<td>Logsum of public transport accessibility to employment opportunities</td>
<td>12.38</td>
<td>0.17</td>
</tr>
<tr>
<td>UnlPublPS/TotalPublPS(500m)</td>
<td>Unlimited public PS/ total public PS in a 500m. radius</td>
<td>0.78</td>
<td>0.2</td>
</tr>
<tr>
<td>PrivPS/TotalPS(200m)</td>
<td>Private PP/ total PP in a 200m. radius</td>
<td>0.82</td>
<td>0.11</td>
</tr>
<tr>
<td>BuildingResidUse</td>
<td>Closest building's floor area with residential use / total floor area</td>
<td>0.38</td>
<td>0.24</td>
</tr>
<tr>
<td>PrivPS(200m)</td>
<td>Number of private PS in a 200m. radius</td>
<td>583.40</td>
<td>304.44</td>
</tr>
<tr>
<td>LimPublicPS(100m)</td>
<td>Number of limited public PS in a 100m. radius</td>
<td>8.96</td>
<td>16.89</td>
</tr>
<tr>
<td>Station(200m)</td>
<td>Dummy variable equals 1 if there is train station within 200m., else zero</td>
<td>0.05</td>
<td>-</td>
</tr>
<tr>
<td>HH12/100sqmRes(300)</td>
<td>Number of households with 1-2 members/ 100sqm. of residential floor area in a 300m. radius</td>
<td>0.98</td>
<td>0.23</td>
</tr>
<tr>
<td>ResidentialUse(100m)</td>
<td>Total floor area with residential use/ total floor area within 100m.</td>
<td>0.32</td>
<td>0.15</td>
</tr>
<tr>
<td>BuildingFloorSpace</td>
<td>Closest building's total floor space [sqm]</td>
<td>2654</td>
<td>7172</td>
</tr>
<tr>
<td>PublPS/100sqm.Floor(100m)</td>
<td>Number of public PS / 100sqm. of floor area in a 100m. radius</td>
<td>0.08</td>
<td>0.07</td>
</tr>
<tr>
<td>OnSitePrivPS/100sqmFloor</td>
<td>Number of on-site private PS / 100sqm. of floor area</td>
<td>1.04</td>
<td>2.84</td>
</tr>
<tr>
<td>OnSiteDummy</td>
<td>Dummy variable equals 1 if OnSitePrivPS/100sqmFloor &lt;2, else zero</td>
<td>0.90</td>
<td>-</td>
</tr>
<tr>
<td>Slope</td>
<td>Closest building's slope [degrees]</td>
<td>3.64</td>
<td>3.35</td>
</tr>
<tr>
<td>Garage</td>
<td>Dummy variable equals 1 if off-street PS is garage, else zero</td>
<td>0.26</td>
<td>-</td>
</tr>
<tr>
<td>DistanceFromCBD</td>
<td>Distance from the main train station [km]</td>
<td>2.93</td>
<td>1.40</td>
</tr>
<tr>
<td>District 2-12</td>
<td>Dummy variables for districts 2 to 12</td>
<td>0.01-0.16</td>
<td>-</td>
</tr>
<tr>
<td>Year 2011-2014</td>
<td>Dummy variables for advertisement years 2011-2014</td>
<td>0.11-0.26</td>
<td>-</td>
</tr>
</tbody>
</table>

**RESULTS - DISCUSSION**

The employment of a semi-log specification as the functional form for our case is preferred for a number of reasons, such as better compliance with linear model assumptions (mitigation of heteroscedasticity issues), non-constant marginal effects, and lower sensitivity to extreme values. In addition, semi-log specification offers appealing parameters’ interpretation allowing for a constant elasticity and semi-elasticity model.

Our qualitative hypothesis is that model results should be aligned with the empirical evidence and intuition concerning the determinants of the off-street rental price. In particular, we expect that parking supply variables should have a negative relation with price, reflecting the fact that as supply lowers, parking alternatives decrease and thus off-street parking prices increase. However, in cases of excessive on-site off-street supply a different relation is expected. On the demand side, we expect the relevant variables to be positively related with the rental price, as the result of more competition for the existing parking spaces. Public transport variables capture essentially patterns associated with higher density of commercial use spaces (since commercial exploitation has developed around places with high accessibility, and especially around train stations), or it can indicate lower car dependence on the course
of daily life, hence lower parking turnover. Smaller households are less likely to own a car and
subsequently we hypothesize the existence of a negative relation with rental price. Garage variable is
expected to have a positive association with price for apparent reasons. Location’s slope is employed as
a proxy for land price, higher values indicating individuals with higher income and consequently higher
willingness to pay for comforts, such as reserved parking space. Last, district dummies are expected to
have negative sign, given that the excluded dummy corresponds to district 1 that is the city center where
the historical compromise in force. Yearly dummies are expected to capture patterns related to the
overall economic growth, which translates into price increases in the observation period.

Model Estimation

At first, an OLS model is estimated to test our hypotheses and quantify the impact of the different
variables. Furthermore, a series of tests is applied to ensure that the estimates are unbiased and the
statistical hypothesis tests are accurate. Regarding the multicollinearity issue, the maximum correlation
among the employed variables is 0.60, which is not alarming. Moreover, a collinearity diagnostic is
estimated (variance inflation factors) where multicollinearity issues are found to occur among the
distance and district dummy variables (value higher than 4), however the inclusion of both variables is
considered not to be problematic, given their highly significant explanatory power (F-statistic=5.44,p-
value=0). A Breusch-Pagan test indicates homoscedastic error terms (p-value=0.975), while based on
Cook’s distance (33) three highly influential observations are excluded from the data set.

The existence of spatial dependence issues on the OLS model is tested in terms of robust
Lagrange multiplier tests (34) for spatial error and spatial lag dependence, and in terms of spatial
autocorrelation existence on the OLS residuals (Moran’s I measure). The spatial weight matrix is
identified experimentally based on the spatial extent of statistically significant autocorrelation. A spatial
weight matrix for a distance of 150 meters and a maximum number of 5 neighbors, with an inverse
distance-based and row standardized weighing scheme, is found to be the best one. Thereinafter, the
relevant tests (Table 2) point to a spatial error dependence case with statistically significant spatial
autocorrelation of 0.099. The estimation results for the OLS model and the spatial error model are
presented in Table 2.

Subsequently, the existence of spatial heterogeneity is tested through the estimation of a GWR
model. More specifically, GWR is estimated with an adaptive bandwidth which is identified on the basis
of minimizing the root mean square prediction error. The results show relatively small variance on the
estimated parameters while in terms of goodness of fit, OLS and spatial error model outweigh GWR.
Moreover, taking into consideration that GWR fails to resolve spatial dependence issues (Moran’s
I=0.11) we conclude that for our study purposes its application can be ambiguous. Therefore, GWR
results are not reported but are available from the authors upon request.
### TABLE 2 Estimation results

<table>
<thead>
<tr>
<th>Dependent variable=log(RentalPrice)</th>
<th>OLS</th>
<th>Spatial Error Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>3.261 *** (1.104)</td>
<td>3.245 *** (1.161)</td>
</tr>
<tr>
<td>log(PuTacc)</td>
<td>0.226 *** (0.086)</td>
<td>0.231 ** (0.091)</td>
</tr>
<tr>
<td>UnlPublPS/TotalPublPS(500m)</td>
<td>-0.299 *** (0.099)</td>
<td>-0.294 *** (0.103)</td>
</tr>
<tr>
<td>PrivPS/TotalPS(200m)</td>
<td>-0.437 *** (0.166)</td>
<td>-0.462 *** (0.171)</td>
</tr>
<tr>
<td>BuildingResidUse</td>
<td>-0.075 (0.053)</td>
<td>-0.065 (0.052)</td>
</tr>
<tr>
<td>PrivPS(200m)</td>
<td>0.0004 *** (0.00005)</td>
<td>0.0001 *** (0.00005)</td>
</tr>
<tr>
<td>LimPublicPS(100m)</td>
<td>0.004 *** (0.001)</td>
<td>0.004 *** (0.001)</td>
</tr>
<tr>
<td>Station(200m)</td>
<td>0.067 (0.056)</td>
<td>0.062 (0.058)</td>
</tr>
<tr>
<td>HH12/100sqmRes(300)</td>
<td>-0.226 *** (0.059)</td>
<td>-0.230 *** (0.061)</td>
</tr>
<tr>
<td>ResidentialUse(100m)</td>
<td>-0.250 ** (0.117)</td>
<td>-0.272 ** (0.120)</td>
</tr>
<tr>
<td>log(BuildingFloorSpace)</td>
<td>0.051 *** (0.013)</td>
<td>0.050 *** (0.013)</td>
</tr>
<tr>
<td>PublPS/100sqm.Floor(100m)</td>
<td>-0.423 * (0.217)</td>
<td>-0.409 * (0.218)</td>
</tr>
<tr>
<td>OnSitePrivPS/100sqm.Floor*OnSiteDummy</td>
<td>-0.154 *** (0.043)</td>
<td>-0.152 *** (0.042)</td>
</tr>
<tr>
<td>Slope</td>
<td>0.005 (0.004)</td>
<td>0.005 (0.005)</td>
</tr>
<tr>
<td>Garage</td>
<td>0.439 *** (0.028)</td>
<td>0.427 *** (0.028)</td>
</tr>
<tr>
<td>DistanceFromCBD</td>
<td>-0.070 *** (0.017)</td>
<td>-0.069 *** (0.018)</td>
</tr>
<tr>
<td>District 2</td>
<td>-0.501 *** (0.116)</td>
<td>-0.509 *** (0.120)</td>
</tr>
<tr>
<td>District 3</td>
<td>-0.518 *** (0.117)</td>
<td>-0.527 *** (0.121)</td>
</tr>
<tr>
<td>District 4</td>
<td>-0.669 *** (0.116)</td>
<td>-0.671 *** (0.120)</td>
</tr>
<tr>
<td>District 5</td>
<td>-0.690 *** (0.127)</td>
<td>-0.710 *** (0.132)</td>
</tr>
<tr>
<td>District 6</td>
<td>-0.553 *** (0.117)</td>
<td>-0.565 *** (0.122)</td>
</tr>
<tr>
<td>District 7</td>
<td>-0.441 *** (0.119)</td>
<td>-0.449 *** (0.123)</td>
</tr>
<tr>
<td>District 8</td>
<td>-0.418 *** (0.114)</td>
<td>-0.427 *** (0.118)</td>
</tr>
<tr>
<td>District 9</td>
<td>-0.593 *** (0.125)</td>
<td>-0.596 *** (0.130)</td>
</tr>
<tr>
<td>District 10</td>
<td>-0.483 *** (0.125)</td>
<td>-0.491 *** (0.129)</td>
</tr>
<tr>
<td>District 11</td>
<td>-0.609 *** (0.121)</td>
<td>-0.611 *** (0.125)</td>
</tr>
<tr>
<td>District 12</td>
<td>-0.600 *** (0.131)</td>
<td>-0.610 *** (0.136)</td>
</tr>
<tr>
<td>Year 2011</td>
<td>0.041 (0.033)</td>
<td>0.037 (0.032)</td>
</tr>
<tr>
<td>Year 2012</td>
<td>-0.027 (0.035)</td>
<td>-0.023 (0.035)</td>
</tr>
<tr>
<td>Year 2013</td>
<td>0.087 ** (0.035)</td>
<td>0.084 ** (0.034)</td>
</tr>
<tr>
<td>Year 2014</td>
<td>0.205 *** (0.041)</td>
<td>0.194 *** (0.040)</td>
</tr>
<tr>
<td>Lambda</td>
<td>0.108 ***</td>
<td></td>
</tr>
<tr>
<td>No. of obs.</td>
<td>1009</td>
<td>1009</td>
</tr>
<tr>
<td>adj. R-squared</td>
<td>0.468</td>
<td></td>
</tr>
<tr>
<td>Pseudo R-squared</td>
<td>-</td>
<td>0.489</td>
</tr>
<tr>
<td>AIC</td>
<td>791</td>
<td>782</td>
</tr>
<tr>
<td>Moran's I measure</td>
<td>0.099 ***</td>
<td>0.002</td>
</tr>
<tr>
<td>Robust LM error</td>
<td>9.38 ***</td>
<td>-</td>
</tr>
<tr>
<td>Robust LM lag</td>
<td>1.125</td>
<td>-</td>
</tr>
</tbody>
</table>

Significant at: 1% ***, 5% **; 10% *, ( ) Standard error

### Discussion

Both estimated models give similar results, however we focus on the spatial error model as the most statistically accurate of the two. In addition, the Akaike Information Criterion (AIC) values and the R-squared values also confirm this, indicating an improvement in terms of goodness of fit. Overall, the estimated parameters confirm our hypotheses and expectations. More specifically, the estimates are interpreted as semi-elasticity and elasticity values. To calculate the percent change for the case of non-transformed variables and avoid giving rise to approximation errors (32), the following formula is applied:
%ΔRP = 100(\exp(\beta \times \Delta X) - 1) \quad (5)

For the case of UnlPublPS/TotalPublPS(500m), if we take the extreme case of having only unlimited parking spaces and deciding to turn them into limited ones, the change in the rental price would be equal to 34.18%. If we assume that the number of limited on-street parking places is doubled from 20 to 40, the parameter of LimPublicPS(100m) implies an additional 8.33% increase on the rental prices, which highlights a substantial total demand response to the supply change related to the provision of limited on-street parking places. In the case where private parking accounts for the half of the parking capacity, and a 10% decrease on the private parking provision occurs, the corresponding parameter of PrivPS/TotalPS(200m) implies a 1.22% increase on the rental price. However, if we assume that the decrease corresponds to 10 parking spaces, according to the parameter of PrivPS(200m), there will be a 0.1% additional decrease on the prices, result which is not in line with our expectation of the response of the supply variables but given its low magnitude it is negligible and it might have arisen as a correction to the impact of the previous variable.

According to Station(200m) estimate, locations within 200 meters from a train station have in average 6.4% higher rental price, all else equal. HH12/100sqmRes(300), ResidentialUse(100m), and DistanceFromCBD parameters are found to be in line with our expectations, reflecting the impact of lower demand levels, while log(BuildingFloorSpace) and Slope reflect the opposite. Of particular interest is the parameter of PublPS/100sqm.Floor(100m) where the provision of on-street parking spaces in relationship to the floor area shows that a removal of on-street parking such as from 1.1 to 1 per 100 sq.m. of floor area, will give rise to 4.17% increase on the rental prices, revealing particularly high sensitivity of the demand response to this supply change. In a similar vein, a 0.1 decrease of the on-site parking spaces (e.g. due to changes in parking ordinances) will lead to 1.53% increase on the rental price. District dummies coefficients affirm the excessive price differential between the rest of districts and the city center where, all else equal, the rental prices can be twice as high. Last, yearly dummies reveal an increase on the rental prices from 2010 to 2014 equal to 21.41%.

In addition to the above, the identified zones of influence of the variables can also be considered as a highly policy-relevant aspect. It should be noted that different radii values were tested before concluding on the chosen ones. Interestingly, different patterns are coming to the surface which can reveal some behavioral aspects concerning the decision to rent an off-street parking place. At first, the availability of off-street parking within a 200 meters radius can be interpreted as the maximum distance that somebody would consider to rent a space. Higher distance would imply higher walking times, and perhaps the total cost (rent and walking time) would be outweighed by the choice of cruising. The 500 meters radius in the variable UnlPublPS/TotalPublPS(500m) can be considered that it includes an extremely big area to be taken into consideration for parking, nevertheless it can be associated to the overall perception of the wider area in terms of parking provision, and also it might be attributed to spillover problems from neighboring locations.

A different pattern is exhibited when focusing on PublPS/100sqm.Floor(100m) and LimPublicPS(100m) where the shorter radius of 100 meters suggests that the parking decision is significantly affected by the provision of on-street parking space in the vicinity of residence. Towards the same direction points also the ResidentialUse(100m) radius, revealing that the demand, and in essence the competition for parking spaces, matters within a close vicinity. The superiority of the on-site parking space variable OnSitePrivPS/100sqmFloor over a short radius counterpart highlights that the decision to rent an off-street parking space essentially depends on local neighborhood characteristics, revealing a localized demand and supply interaction. Furthermore, it should also be noted that the finding of spatial error dependence up to an extent of 150 meters alludes to an unobserved spatial omitted variable, providing further support to the argument that off-street parking rental decision is subject to very local conditions. The identified patterns align with the findings of another study (35) for Zurich where it was found that the walking distance for blue zone residential parking is between 40-110 meters, while for private parking the distance was found to be close 200 meters.
CONCLUSIONS

The current study aims to fill in the gap in the literature about modelling off-street parking rental prices. In summary, the results confirm our initial hypotheses and intuition about the determinants of market-clearing prices, while the impact of the different policies in place is clearly reflected on the results. Notably, the provision of public on-street parking has a very high impact on the rental prices, reflecting that people are willing to potentially cruise on a daily basis in the search of underpriced parking rather than pay a considerate amount of money for rent. This finding can give rise to certain discussions about whether or not the current public parking provision scheme in Zurich offers underpriced parking. The positive relation of the limited time parking spaces and rental prices is also evidence in favor of the responsiveness of the estimated model to the different policies in place.

In addition, the identification of the influence zones of the different employed variables is considered to be of high interest since it reveals behavioral aspects about the residential parking case, aligned with previous research studies (35) which required time consuming on-site observation though. More specifically, it is found that drivers are willing to walk further (200 meters) if they know that they have a reserved parking space, while when they have to search for an on-street parking place the walking distance decreases to 100 meters, as a result of the additional cost of cruising. In summary, the results of the current study highlight the existence of local partial market clearing conditions, a finding which can point directions towards the application of policies with spatially varying conditions (such as RPP fees). In conclusion, the current study makes apparent that modelling of private off-street parking markets has the potential to shed some light on the underlying mechanisms and provide some useful quantified insights, and it can constitute useful supplementary tool for policy-making.

REFERENCES


