Journal of Economic Geography (2018) pp. 1–31 doi:10.1093/jeg/lby003

Unbundling curbside parking costs from housing prices

*Ozan Bakis**, *Eren Inci***,† *and Rifat Ozan Senturk****

*Department of Economics and BETAM, Bahcesehir University, Osmanpasa Mektebi Sk. No. 4-6, Besiktas, 34353 Istanbul, Turkey
**Faculty of Arts and Social Sciences, Sabanci University, Orhanli/Tuzla 34956, Istanbul, Turkey
***Zingat Research, Eski Buyukdere Cd. No:33/4, D:5, Kagithane, 34415, Istanbul, Turkey
†Correspondence to: ereninci@sabanciuniv.edu

Abstract

This article empirically shows that at least some of the costs of curbside parking spaces are capitalized in housing prices even though these parking spaces are not formally bundled with housing units. Making use of Istanbul's transition from free and informal curbside parking to paid and formal, we find that housing prices decreased substantially in response to city operated curbside parking, whereas rents remained statistically the same or, at best, decreased only very slightly.

Keywords: Parking, housing prices, rents
JEL classifications: L91, O17, O18, R31, R41
Date submitted: 3 November 2016 **Editorial decision:** 14 November 2017
Date accepted: 3 January 2018

1. Introduction

When parking is 'free', some people still bear the costs of parking. Shopping malls provide free parking to customers, but embed the parking costs in stores' rents and prices of goods and services sold at the mall (Hasker and Inci, 2014; Ersoy et al., 2016). Employers provide free parking to employees rather than paying higher wages as parking spaces are not taxed as a benefit in kind (van Ommeren and Wentink, 2012). Cities provide cheap curbside parking to residents, but the costs of waiting for parking permits are capitalized in housing prices (van Ommeren et al., 2011).[1] A red flag is raised immediately in economics when the cost of a good or service (in this case parking) is embedded in the price of other goods or services as this situation may have perverse welfare consequences. This article shows that the costs of unpriced or underpriced curbside parking are capitalized in housing prices.

The capitalization of parking costs in property prices is transparent for property with on-site parking. Cities typically require developers to provide enough parking spaces on the property they construct, usually more than one per housing unit. Most developers prefer to provide parking spaces bundled with the property. Thus, if one buys a property, its parking spaces may seem to come for free, but in fact, their cost is already included in the property price. As Shoup (2005, Ch. 20) argues in detail, if on-site

1 See Inci (2015) for a review of similar examples.

parking requirements are canceled or relaxed, developers do not need to provide as many parking spaces and, provided that the housing market is competitive enough, they pass the savings on to customers. Therefore, property prices decrease when parking is unbundled from the price of the property and sold separately. Making use of legislation that exempts developers from on-site parking requirements, Manville (2013) finds that, in Los Angeles, bundled parking increases the asking price of an apartment by 22 dollars per square foot and the asking rent by 200 dollars. He also finds that a condominium with bundled parking is 43,000 dollars more expensive. In their case study of six neighborhoods in San Francisco, Jia and Wachs (1999) find that condominiums with parking units are 13% more expensive.

A related (but more subtle) mechanism is at work in the case of curbside parking spaces although these spaces are not legally bundled with housing units. If curbside parking spaces near a property are free, residents use those spaces as their own parking garage, whose cost is embedded in the property price in some way or another. Thus, housing prices should decrease if the city starts charging for these spaces. In other words, the availability of free curbside parking is a privilege for residents. When parking spaces are converted into paid parking spaces, this privilege disappears and, eventually, parking costs are unbundled from housing prices. In this article, we empirically show that this has been the case in Istanbul, where there has been a gradual transition from free to paid curbside parking starting at the end of 2005.

The city of Istanbul was not operating its curbside parking spaces prior to 2005. Curbside parking was largely free. However, as occasionally occurs in the absence of a formal market, self-appointed informal parking attendants operated on some busy streets, collecting parking fees in exchange for 'looking after' your car.[2] On 1 December 2005, the city established a parking company called ISPARK. As of now, ISPARK operates most of the designated curbside parking spaces in the city.[3] The company expanded gradually over time, neighborhood by neighborhood. In this article, we make use of these variations across neighborhoods and over time to identify the effects of the introduction of formal paid curbside parking on housing prices and rents. In particular, using a difference-in-differences (DD) identification strategy coupled with propensity score matching, we estimate that housing price per square meter decreased by about 198 liras (CPI-adjusted to the price level in June 2007, about 151 dollars)[4] in response to the city oversight of curbside parking, whereas rents remained statistically the same (or at best decreased only very slightly) 1 year after the treatment time. The depreciation in housing prices corresponds to 9.2% of the average housing price per square meter in neighborhoods that ISPARK started operating curbside parking locations.

Shockingly high as it may seem, this impact on housing prices is, in fact, very reasonable. For a typical 100 m^2 flat in Istanbul, total depreciation in the housing price is about 19,780 liras. If we think of this amount as some kind of annuity and assume a typical complete depreciation period of 25 years, the monthly accrual of depreciation is 66 liras (or 124 liras given the price level in June 2015). Thus, if the only difference between two flats in two similar neighborhoods is the availability of free curbside parking, a resident living in the neighborhood with paid curbside parking is willing to

2 Such issues can create more harm than one may think. In the developing world, transportation structure in a city, including parking, is usually an impediment to economic growth (Duranton, 2015).

3 Kadikoy, a large town in Istanbul, is overseeing some of the curbside parking spaces within its borders.

4 The exchange rate between lira and the dollar was 1.31 on 1 June 2007.

pay 2.2 liras (or 4.1 liras given the price level in June 2015) per day for parking to be equally well off as living in another neighborhood with free parking.

The article is organized as follows. Section 2 provides a theoretical framework for our findings by introducing three different effects. It also briefly reviews the institutional framework of Istanbul's parking market. Section 3 describes the data, whereas Section 4 provides our estimation strategy. Section 5 explores the impact on housing prices and rents. Section 6 undertakes a welfare analysis from a housing affordability perspective. Section 7 provides five robustness checks to report how our results are sensitive to different specifications, whereas Section 8 provides our conclusions. The Appendix reports the impact on housing prices and rents without using propensity score matching.

2. Theoretical and institutional framework

Curbside parking in the residential neighborhoods of Istanbul has always been an important amenity. Before the transition to paid and formal parking, the benefits of parking mainly accrued to residents. They regularly park near their premises and it is less costly and easier for them to search for a vacant space than for a nonresident. It was also the case that informal parking attendants had greater incentives to favor residents over nonresidents as they were primarily paid by residents. Although they were engaging in an illegal business, the city did not necessarily enforce the law as they were also serving a useful function in rationing parking that the city was unable to provide on its own at that time.[5] However, if someone insisted on complaining about a particular parking attendant, the attendant could very easily get into trouble.

Usually, the complaint was charged by residents as they had a greater stake (i.e., parking there more often) and was able to identify the informal parking attendant. The way to prevent them from filing legal complaints was to favor them. In fact, informal parking attendants would reserve parking spaces for residents by putting barrels or rocks on the curb, making those spaces unavailable for others. Sometimes, even janitors took care of the parking spaces around residences where they were employed. There was also price discrimination in favor of residents. Residents typically did not pay for parking each time they parked. Rather, they made lump sum payments to the parking attendants, and the per hour equivalents of these payments were usually less than the price immediately after the transition to formal paid parking.[6]

The city's action removed informal parking attendants from the market while making many parking locations paid. Our main contribution in this article is to show empirically that the cost of curbside parking were capitalized in housing prices although these parking spaces are not on the same parcel as the housing units. The driving force behind this result is the prevention of residents from using curbside parking as their own parking garage. We call this the *unbundling effect*.

5 Although there is work on the political economy of downtown parking (e.g., Russo, 2013; De Borger and Russo, 2017), no work we are aware of concentrates on the local incentives feeding informality in the parking market.

6 We do not have data for these informal transactions. We make this claim based on our own experience. However, we are able to find lots of news in the media about residents' protests right after the start of the transition.

Table 1. Expected impact of the three effects on housing prices

	Sign
Unbundling effect	(–)
Trust-enhancing effect	(+)
Reduced-cruising effect	(+)

There are two countervailing effects. One of them is the positive effect associated with the transition from an informal to a formal market. In a formal parking market, there is a legal formal entity (in our case the parking company) that is supposed to meet certain business and quality standards. ISPARK has ISO 9001 quality certification. Thus, the transition to a formal parking market enhances trust and improves quality in the market. In fact, this is one of the marketing pitches of ISPARK. The average parker trusts a formal entity more than he trusts a self-appointed informal parking attendant who stands by the street and implicitly agrees to 'look after' his car against possible damages. All parking attendants working for ISPARK are trained for 42 hours per year on how to provide high-quality and polite service. Thus, the transition to a formal parking market in and of itself should increase housing prices near those parking spaces. We call this the *trust-enhancing effect*.[7]

The second countervailing effect is associated with the transition from free to paid parking spaces. Paid parking decreases the demand for parking, as such the level of cruising for parking, thereby mitigating traffic congestion in the area (Arnott and Inci, 2006, 2010; Arnott et al., 2015).[8] This effect should increase housing prices and rents in those neighborhoods with substantial cruising for parking. We call this the *reduced-cruising effect*.

Table 1 summarizes the expected impact of the three effects on housing prices. While the unbundling effect is expected to decrease housing prices, the other two effects increase them. It is important to note that the degree in which these effects operate should vary from neighborhood to neighborhood and from time to time. Thus, the net impact could be heterogenous across space and time. We estimate the (average) net impact of all three effects combined on housing prices and find it to be negative implying that the unbundling effect dominates the other two. In addition, if cruising for parking is high in a neighborhood, the ability to use curbside parking as one's own parking garage becomes even more important. Thus, whenever the reduced-cruising effect is high, we also expect a higher unbundling effect.

7 The trust-enhancing effect stems from the difference in the levels of trust and service quality between the informal curbside parking operated by informal parking attendants and the formal parking market operated by the city. There are various other security aspects of different parking forms and this varies by country. For example, in the USA, curbside parking is perceived to be relatively safer than garage parking in terms of personal security. The Bureau of Justice Statistics reports that more than one in 10 property crimes occurred in parking lots or garages from 2004 to 2008 in the USA. In contrast, in Istanbul, garage parking is perceived to be safer in terms of personal safety, whereas curbside parking involves a higher risk of burglary or hit and run.

8 Higher parking fees are not always associated with lower cruising levels. Glazer and Niskanen (1992) find that traffic congestion may sometimes increase in response to higher parking fees as they may extensively increase parking turnover by making parking durations shorter. However, this is not the usual outcome.

To illustrate the heterogenous nature of these three effects, we employ two sensitivity analyses. In one of them, we examine what happens when we exclude some old counties in Istanbul, in which cruising for parking is known to be excessive. In line with the theoretical expectations here, the results become weaker. In another, we obtain our estimates for the European and Asian sides of the city separately. We do so as both the housing market dynamics and the operation of the parking market in residential areas are different on each side of the city. To that end, we find that the other two effects dominate the unbundling effect on the Asian side, whereas they continue to be dominated on the European side. This difference can be attributed to the fact that Asian-side residents rely more on on-site parking rather than curbside parking.

How are these effects on housing values expected to be passed on to rents? We concentrate on the impact on housing prices and rents one year after the treatment time. One can view housing prices as the presented discounted value of the present and future stream of rents. In that sense, rent is a flow variable, whereas housing price is a stock variable. If so, one is tempted to conclude that rental prices co-move with housing prices.[9] As such, Table 1 would also apply to rents. This perspective is only partially correct. We find that the reaction of rents over 1 year is statistically significant and slightly negative. Thus, rents do co-move after some time. However, this way of thinking is still problematic for various reasons. Housing units are not necessarily rental units. In Istanbul, only 31.5% of households live in rental housing (TUIK, 2011). The relationship between housing prices and rents is not a direct one. As Glaeser and Gyourko (2007) argue in detail, there are strong reasons to be skeptical that rental data can say much about housing prices. Dokmeci et al. (2003) find that a set of neighborhoods in Istanbul has higher values, whereas a different set of neighborhoods has higher rents, resulting in different rent-to-price ratios over space. Future expectations, macro variables, especially cyclicality, are very important in rent-to-price ratios. Thus, depending upon where we are in the business cycle, rents may react quite differently.

An important empirical regularity across countries is that rents are downward sticky. Lai et al. (2007) and Wang and Zhou (2000) provide theoretical frameworks incorporating downward stickiness of rents. Genesove (2003) documents them for the USA, whereas Aysoy et al. (2014) document them for Turkey. One explanation is that although rents can easily be updated in turnover contracts, it is difficult to change them in rollover rental contracts. Another explanation is grid pricing in which rent is rounded to the nearest multiple of a number. Aysoy et al. (2014) also find that search and moving costs magnify this result, especially for high-income tenants. Our findings are consistent with these price rigidities as we find that rents hardly respond to the depreciation in housing prices, while they do to the appreciation.

3. Data and descriptive statistics

Our empirical analysis utilizes four different datasets. The first dataset includes housing prices and (house) rents data for Istanbul collected by the real estate information company REIDIN. For brevity, we call this the *housing data* hereafter. The data consist

9 There is no rent control in Istanbul. The only restriction is that rent cannot be increased more than the official inflation rate for rollover rental contracts. However, this rule is rarely enforced.

of *monthly* neighborhood averages of housing prices and rents in square meters for 278 random-sampled neighborhoods of 38 counties in Istanbul from July 2007 to August 2013 (73 months).[10] We dropped Adalar, Arnavutkoy, Beykoz, Catalca, Sile and Silivri from our analysis as the parking market is negligible in these periphery counties. All prices in our analysis are CPI-adjusted to June 2007 prices.

The second dataset is ISPARK's administrative parking data from which we extracted the exact establishment dates of all designated curbside parking locations in Istanbul. For brevity, we call this the *parking data* hereafter. There are 797 ISPARK curbside parking locations in 206 neighborhoods in the data. The data are collected by ISPARK's staff with electronic hand terminals and there are no parking meters in the city.[11] As ISPARK established its first parking location on 1 December 2005, one potential issue is the fact that the housing data do not cover the first 19 months of operations. We excluded the 275 parking locations that were established before the start date of our housing data. Most of these initial parking locations were in either major transportation points or busy commercial districts with no or few residential areas. More than 75% of these initial locations have no residential areas, and more than 90% have more commercial areas than residential areas. Thus, they are unlikely to affect housing prices and rents.

After matching the remaining parking locations with our housing data, we end up with 50 neighborhoods in which ISPARK began operating curbside parking locations and 211 neighborhoods in which it did not. The former neighborhoods are our treatment groups and the latter neighborhoods our control groups. ISPARK operates one free and 246 paid curbside parking locations in these neighborhoods.[12] Table 2 documents some summary statistics. The first five columns present the averages of our dependent variables of housing prices and rents in the full sample, in Europe only, in Asia only and in the treatment and control groups, respectively. Column (6) lists the differences between the control and the treatment groups in terms of the dependent variables, whereas column (7) does the same after we match similar neighborhoods based on their observable characteristics by using propensity score matching (PSM hereafter).[13]

As Table 2 reveals, the average housing price per square meter is 1442.5 liras in the whole sample, whereas the average rent per square meter is 6.49 liras. Istanbul lies over two continents, Europe and Asia, separated by Bosporus. Both housing prices and rents are higher on the European side (1451.08 liras and 6.71 liras per square meter,

10 The company collects housing prices and rents from real estate companies and chains on a systematic basis and calculates the neighborhood averages. These are all *asking* prices and, as such the real transaction prices are expected to be lower. REIDIN reports that the generally accepted bargaining margin is between 10% and 15% for housing and 3% and 6% for rents. One should not expect these margins to be biased across neighborhoods. Note that our data are not composed of indices and there is no interpolation or smoothing.

11 Parking fees are mostly charged per hour and they are not much differentiated based on the location at the beginning of the transition, although they are becoming more and more differentiated both temporally and spatially.

12 Although we do not have data for private off-street parking spaces in Istanbul, we have some data for the parking garages and surface lots operated by ISPARK. There are 124 surface lots and 31 multistorey parking garages in our data. The signs and significance of the estimates remain largely the same when we include them in our analysis.

13 As in any other PSM exercise, our estimates are unable to capture any *unobservable* differences between the treatments and the controls.

Table 2. Summary statistics of and differences between dependent variables

	Full sample	Europe only	Asia only	Treatments	Controls	Estimates	
						Raw	Matched
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Housing prices	1442.5	1451.08	1431.93	2158.7	1377.7	781.0	481.8
	(893.6)	(1067.5)	(613.8)	(1499.5)	(785.4)	(44.9)	(52.7)
Rents	6.49	6.71	6.22	8.66	6.30	2.35	1.27
	(2.96)	(3.47)	(2.52)	(4.3)	(2.05)	(0.12)	(0.15)
Sample size	13,740	7596	6144	1140	12,600	13,740	11,244

Notes: The housing prices and rents are per square meter. The last row indicates the sample size for each column. Column (1) reports the average housing prices and rents in the whole sample (CPI-adjusted to prices in June 2007). Columns (2) and (3) do the same for the European and Asian sides of Istanbul separately. Columns (4) and (5) report the same for the treatment groups (neighborhoods in which ISPARK started operating curbside parking) and the control groups (neighborhoods in which ISPARK does not operate curbside parking), respectively. Column (6) shows the raw differences between the treatment and control groups. Column (7) provides the differences in the matched sample created by propensity score matching using the radius matching within a caliper method. As shown in Section 7.5, other matching methods yield similar results. The numbers in parentheses are standard deviations in the first six columns and standard errors in the last one.

respectively) than on the Asian side (1431.93 liras and 6.22 liras per square meter, respectively). The Asian side is primarily residential. Many people prefer to live on the Asian side and work on the European side despite the fact that there is heavy traffic congestion on the three bridges and the tunnel connecting the two continents. We also report the averages within the treatment group. The average housing price is 2158.7 liras per square meter in the treated sample, whereas the average rent is 8.66 liras per square meter. The counterparts on the European side are 2333.6 liras and 9.29 liras per square meter, respectively, and the counterparts on the Asian side are 1641.4 liras and 6.79 liras per square meter, respectively.

The third dataset includes information about the educational and financial characteristics of neighborhoods collected by the Turkish Statistical Institute (TurkStat). We control for the fraction of inhabitants according to their educational attainment in a neighborhood, which was collected in the scope of the Address-Based Population Registration System (ADNKS). We also control for the fraction of free health care receivers in a neighborhood, which we call the *poverty measure*.[14] We expect to see higher housing prices and rents in neighborhoods with higher educational attainment and lower poverty measures. We further control for *population density*, which is defined as the number of inhabitants in a neighborhood divided by the total land area of that neighborhood. The population density should be controlled for since it is highly related to parking demand and availability.

The fourth dataset comes from a survey conducted by the Istanbul Metropolitan Municipality in 2007 while developing the city's transportation master plan. We use the

14 This health care program, called green card (Yesil Kart) in Turkey, is a noncontributory health insurance program that aims to provide health services to the poor.

Table 3. Summary statistics of independent variables

	Full sample			Treatments			Controls		
	Ave.	SD	Obs.	Ave.	SD	Obs.	Ave.	SD	Obs.
Uneducated (%)	9.4	5.7	13,740	8.2	5.2	1140	9.6	5.7	12,600
Primary school (%)	24.8	8.9	13,740	22.7	9.0	1140	25.0	8.8	12,600
High school (%)	24.5	5.3	13,740	25.2	4.7	1140	24.4	5.3	12,600
University (%)	16.6	11.7	13,740	24.2	13.2	1140	14.9	10.6	12,600
Population density	13.7	11.6	13,740	15.0	11.9	1140	13.6	11.5	12,600
Poverty measure	17.0	0.4	12,708	18.5	0.4	1019	16.0	0.4	11,689
Average rent	415.6	210.3	1750	574.7	300.6	329	379.4	163.3	1421
Average income	1189.1	878.1	1750	1530.4	904.4	329	1111.3	853.5	1421
Ave. household size	3.3	0.54	1750	2.93	0.58	329	3.4	0.5	1421
Vehicle ratio	0.19	0.153	1750	0.24	0.160	329	0.17	0.149	1421
Parking ratio	0.14	0.176	1750	0.18	0.217	329	0.13	0.164	1421

Notes: Average rent is per housing unit. The population density is the number of inhabitants in a neighborhood divided by the total land area of that neighborhood. The poverty measure is the fraction of free health care receivers in a neighborhood. The vehicle ratio is the number of vehicles per person in a neighborhood. The parking ratio is the number of parking spaces per person in a neighborhood.

information gathered by this survey in undertaking the PSM used in the empirical analysis. The survey documents neighborhood averages of income, rents and household size. It also documents the number of vehicles and the number of curbside parking spaces in a neighborhood. From these, we calculate the *vehicle* and *parking ratios* for each neighborhood. The vehicle ratio is the number of vehicles per person in a neighborhood, whereas the parking ratio is the number of parking spaces per person in a neighborhood.

Compared with the average number of vehicles, the parking capacity put into operation by ISPARK is sizable enough to make a substantial impact on the availability of parking in a neighborhood. There are on average 9.29 (on- and off-street) parking locations operated by ISPARK in a treated neighborhood and the average capacity of a parking location is 102 cars. According to the 2007 survey, the average number of inhabitants in a neighborhood (based on the raw data) is 19,185, whereas the average number of vehicles is 3004. This results in 0.16 vehicles per person, which is consistent with the vehicle ownership rates calculated for Istanbul in other studies.

Table 3 provides the summary statistics of the independent variables, including educational attainment (ratio of uneducated people and the ratios of primary school, high school and university graduates),[15] population density, poverty measure, average rent, average income, average household size, vehicle ratio, and parking ratio.

15 The TurkStat ADNKS has eight educational attainment categories: illiterate, literate but no school completed, primary school, primary education, junior high school or vocational school at the same level, high school or vocational school at the same level, higher education or more and literacy status unknown. We grouped the first two categories as ‘Uneducated’ and the next three groups as ‘Primary School’.

Combining and matching the four different datasets requires some tedious tasks as some of the neighborhood names in the different datasets are different and the borders of counties and neighborhoods have changed over the years. We match our datasets with each other by overlapping the neighborhoods from different sources on the map using ArcGIS software. We modify the data properly if a border change makes it inevitable. In such cases, we assume that inhabitants and vehicles are evenly distributed over space. If there is more than one parking location in a neighborhood, we use the establishment date of the first one in our analysis.[16] If a parking location is between two neighborhoods (which is usually the case when one side of a street belongs to one neighborhood and the other side to the other neighborhood), we count it in both neighborhoods.

4. Estimation strategy

Within our data period, ISPARK began operating curbside parking locations in different neighborhoods of Istanbul at different times. Exploiting the variation in this quasi-experiment, we analyze the causal impact of the transition from free and informal curbside parking to paid and formal on housing prices and rents. Specifically, we estimate a DD model with many groups and time periods:

$$Y = \alpha + \beta(\text{ISPARK}_{it}) + \gamma(\text{Neighborhood Characteristics}_{it}) + \theta_i + \tau_t + \epsilon_{it}, \quad (1)$$

where Y is either housing prices or rents, α is the regression constant, β is the coefficient we estimate that shows the causal impact of curbside parking spaces on housing prices and rents, subscript i denotes neighborhood and subscript t denotes time. The neighborhood characteristics include the demographic characteristics of neighborhoods and the educational attainment and financial characteristics of its inhabitants. γ is their vector of coefficients. θ_i controls for neighborhood-fixed effects, whereas τ_t controls for time-fixed effects, and finally ϵ_{it} is the time- and neighborhood-varying error term capturing unobserved characteristics.

Because some variables are not available for all years, we devise different specifications to fully exploit the relevant information. In all estimation specifications, we use neighborhood and time dummies to control for neighborhood- and time-fixed effects. To deal with the possibility of serial correlation, we considered applying the methods described by Bertrand et al. (2004) and Hansen (2007). While their models assume independence across clusters, in our case, high correlation among neighborhoods makes it impossible to cluster at the neighborhood level. It is also infeasible to cluster at the county level as then we would end up with only 33 clusters. Wooldridge (2006) finds that there is no theoretical or practical reason to expect efficient results in

16 If our data were at the street level, one could also introduce the *intensity* of treatment by interacting the treatment variable with the established parking capacities. We use the establishment date of the first parking location in a neighborhood by incorporating it as an indicator variable. This allows us to capture the establishment as a 'shock'. It would be problematic to introduce the intensity of treatment in our neighborhood-level analysis as then the shocks are likely to be expected in the subsequent development of parking locations since parking locations in a given neighborhood are introduced at different times.

such a case.[17] We prefer to use levels of the dependent variables rather than a logarithmic specification.[18]

For consistent DD estimates, there should be common trends between the control and the treatment groups in the pretreatment periods. With many groups and time periods, it is not feasible to demonstrate the presence of common trends using figures. As such, we tested this by allowing for leads and lags of the treatment variables, as done by Autor (2003). As Table 8 in Section 7.2 will reveal, all lead variables are insignificant and as such our estimates pass the test.

We were also concerned with the possibility of a spatial correlation between treatments. If the parking company starts operating a parking location somewhere, adjacent areas are more likely to be treated in the future. However, such spatial correlations are more of a concern for *street-level* analyses rather than a *neighborhood-level* analysis like ours. The neighborhoods in Istanbul are relatively large with an average size of 3.2 km^2. Thus, we do not expect the treatment of a neighborhood to have a significant impact on the treatment probability of an adjacent neighborhood. Nor do we expect a significant number of drivers chronically looking for parking in adjacent neighborhoods, which primarily occurs when one happens to live near the border. Thus, we do not expect to have a significant spatial correlation between neighborhoods.[19]

In a DD framework, residents should ideally have no prior information about the timing of treatments. Newspaper articles we have browsed indicate that this assumption is largely satisfied in our case. In particular, the establishment of ISPARK locations and subsequent entries to the neighborhoods come as a surprise to the public.[20] Moreover, it would be ideal if ISPARK established parking locations independently and randomly. However, our correspondence with ISPARK staff revealed that the selection of parking locations is not random. The company tries to establish parking locations in the neighborhoods with higher revenue potential.[21] If the initial differences between neighborhoods stem from this nonrandom selection, our estimates will be biased. We deal with this problem by matching the treatment groups with observationally similar control groups before estimating the DD model. We undertake PSM on the base year using the municipality's survey in 2007, and then conduct a weighted DD on the units

17 As a robustness check, we have also obtained our estimates using block bootstrapping. In that case, the changes in standard errors are negligible for the estimates from the unmatched sample. The coefficients in the PSM estimations are slightly different, but have the same statistical significance. The changes in coefficients are expected as we did not define seeds in the PSM routine. These results are available upon request.

18 It is well recognized that the choice of functional form matters in regressions (Halvorsen and Pollakowski, 1981; Cassel and Mendelsohn, 1985; Cropper et al., 1988). In our case, semilog regression of housing prices yields qualitatively the same results with level regressions, while that of rents is not entirely consistent with our economic intuition.

19 This point is very important as there could be displacement effects in a more micro-level analysis (such as a street-level analysis). Thus, control groups could potentially be affected by the treatment. We do not expect this to happen in our neighborhood-level analysis as neighborhoods are relatively large in Istanbul.

20 See also our test in Section 7.2 indicating that the lead variables in a dynamic impact analysis are insignificant. This suggests that residents did not anticipate ISPARK's establishment of parking locations in their neighborhood or at least they did not reflect it in the housing prices or rents immediately.

21 Given that we excluded the initial parking locations, most of which are located at major transportation points or busy commercial districts, the remaining locations are mainly residential and dispersed within the city.

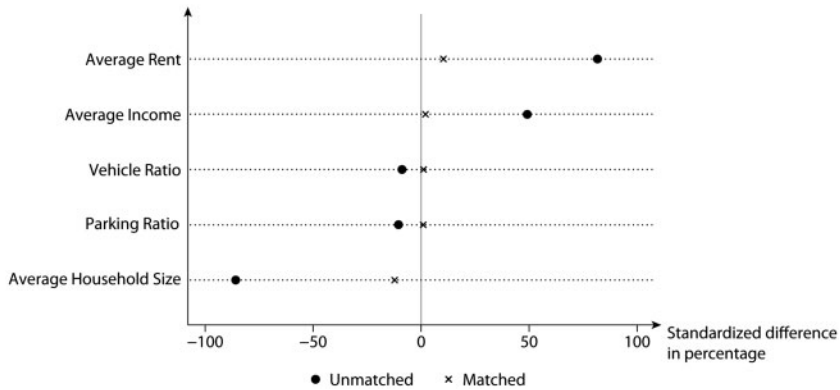

Figure 1. Evaluation of matching quality.
Notes: The vehicle ratio is the number of vehicles per person in a neighborhood. The parking ratio is the number of parking spaces per person in a neighborhood.

that remain on common support. This estimation design allows us to concentrate on the characteristics that determine 'participation'.

We match the neighborhoods using their pretreatment characteristics including average rent, average income, average household size, vehicle ratio and parking ratio. Unlike many North American cities, the neighborhoods are not as homogeneous in terms of income in Turkey. It is usually the case that streets, where richer households reside, are surrounded by poorer residential blocks, and occasionally the latter group works for the former group. Such a polycentric urban form makes sense in terms of optimizing transportation costs. More importantly, one cannot really say that the new parking regime in Istanbul was rolled out from the most congested and high priced neighborhoods to the less congested lower priced neighborhoods over time. A neighborhood has both rich and poor streets and it may be profitable to establish parking locations on either street.

Our DD estimates are based on a weighted-least-squares regression by weighting the observations according to the weights derived from the matching. As demonstrated by Hirano et al. (2003), this procedure yields a fully efficient estimator. The DD estimator has the following form:

$$DD = \frac{1}{N}\left[\sum_{i\epsilon T}\left(Y_{i2}^{T} - Y_{i1}^{T}\right) - \sum_{j\epsilon C}\omega(i,j)\left(Y_{j2}^{C} - Y_{j1}^{C}\right)\right], \tag{2}$$

where T represents the treatment neighborhoods and C the control neighborhoods, Ys are either housing prices or rents in a neighborhood, N is the sample size, and $\omega(i,j)$ is the weight obtained from PSM. This estimation method is different from a standard DD estimation in that the weights, $\omega(i,j)$, are derived from the corresponding PSM.

Since the survey we use for PSM is conducted before the starting point of our data, the measures we use in the propensity scores are not confounded with the outcomes of the treatment. The quality of matching also lies in balancing the characteristics between treated and untreated neighborhoods. Figure 1 indicates that the balancing between these groups is pretty much satisfied. In particular, the differences based on observable pretreatment characteristics are clearly diminished after matching. In fact, they are no

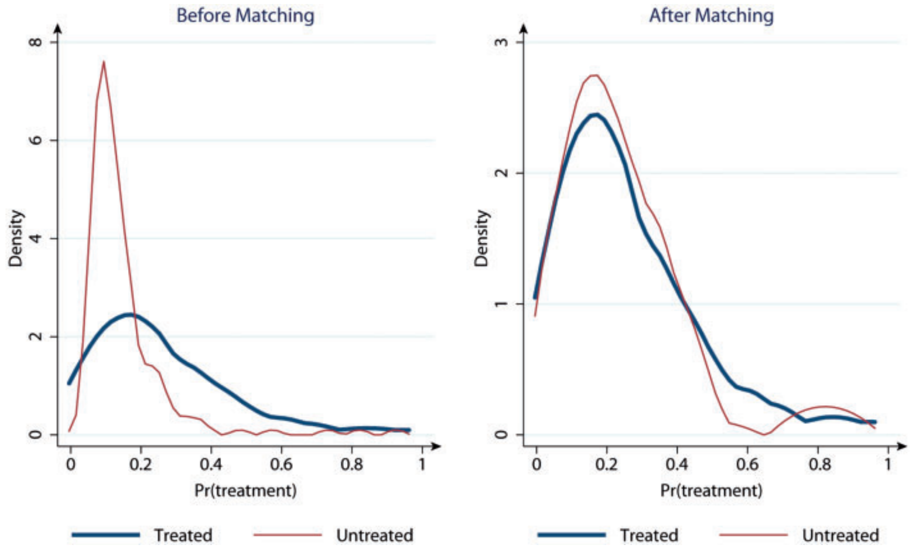

Figure 2. Propensity score distributions for treated and untreated neighborhoods.

longer statistically significant after matching, suggesting that the matching process helped to reduce the bias associated with the observable characteristics.

We use radius matching with a caliper of 0.01 and find that the PSM is successful in making the distributions of the propensity scores for treated and untreated neighborhoods similar.[22] To visualize the performance of our PSM exercise, Figure 2 displays these distributions. This figure clearly reveals that the overlapping condition for the distributions of the propensity scores for treated and untreated neighborhoods is satisfied. Thus, the common support assumption holds.

5. Empirical estimates

Table 4 reports the regression results based on the DD estimation coupled with PSM. The first two columns concentrate on the impact on housing prices. The estimates presented in column (1) use the variables available for all years. To better control for financial characteristics in a neighborhood, the estimates presented in column (2) also use the poverty measure, but this measure is missing for 2011 and 2013. The last two columns follow the same procedures as the first two, but this time to obtain the impact on rents. We control for neighborhood- and time-fixed effects in all estimations in this and subsequent sections.

The impact on housing prices is statistically and economically significant. The estimates presented in column (1) indicate that housing prices decreased by 180.478 liras per square meter, on average, in response to city operated curbside parking. The impact is slightly higher (197.761 liras per square meter) when we control for the poverty

22 Table 11 in Section 7.5 shows that the nearest neighbor, Kernel with normal distribution, and the Mahalanobis matching methods provide similar outcomes.

Table 4. Estimated impact of ISPARK parking locations on housing prices and rents

	Housing prices (1)	Housing prices (2)	Rents (3)	Rents (4)
ISPARK	–180.478***	–197.761***	–0.079	–0.043
	(47.424)	(50.854)	(0.135)	(0.153)
Uneducated	–6.632**	–86.809***	–0.007	–0.202***
	(3.307)	(10.111)	(0.007)	(0.035)
Primary school	–13.936***	–0.147	–0.073***	–0.035***
	(2.982)	(4.081)	(0.006)	(0.011)
High school	–35.443***	–64.770***	–0.006	–0.031*
	(8.120)	(9.939)	(0.016)	(0.018)
Population density	1.209**	5.248***	0.003**	0.017***
	(0.520)	(1.157)	(0.001)	(0.003)
Poverty measure		–0.258***		0.001**
		(0.080)		(0.000)
R^2	0.961	0.961	0.971	0.969
N	10,080	8016	10,080	8016

Notes: The dependent variables are housing prices per square meter (first two columns) and rents per square meter (last two columns). The population density is the number of inhabitants in a neighborhood divided by the total land area of that neighborhood. The poverty measure is the fraction of free health care receivers in a neighborhood. The Huber–White standard errors are reported in parentheses. Neighborhood and time dummies are included in all specifications. PSM is employed using radius matching with a caliper of 0.01 as defined by Dehejia and Wahba (2002). The idea is to use all neighborhoods within a caliper for matching. The results using other matching methods are reported in Section 7.5. University graduates are the omitted group in the regressions.
*Significant at the 10% level, **significant at the 5% level, ***significant at the 1% level.

measure in column (2).[23] These are the impacts 1 year after the treatments. Section 7.2 undertakes a dynamic impact analysis to demonstrate that the impact on housing prices grows in time.[24]

23 Table A1 in the Appendix reports the estimates using the unmatched sample. The estimates in this section based on the matched sample are somewhat lower than their counterparts in Table A1. Such a difference hints at the existence of an upward omitted variable bias in the unmatched sample.

24 One important point to mention here is that the housing prices and rents are neighborhood averages. This means that the composition may change over time, causing biased estimates. A long-standing literature discusses how to deal with such biases (see, e.g., Dorsey et al., 2010). Two well-known methods are using coefficients from hedonics or following repeat sales a la Case–Schiller. As we have no data about repeat sales, we cannot use the Case–Schiller method. We are not able to have a hedonic estimation, either, because we only have the price, but not housing attributes. Our time and neighborhood fixed effects control for time and neighborhood-invariant biases. PSM improves the comparison set by matching neighborhoods with observationally similar neighborhoods. The neighborhood averages of housing prices could still be biased because housing size and quality differ in time. We use price per square meter to avoid biases due to housing size. As for quality differences, one would expect housing quality to increase over time as the construction technology advances. If quality improvement is common across neighborhoods, our estimation strategy takes care of this. If quality improves faster in some other neighborhoods than others, then there should be an upward bias. But note that we obtain a negative impact on housing prices. Hence, if there is such an upward bias, our estimates serve as lower bounds.

Our analysis is short-run as a large fraction of cars is still able to park for free. There are close to three million cars in Istanbul, whereas the total number of designated parking spaces (including parking spaces at shopping malls, hospitals and hotels) amounts to only 0.6 million. More importantly, the total number of operated curbside parking spaces is only 16,781 (IBB, 2016). As paid curbside parking becomes widespread in the city, people will have less ability (or higher costs) to 'escape' from it. Thus, the effects we estimate are likely to level off in the long run.

To better understand the impact on housing prices, consider a typical housing unit in Istanbul, which is about 100 m^2. We estimate that the price of this housing unit depreciates by 19,780 liras 1 year after ISPARK begins parking operations in its neighborhood. Viewing the total depreciation amount as an annuity and assuming a full amortization period of 25 years, the monthly accrual of depreciation is 66 liras. Thus, a resident should be willing to pay 2.2 liras daily to park curbside. These money terms are CPI-adjusted to the price level in June 2007. The present value of this amount is above 4 liras. Therefore, the impact of curbside parking on housing prices is substantial.

The impact on rent is close to zero and, in fact, statistically insignificant. Thus, the depreciation in house values is not passed on to rents. As we explain in Section 2, it is well documented that rents are downward sticky and, as such, do not respond to housing price depreciation much (see, e.g., Genesove (2003) for documentation for the USA, and Aysoy et al. (2014) for Turkey). There could also be sorting across neighborhoods. In particular, tenants owning cars could have relocated from neighborhoods with paid parking to other neighborhoods (some may even disown their cars), whereas those who do not have cars move into more central locations. As a result, the demand for rental units in a neighborhood does not substantially change overall. Thus, rents remain largely the same across neighborhoods. Nevertheless, although we have no data to measure the extent of sorting in the city, we expect such sorting to be limited within a 1-year period. Another reason could be that renters are less likely to own cars than house owners, so that their demand is unaffected by the policy change.

The following facts about the housing market in Istanbul further enforce the downward rigidity in rents. Housing is not just a consumption good, but also an investment good for landlords. A landlord's return on his real estate investment is a combination of the appreciation of the property and the rental income. Since there has been a huge appreciation in housing prices in Istanbul, the rental income portion has become less important.[25] Thus, landlords can reasonably tolerate vacancy. In addition, there has been a massive internal migration to Istanbul making landlords' vacancy risk even less important.[26] However, rental housing is only a consumption good for tenants. As documented by Aysoy et al. (2014), search and moving costs are important for tenants, not just in Istanbul, but in Turkey in general.

Finally, Table 4 indicates that increased population density is associated with higher housing prices and rents in all of the four specifications, as expected. Other independent variables also have the expected signs. In particular, increased educational attainment and decreased poverty measure are associated with higher housing prices and rents.

25 According to the housing price index published by the Central Bank of Turkey, the appreciation from 2010 to 2015 is 154%.

26 The population of the city increased from 1 million in 1950s to 14 million in 2016.

Note that university graduates are the omitted group in our regressions. Thus, the signs of the other educational attainment categories, which are all negative, are relative to the impact of university graduates. As such, educational attainment has a positive impact on housing prices and rents in a neighborhood.[27]

6. Housing affordability

Our data do not allow for a comprehensive welfare analysis of the transition from informal to formal parking in Istanbul. In this section, we look at welfare only from a housing affordability perspective, which obviously excludes several important dimensions of welfare changes. Even if we were to come up with perfect welfare measures from our estimates, one should still be cautious in interpreting them in our context. We estimate the impact on housing prices and rents at the end of the first year after the establishment of parking spaces. Thus, the welfare analysis can only be short run. However, the price changes are persistent affecting housing affordability in the long run. People have greater ability to avoid paid parking in the short run as only a limited number of neighborhoods are treated. This induces the housing price changes. As the treatment becomes more widespread in the city, one should expect a lower impact on housing prices. Given that parking revenue is distributed back to the people, the overall change may virtually be redistribution from car-owning people to other people who do not own cars. As the latter group tends to be poorer than the former and people are risk averse, societal welfare should increase.

To derive a short-run welfare analysis, we consider a neighborhood that will be treated next year and choose a housing unit at random. We then compare the monetary costs of housing and parking before and after the treatment. We specifically ask how much a random household gains/loses if it buys/rents a housing unit next year after the formal parking market is introduced rather than buying/renting this year when there is an informal parking market. We implicitly assume that all people are identical and risk neutral caring only about money changes.

Welfare changes are caused by changes in both housing and parking costs. We first concentrate on the change in the average housing cost. As Table 2 reports, average housing price per square meter is 2158.7 liras in the treated neighborhoods. In Section 5, we find that housing prices decrease, on average, by 197.8 liras after treatments. A typical housing unit in Istanbul is about 100 m^2, for which the total depreciation in the housing price is 19,780 liras. Assuming a full amortization of 25 years, the daily accrual of depreciation is about 2.2 liras. As for rents, we know from Table 2 that the average rent per square meter is 8.66 liras in the treated neighborhoods, but Section 5 indicates that rents remain statistically the same after the treatment.

27 Although the signs of the educational attainment categories are as expected, the ranking between them is convoluted. In particular, one expects the magnitude of the coefficient to decrease as educational attainment increases, but it does not do so in our regressions. The reason for this is that there is not much variation in educational attainment over time. Thus, although we get the expected signs, we do not identify educational attainment's impact perfectly. In fact, when we control for only university graduates, neither the coefficient of interest nor its statistical significance changes much. Because educational attainment categories are only control variables in our regressions that make use of exogenous changes in parking, only their signs should be taken into account, not their magnitude.

Changes in parking costs affect only car owners.[28] We know that parking was largely free prior to the treatments. If there was paid informal parking (for which we do not have transaction data), it was cheap for residents and definitely less than the formal parking fees enacted after the treatments. It will be clear later on that all that matters across different scenarios is not the level of parking fees before and after the treatment, but rather the difference between them. The initial parking fees that ISPARK charged were different at different times and locations. There were no discounts for residents in the early years, whereas discounts as high as 75% have been introduced in the later years. Moreover, the effective parking fee residents pay is the average fee that they pay after taking into account that they do not pay over weekends and after business hours. Thus, the parking fee we use is only an average, just like the empirical estimates we have. The welfare exercise here is also an average, whereas, in reality, welfare gains should be expected to vary from neighborhood to neighborhood. Our sensitivity analyses in Section 7 indicates that the magnitude of the impact varies across time and space.

In sum, for a car-owning buyer, while housing becomes more affordable, parking costs are going to be higher after the treatment. However, households without cars are not affected by the increase in parking costs. For renters, there is no change in both housing and parking costs after the treatment if they do not own cars, whereas only parking costs are higher if they are car owners. One disadvantage of welfare analysis from a housing affordability perspective is that it will ignore the changes in the welfare of house owners who will continue to own their housing units in the interval of our welfare analysis. At first look, this may seem too restrictive. However, although the housing price depreciates, they continue to own the same housing unit. Thus, one can even argue that they do not have a *real* welfare change if they do not own a car. And, if they own a car, our analysis implicitly takes into account their welfare change in terms of parking costs.

We use house ownership rates as a rough measure of potential buyers in the market. TUIK (2011) reports that 31.5% of households in Istanbul are renters, 0.9% live in housing provided by their employer, 60.6% are house owners and 7% are not owners but do not pay rent, either. Thus, the percentage of households that do not have any interest in the price of the housing unit that they are currently living in is $31.5 + 0.9 = 32.4\%$. The rest, 67.6% of households, are either a house owner or someone (for instance a close relative) who has at least some interest in the price of the housing unit. We assume that a random-chosen housing unit is rented with 32.4% probability and purchased with 67.6% probability.

We know that 11.3% of the population in Istanbul have cars (IBB, 2016). Table 3 reports that the average household has 3.3 people. Therefore, we assume that $11.3 \times 3.3 = 37.3\%$ of households have cars, whereas 62.7% do not have cars. In reality, car ownership should be expected to be higher among high-income households (see. e.g., De Groote et al., 2016) and high-income households in Istanbul tend to be house owners rather than renters. For simplicity, we assume that this percentage is

28 We should note here that there can be possible composition effects. For example, house owners are more likely to have cars than renters, and owners of larger housing units are more likely to have cars than owners of small housing units. If there is a negative effect on the supply of affected units, one would expect to see an increase in larger, more valuable units on the market, thereby leading to an understatement of estimated effects.

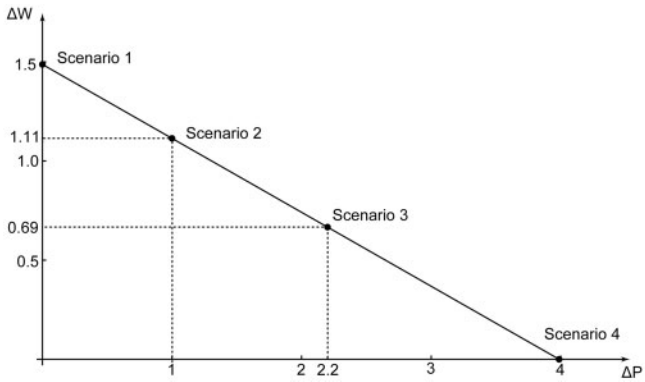

Figure 3. Welfare change as a function of parking fee differential.

uniform across buyers and renters and stays the same within a year. We also assume that no household owns more than one car, which is largely realistic for Istanbul.

Let parking fee in the informal market be P_1 and parking fee in the formal market be $P_2 > P_1$, and define $\Delta P = P_2 - P_1 > 0$ as the parking fee differential. Then, given our assumptions above, we can calculate the welfare change as follows. A random household is a buyer with 67.6% probability. It does not own a car with 62.7% probability, in which case its welfare increases by 2.2 liras per day if it buys the housing unit after the treatment. It owns a car with 37.3% probability, in which case its welfare decreases by ΔP liras per day as its parking costs will be higher although the housing unit it buys will be more affordable after the treatment. The household is a renter with 32.4% probability. Its welfare does not change if it does not own a car as rents remained statistically the same after the treatments. This happens with 62.7% probability. If it owns a car, which happens with a probability of 37.3%, its welfare decreases by ΔP liras per day. Overall, the welfare change of a randomly selected household, ΔW, is given by

$$\Delta W = 0.676 \times [(0.627) \times (2.2) + (0.373) \times (2.2 - \Delta P)] + 0.324 \times [(0.627) \times (0) + (0.373) \times (-\Delta P)], \quad (3)$$

which simplifies to $\Delta W = 1.4872 - 0.373\Delta P$. The welfare change is a continuously decreasing linear function of the parking fee differential, and it varies between zero and 1.49. Figure 3 plots the relationship between the two.

There are four different scenarios that are of particular interest. We list them in Table 5. Scenario 1 is more of a hypothetical exercise where ΔP is arbitrarily close to zero ($\Delta P \to 0$). That is, ISPARK takes over parking locations and makes a negligible parking fee change. It only somewhat prevents residents from using parking spaces as their own parking garages. This is unrealistic, yet it sets an upper bound for the welfare gain, which is about $\Delta W^1 = 1.49$ per household per day.

Scenario 2, $\Delta P = 1$. For instance, it could be the case that parking was free prior to the treatment, while becoming 1 lira per day after the treatment. Or it could be that parking was 3 liras per day and becomes 4 liras after the treatment. As a result, the welfare increase per household per day is $\Delta W^2 = 1.11$ liras. This is substantial and in the same order of magnitude with the external cruising costs of parking (or even

Table 5. Welfare change under different scenarios

	Housing cost (per household-day)	Parking cost (w/car) (per household-day)	Parking cost (w/o car) (per household-day)	Welfare change (per household-day)
Scenario 1				+1.49
Buyer	–2.2	0	0	
Renter	0	0	0	
Scenario 2				+1.11
Buyer	–2.2	+1	0	
Renter	0	+1	0	
Scenario 3				+0.67
Buyer	–2.2	+2.2	0	
Renter	0	+2.2	0	
Scenario 4				0
Buyer	–2.2	+4	0	
Renter	0	+4	0	

external traffic congestion costs) that Inci et al. (2017) calculate for a shopping street in Istanbul. Scenario 3 provides a case in which the parking fee differential is exactly 2.2 liras per day. Thus, ISPARK completely extracts the welfare gain of car-owner households. As a result, the welfare gain of car-owning buyers is null, but that of non-car owners, who are a larger group, increases. The net welfare gain is $\Delta W^3 = 0.67$ liras per household per day. Finally, scenario 4 presents the case in which the short-run welfare change is zero ($\Delta W^4 = 0$), which occurs if ISPARK raises the parking fee by about 4 liras after the treatment.

The welfare analysis we provide here makes various assumptions and simplifications, which lead us to underestimate the welfare gain. We ignore new housing developments. We ignore the distortions in housing sizes as curbside parking costs are capitalized in housing prices in the informal market regime. We ignore the external costs of traffic congestion and cruising for parking (see, e.g., Inci et al., 2017, for an estimate on a busy shopping street in Istanbul).[29] All of these are important not just for car owners, but also for everyone else living in the neighborhood as they negatively affect emissions, commute times and noise level. We ignore the welfare gain of nonresidents although their welfare as residents of somewhere else is implicitly included in our welfare calculations. Finally, we assume that the parking revenue is not redistributed back to the people. Thus, our welfare calculations serve mostly as lower bounds.[30]

7. Sensitivity checks

It should be clear thus far that ISPARK's establishment of parking locations prevented residents from using the curbside as their own parking garage, which unbundles parking

29 Although we think that congestion costs are high in Istanbul, we have no evidence that they have decreased in treated neighborhoods. Ours is more of a theoretical argument in that imposing parking fees are supposed to decrease congestion if there were no parking fees on a busy street (Arnott and Inci, 2006).

30 Another important welfare-improving aspect of introduction of paid parking that we ignore in this article is that people ration their use of parking more effectively.

costs from housing prices. The unbundling effect dominates the trust-enhancing and reduced-cruising effects combined in the overall city. Thus, the net impact on housing prices is negative. To bolster confidence in our results, this section provides five robustness checks.

Section 7.1 obtains the estimates separately for the European and Asian sides of Istanbul in order to illustrate the interplay among the three effects. Section 7.2 analyzes the impact on housing prices and rents over time, not just to explore the dynamics of the impact, but also to support the common trend assumption. This section also substantiates the claim that the establishment of parking locations was unexpected. Section 7.3 applies a placebo test to show that the estimates of the impact on housing prices are not influenced by unobservable prior trends, whereas the estimates of the impact on rents could be affected by a prior upward trend. As such, rents could have decreased (rather than remaining statistically the same), but only very slightly. To illustrate how the relative importance of the three effects vary over space, Section 7.4 provides the results when older counties, where traffic congestion is severe, are excluded. Section 7.5 obtains the results with different (propensity score) matching methods to demonstrate that they would yield similar results.

7.1. European side versus Asian side

The analysis thus far has indicated that the costs of parking spaces are capitalized in the housing prices. However, the city of Istanbul lies over both Europe and Asia separated by Bosporus, and the dynamics of the housing markets on each side are quite different. As Table 3 reports, average housing price and rent are lower on the Asian side. It is especially noteworthy that the Asian side of Istanbul is primarily residential. Gercek and Sengul (2007) find that 71% of employment takes place on the European side. To determine whether there are any underlying differences between the Asian and European sides, in this section, we obtain our estimates separately for each side of the city. In the end, we obtain different (in fact opposite) impacts of ISPARK parking locations on housing prices and rents.[31]

Table 6 develops the counterpart of Table 4 by concentrating on each side of the city separately.[32] Columns (1) and (2) report the effects on housing prices on the European side. Column (1) indicates that housing prices decreased by 220.130 liras per square meter in response to the city operated curbside parking. Column (3) reports that this effect becomes slightly less negative when we control for the poverty measure. Columns (2) and (4) report the effects on housing prices on the Asian side. Unlike the European side, the impact on housing prices is statistically significant and positive. Column (2) indicates that housing prices increased by 47.483 liras per square meter in response to city operated curbside parking on the Asian side. The effect is slightly higher when we control for the poverty measure (58.596 liras per square meter).

31 Our results in this section should be interpreted only as a robustness check for at least two reasons. First, within our data period, only 12 neighborhoods are treated on the Asian side, whereas all of the remaining 38 treatments are on the European side. In addition, the most important parking market on the Asian side is in Kadikoy, which is one of the largest counties in the city. Many parking locations in this county, but not all, are operated by the Kadikoy Municipality, for which we have no data. Thus, although the results provided in this section make great sense in reflecting the different housing dynamics on the Asian side, we prefer to be cautious about making any general conclusions.

32 Table A2 in the Appendix develops the same table without using PSM.

Table 6. Estimated impact of ISPARK parking locations on housing prices and rents/European and Asian sides separately

	Housing prices (Europe) (1)	Housing prices (Asia) (2)	Housing prices (Europe) (3)	Housing prices (Asia) (4)	Rents (Europe) (5)	Rents (Asia) (6)	Rents (Europe) (7)	Rents (Asia) (8)
ISPARK	–220.130***	47.483***	–216.011***	58.596***	–0.101	0.247***	–0.083	0.419***
	(59.404)	(16.006)	(57.666)	(22.173)	(0.176)	(0.046)	(0.181)	(0.047)
Uneducated	–12.943***	4.819**	–144.866***	–33.129***	–0.002	–0.002	–0.243***	–0.134***
	(3.664)	(2.443)	(11.677)	(8.544)	(0.010)	(0.007)	(0.041)	(0.024)
Primary school	–50.899***	14.368***	–16.517***	24.997***	–0.105***	–0.054***	–0.045***	–0.012
	(3.589)	(2.102)	(5.196)	(3.857)	(0.008)	(0.006)	(0.015)	(0.008)
High school	–19.020**	–30.571***	–8.162	–30.313***	0.032	–0.001	0.073***	–0.001
	(8.175)	(5.189)	(10.620)	(5.322)	(0.020)	(0.012)	(0.024)	(0.012)
Population density	1.314***	–4.606***	–0.467	–18.056***	0.005***	0.012**	0.006*	0.014**
	(0.458)	(1.775)	(1.182)	(1.775)	(0.001)	(0.005)	(0.003)	(0.006)
Poverty measure			–1.837***	–0.388***			–0.003***	0.001***
			(0.266)	(0.079)			(0.001)	(0.000)
R^2	0.970	0.962	0.971	0.959	0.971	0.971	0.970	0.969
N	6672	4836	5304	3840	6672	4836	5304	3840

Notes: The dependent variables are housing prices per square meter (first two columns) and rents per square meter (last two columns). The population density is the number of inhabitants in a neighborhood divided by the total land area of that neighborhood. The poverty measure is the fraction of free health care receivers in a neighborhood. The Huber–White standard errors are reported in parentheses. Neighborhood and time dummies are included in all specifications. PSM is employed by using radius matching with a caliper of 0.01 as defined by Dehejia and Wahba (2002). The idea is to use all neighborhoods within a caliper for matching. The results using other matching methods are reported in Section 7.5. University graduates are the omitted group in the regressions.

*Significant at the 10% level, **significant at the 5% level, ***significant at the 1% level.

Columns (5) through (8) in Table 6 report the impact on rents. When we look at the European and Asian sides separately, the impact on rents continues to be insignificant on the European side, as in the baseline regressions reported in Table 4. However, there is now a positive effect on the Asian side. In particular, the estimates reported in column (6) demonstrate that rents increased by 0.247 liras per square meter when ISPARK began operating curbside parking on the Asian side. When we control for the poverty measure in column (8), the effect is substantially higher (0.419 liras per square meter).

In sum, housing prices decreased on the European-side neighborhoods where ISPARK began operating curbside parking, but the depreciation in house values is not reflected in the rents. Housing prices increased on the Asian-side neighborhoods when ISPARK started operating curbside parking, but this time the appreciation in house values is reflected in the rents. What do these results tell us? First, we learn that the overall impact of ISPARK's establishment of parking spaces on housing prices and rents is largely derived from the locations on the European side. When we concentrate on the Asian side, we see a completely new housing and rental market dynamic. It appears that the positive impacts associated with the transition to formal and paid parking, the reduced-cruising and trust-enhancing effects, dominate the unbundling effect on the Asian side.

Table 7. Importance of on-site parking on European and Asian sides

	Asian side	European side
Population	4,600,187	8,543,482
Car ownership	0.115	0.125
Number of cars	529,022	1,067,935
Parking in residences	366,350	385,583
Coverage ratio	0.69	0.36

Notes: Population numbers are based on TUIK (2012) and car ownership is the percentage of the population owning a car, which is taken from the Istanbul Parking Master Plan (IBB, 2016), but the data come from a 2012 survey. The number of cars is calculated by multiplying the first two columns. The number of parking spaces in residences is collected by ISPARK in 2012. The coverage ratio is the percentage of the number of cars that can be accommodated in on-site parking.

This result is not surprising at all. The residential land on the Asian side used to be occupied by mansions (i.e., 'konak' in Turkish) constructed on large independent parcels with their gardens (IBB, 2016). In time, these parcels have been turned into residential complexes with surface lots to satisfy the residents' parking demands. The residential areas on the European side are more historical with attached housing along narrow roads, like in many old European cities.

In line with the architectural differences, as Table 7 illustrates, on-site parking on the Asian side is sufficient to cover 69% of cars registered on that side, whereas the same percentage is only 36% for the European side. Thus, the European-side residents rely more heavily on curbside parking, whereas their Asian-side counterparts primarily park in surface lots. In other words, curbside parking is mainly for nonresidents on the Asian side. Thus, the unbundling effect should be substantially lower on the Asian side.[33] As for rents, our results are in line with the downward rigidity of rents, which states that rents do not respond to depreciation although they do respond to the appreciation in housing values.[34]

7.2. Dynamic impacts

Because parking fees are modest compared to house values, it takes time for them to be reflected in the housing prices and probably even more time for them to be reflected in rents. To identify the dynamic impacts, we use lags and leads of the treatment variables instead of using a single treatment variable. In particular, we add indicator variables for each of the two quarters before (leads) and four quarters after (lags) ISPARK's

33 A more proper way of dealing with this effect would be controlling for the number of on-site parking across time. Unfortunately, we have data only for 2012.

34 There is also an additional difference between the Asian and European sides that could have inflated rents on the Asian side. There have been many urban transformation projects due to earthquake risks in the coastal region of the Asian side. When developers agree with owners to demolish an existing building and construct a new one, they are supposed to pay a predetermined fee to cover the rental costs of owners during the construction period. These fees are usually high. Because they also serve as benchmarks for the nearby locations, rents in these locations can also be increased.

Table 8. Estimated impact of ISPARK parking locations on housing prices and rents over time

	Housing prices (1)	Rents (2)
$ISPARK_{six\ months\ before}$	–72.996	–0.209
	(81.401)	(0.247)
$ISPARK_{three\ months\ before}$	19.046	0.287
	(150.916)	(0.467)
$ISPARK_{establishment\ time}$	4.194	0.261
	(114.524)	(0.394)
$ISPARK_{three\ months\ later}$	13.745	–0.002
	(112.830)	(0.335)
$ISPARK_{six\ months\ later}$	–39.313	–0.066
	(101.615)	(0.216)
$ISPARK_{nine\ months\ later}$	–70.285	0.061
	(84.621)	(0.127)
$ISPARK_{twelve\ months\ later}$	–152.155***	0.031
	(58.457)	(0.119)
$ISPARK_{more\ than\ twelve\ months}$	–299.135***	–0.348***
	(35.938)	(0.099)
R^2	0.963	0.971
N	10,980	10,980

Notes: $ISPARK_{six\ months\ before}$ is an indicator variable that equals 1 if a housing price or rent observation is 6 months before ISPARK's establishment of a parking location in a neighborhood. The other indicator variables are defined analogously. The dependent variables are housing prices per square meter and rents per square meter. All population variables, except the average household size, are recorded in thousands and have been controlled for as well. The Huber–White standard errors are reported in parentheses. Neighborhood and time dummies are included in all specifications. PSM is employed by using radius matching with a caliper of 0.01 as defined by Dehejia and Wahba (2002).
*Significant at the 10% level, **significant at the 5% level, ***significant at the 1% level.

establishment of parking locations in a neighborhood. We also add another indicator variable for all periods after the first year.

Table 8 reports the estimates with lags and leads.[35] The first column presents the estimates for housing prices. As expected, the coefficients on leads and the first three lags are statistically insignificant for housing prices. They only become significant at least 12 months after the treatment. The insignificance of the lead variables signals that residents did not anticipate the establishment of ISPARK parking locations in their neighborhoods. They also reveal the presence of common trends prior to the treatments (Autor, 2003). To help visualize these results, Figure 4 displays the point estimates of the coefficients for the lags and leads of housing prices along with their confidence intervals. The decrease in housing prices starts after 6 months.[36]

The second column in Table 8 presents the estimates for rents. The impact is statistically insignificant within 1 year. It becomes significant and negative only over

35 Table A3 in the Appendix develops the same table without using PSM.
36 We have also split the data into two to find out how neighborhoods treated before 2010 differ from those treated after 2010. As expected, we have found that the former group experiences a larger depreciation of housing prices.

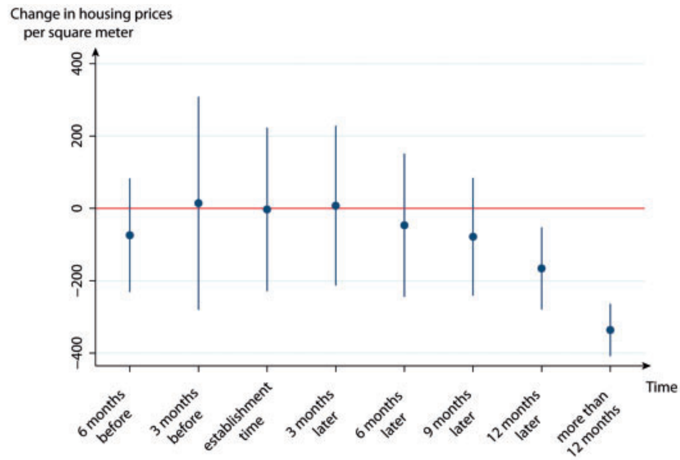

Figure 4. Estimated impact of ISPARK parking locations on housing prices over time.
Notes: The figure plots the coefficients for the lags and leads of housing prices obtained from the matched sample, reported in column (2) of Table 8. The dots represent the point estimates of the coefficients for each of the two quarters before to four quarters after ISPARK's establishment of parking locations. The vertical bands represent the confidence intervals (±1.96 times the standard error of the point estimate).

12 months. Why is that? In Section 7.3, we perform a placebo test and apply fake treatments 1 year prior to the actual ones. With fake treatments, the impact on rents becomes statistically significant and positive. Thus, our estimates of the impact on rents could be affected by a prior upward trend. This upward trend could have been eroding the negative impact on rents leaving us with insignificant estimates within the first year after the treatment. Over 12 months, however, the negative impact becomes sufficiently high enough that we still obtain statistically significant and negative estimates in the net. In sum, the impact on rents could have actually been negative even in the first year, but we still expect them to be smaller in magnitude.

7.3. Placebo test

As a placebo test, we create a fake treatment variable for ISPARK's establishment of parking locations in a neighborhood. The fake treatments are applied 1 year before the actual treatments to determine whether the estimates are driven by unobservable prior trends in the treated neighborhoods relative to the untreated ones. The placebo test largely validates our estimation approach.

Table 9 presents the results of the placebo test. The first two columns report the estimates for housing prices. These estimates indicate that housing prices are not affected by the fake implementation of ISPARK's establishment of parking locations in a neighborhood. The last two columns report the estimates for rents. Rents are affected positively implying that the previously insignificant estimates in Table 4 (also those reported in Table A1 in the Appendix) could have been influenced by a previous upward trend in rents prior to the implementation. Thus, rather than being insignificant, the impact on rents could have been negative, although its magnitude is still expected to be small, and the prior upward trend erodes this negative impact

Table 9. Placebo test

	Housing prices (1)	Housing prices (2)	Rents (3)	Rents (4)
ISPARK	–12.649	24.836	0.236***	0.334***
	(29.227)	(30.478)	(0.065)	(0.074)
Uneducated	–18.016***	–142.951***	–0.008	–0.333***
	(2.377)	(7.317)	(0.006)	(0.025)
Primary school	–30.284***	12.054***	–0.080***	0.024***
	(2.048)	(3.000)	(0.005)	(0.009)
High school	–23.634***	–17.488***	–0.038***	–0.021
	(2.899)	(3.339)	(0.011)	(0.014)
Population density	0.332	4.127***	0.006***	0.023***
	(0.383)	(0.723)	(0.001)	(0.003)
Poverty measure		–0.184***		0.001**
		(0.059)		(0.000)
R^2	0.965	0.965	0.973	0.973
N	13,740	10,980	13,740	10,980

Notes: The dependent variables are housing prices per square meter (first two columns) and rents per square meter (last two columns). The population density is the number of inhabitants in a neighborhood divided by the total land area of that neighborhood. The poverty measure is the fraction of free health care receivers in a neighborhood. The Huber–White standard errors are reported in parentheses. Placebo treatment is employed 1 year before the actual treatment date. PSM is employed by using radius matching with a caliper of 0.01 as defined by Dehejia and Wahba (2002). Neighborhood and time dummies are included in all specifications. University graduates are the omitted group in the regressions.
*Significant at the 10% level, **significant at the 5% level, ***significant at the 1% level.

resulting in an insignificant impact in the net. The dynamic impact analysis that we report in Table 8 demonstrates that although the impact on rents is insignificant within 1 year, it becomes significant (and negative) over 1 year.

7.4. Old counties excluded

The old residential locations of Istanbul are full of historical buildings and monuments. The streets tend to be narrow, cruising for parking is high, and traffic congestion is severe. If there are positive effects associated with reduced cruising, they should be the highest in these neighborhoods. Nevertheless, we also expect the unbundling effect to be larger in these neighborhoods because where there is a parking problem, the ability to use the curbside as one's own parking garage also becomes important. To check this expectation, we obtain our estimates by excluding neighborhoods in the old counties of Beyoglu, Eyup, Fatih and Sisli, all of which are on the European side and obtain results consistent with our expectation.

Table 10 presents the estimates. We use the same order of specifications we used in Table 4. The estimates become less negative when we exclude the old counties. In particular, the establishment of ISPARK parking locations leads to 162.837 liras per square meter depreciation in housing prices. Cruising for parking in the old counties is likely to be substantial, but, for the same reason, self-appointed parking attendants,

Table 10. Estimated impact of ISPARK parking locations on housing prices and rents after excluding old counties

	Housing prices (1)	Housing prices (2)	Rents (3)	Rents (4)
ISPARK	–148.856***	–162.837***	–0.046	–0.012
	(42.558)	(44.633)	(0.122)	(0.136)
Uneducated	–7.172**	–108.690***	–0.003	–0.163***
	(3.136)	(9.453)	(0.007)	(0.032)
Primary school	–23.349***	1.414	–0.079***	–0.040***
	(2.771)	(4.087)	(0.006)	(0.011)
High school	–31.222***	–46.153***	0.018	0.019
	(6.769)	(8.368)	(0.014)	(0.017)
Population density	1.479***	5.269***	0.004***	0.016***
	(0.427)	(0.891)	(0.001)	(0.003)
Poverty measure		–0.174**		0.001**
		(0.073)		(0.000)
R^2	0.963	0.963	0.970	0.968
N	10824	8604	10824	8604

Notes: The old counties are Beyoglu, Eyup, Fatih and Sisli, where cruising for parking is known to be severest. The dependent variables are housing prices per square meter (first two columns) and rents per square meter (last two columns). The population density is the number of inhabitants in a neighborhood divided by the total land area of that neighborhood. The poverty measure is the fraction of free health care receivers in a neighborhood. The Huber–White standard errors are reported in parentheses. Neighborhood and time dummies are included in all specifications. PSM is employed by using radius matching with a caliper of 0.01 as defined by Dehejia and Wahba (2002). The idea is to use all neighborhoods within a caliper for matching. The results using other matching methods are reported in Section 7.5. University graduates are the omitted group in the regressions.

*Significant at the 10% level, **significant at the 5% level, ***significant at the 1% level.

who tend to favor residents, are also more likely to be operating parking locations in these neighborhoods. Thus, the unbundling effect is also expected to be large in neighborhoods where the reduced-cruising effect is large.

7.5. Different matching methods

In all matched sample estimations presented thus far, we employ PSM by using radius matching with a caliper of 0.01, as defined by Dehejia and Wahba (2002). Columns (2) through (8) in Table 11 indicate that our results do not change much when we use other matching methods, including Kernel matching (columns (2) and (6)), nearest neighbor with replacement (columns (3) and (7)), and Mahalanobis covariate matching (columns (4) and (8)). In particular, in all specifications, the impact on housing prices is statistically significant and negative, whereas the impact on rents is statistically insignificant, except when we use Kernel matching, in which the impact on rents is significant only at the 10% level.

Table 11. Estimated impact of ISPARK parking locations on housing prices and rents with different matching methods

	Housing prices (radius) (1)	Housing prices (Kernel) (2)	Housing prices (nearest) (3)	Housing prices (Mahalanobis) (4)	Rents (radius) (5)	Rents (Kernel) (6)	Rents (nearest) (7)	Rents (Mahalanobis) (8)
ISPARK	–197.761***	–217.178***	–247.161***	–153.395***	–0.043	–0.378*	–0.160	0.031
	(50.854)	(61.504)	(51.289)	(52.122)	(0.153)	(0.209)	(0.155)	(0.158)
Uneducated	–86.809***	–72.126***	–78.280***	–135.725***	–0.202***	0.061	0.133	–0.339***
	(10.111)	(13.247)	(20.469)	(15.770)	(0.035)	(0.078)	(0.106)	(0.041)
Primary school	–0.147	–45.516***	–13.962**	17.834***	–0.035***	–0.161***	–0.145***	0.040***
	(4.081)	(7.062)	(5.919)	(5.490)	(0.011)	(0.026)	(0.026)	(0.015)
High school	–64.770***	–78.927***	–76.653***	–8.947	–0.031*	–0.098***	–0.032	0.122***
	(9.939)	(15.603)	(12.877)	(12.001)	(0.018)	(0.034)	(0.027)	(0.030)
Population density	5.248***	10.698***	6.452***	1.342	0.017***	0.028***	0.014***	0.029***
	(1.157)	(1.598)	(1.465)	(2.260)	(0.003)	(0.005)	(0.004)	(0.006)
Poverty measure	–0.258***	0.328***	–0.592***	–0.840***	0.001**	0.003***	0.001	0.001*
	(0.080)	(0.123)	(0.156)	(0.174)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.961	0.969	0.960	0.960	0.969	0.966	0.966	0.973
N	8016	2052	2208	2280	8016	2052	2208	2280

Notes: The dependent variables are housing prices per square meter (first two columns) and rents per square meter (last two columns). The population density is the number of inhabitants in a neighborhood divided by the total land area of that neighborhood. The poverty measure is the fraction of free health care receivers in a neighborhood. The Huber–White standard errors are reported in parentheses. Neighborhood and time dummies are included in all specifications. PSM is employed by using radius matching with a caliper of 0.01 as defined by Dehejia and Wahba (2002) in columns (1) and (5), Kernel matching in columns (2) and (6), nearest neighbor with replacement in columns (3) and (7), and Mahalanobis covariate matching in columns (4) and (8). University graduates are the omitted group in the regressions.
*Significant at the 10% level, **significant at the 5% level, ***significant at the 1% level.

8. Conclusion

People tend to think about parking spaces only when they are looking for one. However, whether they realize it or not, parking spaces substantially affect their lives in various dimensions in many subtle ways. In this article, we concentrate on the impact of curbside parking spaces on housing prices and rents. In particular, we empirically examine what happens to housing prices and rents when a city starts charging for curbside parking spaces that were previously either free or operated by self-appointed informal parking attendants.

The transition from free parking to paid parking is expected to decrease housing prices by preventing residents from using the curbside as their own parking garages, which virtually unbundles parking costs from housing prices (the unbundling effect). At the same time, it may increase housing prices by decreasing cruising for parking in the area, thereby mitigating traffic congestion (the reduced-cruising effect). The transition from an informal curbside parking market operated by self-appointed parking attendants to a formal one operated by a legal entity is also expected to increase housing prices by enhancing trust and the quality of service in the market (the trust-enhancing effect).

Istanbul went through such a transition starting in late 2005. Prior to 2005, curbside parking was either free or operated by self-appointed informal parking attendants. The city established a parking operator and started eliminating free and/or informal parking across neighborhoods and over time. Making use of these variations, we estimate the impact of establishing formal and paid curbside parking locations on housing prices and rents in the city. Using a DD analysis on a sample matched based on propensity scores, we find that the establishment of formal and paid curbside parking locations lead to a statistically and economically significant decrease in housing prices.[37] Thus, the unbundling effect dominates the trust-enhancing and reduced-cruising effects. The impact on rents is close to zero and mostly statistically insignificant.

Various estimates obtained in this article point to the sizable impact of curbside parking spaces on housing prices in Istanbul. It should be clear after all our analyses that at least some of the costs of curbside parking spaces are embedded in housing prices in Istanbul. This is a very important result in its own right. Past work made it clear that unbundling on-site parking spaces from housing units decreases housing prices. This comes by definition as parking units are sold bundled with those housing units. In our case, despite the fact that public curbside parking spaces are not formally bundled with housing units, their costs are substantially capitalized in housing prices.[38]

What is the takeaway from this exercise? This article finds that curbside parking spaces that are not formally bundled with residences can have a statistically and economically significant effect on their sale prices. We determine that a smart policy change implemented in Istanbul unbundled the costs of curbside parking spaces from housing prices. This policy also wiped out the informal parking market. All of these results hint that parking greatly affects societal welfare and as such, so can better parking policies.

Acknowledgments

This article is screened by ISPARK and REIDIN, which supplied some of the data used in the analysis, to ensure that no confidential information is revealed. The opinions expressed in this article are solely that of the authors and do not reflect the opinions of the Istanbul Metropolitan Municipality, ISPARK, and REIDIN. This article won the *Best Overall Paper Prize* at the Annual Conference of the International Transportation Economics Association (2016). The authors would like to thank Recep Kahraman, Ali Karsli, Orhan Vatandas and especially Omer Er for their continuous support about data, Fatih Cakmak for excellent research assistance, Bill Kerr (the editor) and the two anonymous referees for useful feedback, seminar participants at ETH Zurich, the Free University of Amsterdam, Ozyegin University, the Sauder School of Business at the University of British Columbia, Universitat Autònoma de Barcelona, Istanbul

37 One could potentially ask why the city would enforce parking given that it will decrease house prices and, as a result, property tax revenues. The key issue here is the widespread tax evasion in Turkey. In particular, in the legal data, most property transactions are recorded to take place at the legal minimums announced by the government.

38 In this article, we provide a limited welfare analysis from a housing affordability perspective. A much detailed analysis of the exact welfare effects, as done by Parry and Small (2009) in a different context, would be valuable.

Technical University, TOBB ETU and Bogazici University, and participants at the 4th International Transportation and Park Areas Management Symposium, the 5th Annual All-Istanbul Economics Workshop, the Meeting of the Turkish Academy of Sciences in Nevsehir, the Workshop on Socioeconomic Interaction in Transportation in Istanbul, the Annual Conference of the International Transportation Economics Association in Santiago for valuable comments. All remaining errors are the authors' responsibility.

Funding

EI would like to acknowledge financial support from the Turkish Academy of Sciences (Outstanding Young Scientist Award, TUBA-GEBIP) and the recognition by the Science Academy (Turkey) via its Young Scientist Award (BAGEP).

Appendix: Estimates without PSM

Table A1. Estimated impact of ISPARK parking locations on housing prices and rents/unmatched sample

	Housing prices (1)	Housing prices (2)	Rents (3)	Rents (4)
ISPARK	–244.926***	–250.653***	–0.187*	–0.207*
	(37.566)	(39.412)	(0.104)	(0.115)
Uneducated	–4.323**	–41.772***	–0.013***	–0.058***
	(1.695)	(4.671)	(0.005)	(0.020)
Primary school	–17.056***	–5.982***	–0.072***	–0.064***
	(1.429)	(1.792)	(0.004)	(0.007)
High school	–17.267***	–11.851***	–0.023***	–0.013
	(2.875)	(3.313)	(0.008)	(0.009)
Population density	0.089	–0.136	–0.001**	–0.002
	(0.164)	(0.347)	(0.001)	(0.001)
Poverty measure		–0.258***		–0.004***
		(0.032)		(0.001)
R^2	0.961	0.960	0.964	0.962
N	13,740	10,908	13,740	10,908

Notes: The dependent variables are housing prices per square meter (first two columns) and rents per square meter (last two columns). The population density is the number of inhabitants in a neighborhood divided by the total land area of that neighborhood. The poverty measure is the fraction of free health care receivers in a neighborhood. The Huber–White standard errors are reported in parentheses. Neighborhood and time dummies are included in all specifications. University graduates are the omitted group in the regressions.
*Significant at the 10% level, **significant at the 5% level, ***significant at the 1% level.

Table A2. Estimated impact of ISPARK parking locations on housing prices and rents/unmatched sample/European and Asian sides separately

	Housing prices (Europe) (1)	Housing prices (Asia) (2)	Housing prices (Europe) (3)	Housing prices (Asia) (4)	Rents (Europe) (5)	Rents (Asia) (6)	Rents (Europe) (7)	Rents (Asia) (8)
ISPARK	–380.093***	–3.677	–337.717***	–19.910	–0.350**	0.170***	–0.364**	0.266***
	(55.771)	(13.798)	(54.386)	(16.118)	(0.160)	(0.036)	(0.166)	(0.033)
Uneducated	–9.843***	2.020	–89.539***	–11.717**	–0.011	–0.013**	–0.082***	–0.098***
	(2.312)	(1.971)	(6.650)	(5.836)	(0.007)	(0.006)	(0.030)	(0.017)
Primary school	–39.024***	3.565**	–23.261***	10.526***	–0.107***	–0.036***	–0.109***	–0.004
	(2.019)	(1.668)	(2.439)	(2.233)	(0.006)	(0.005)	(0.010)	(0.007)
High school	–8.730**	–25.053***	7.901*	–23.867***	–0.003	–0.036***	0.023	–0.040***
	(4.097)	(2.835)	(4.549)	(3.087)	(0.012)	(0.008)	(0.014)	(0.009)
Population density	–0.038	–6.124***	–5.435***	–9.587***	–0.003***	0.021***	–0.017***	0.024***
	(0.168)	(0.747)	(0.481)	(0.889)	(0.001)	(0.003)	(0.002)	(0.004)
Poverty measure			–1.681***	–0.050			–0.004***	0.001***
			(0.087)	(0.032)			(0.000)	(0.000)
R^2	0.970	0.944	0.970	0.942	0.967	0.959	0.965	0.957
N	7596	6144	6036	4872	7596	6144	6036	4872

Notes: The dependent variables are housing prices per square meter (first two columns) and rents per square meter (last two columns). The population density is the number of inhabitants in a neighborhood divided by the total land area of that neighborhood. The poverty measure is the fraction of free health care receivers in a neighborhood. The Huber–White standard errors are reported in parentheses. Neighborhood and time dummies are included in all specifications. University graduates are the omitted group in the regressions. *Significant at the 10% level, **significant at the 5% level, ***significant at the 1% level.

Table A3. Estimated impact of ISPARK parking locations on housing prices and rents over time/unmatched sample

	Housing prices (1)	Rents (2)
$\text{ISPARK}_{\text{six months before}}$	–34.162	–0.184
	(65.662)	(0.171)
$\text{ISPARK}_{\text{three months before}}$	9.221	0.152
	(114.131)	(0.373)
$\text{ISPARK}_{\text{establishment time}}$	–29.018	0.114
	(88.559)	(0.321)
$\text{ISPARK}_{\text{three months later}}$	–43.167	–0.072
	(96.865)	(0.270)
$\text{ISPARK}_{\text{six months later}}$	–82.748	–0.081
	(86.042)	(0.165)
$\text{ISPARK}_{\text{nine months later}}$	–105.049	0.015
	(71.341)	(0.100)
$\text{ISPARK}_{\text{twelve months later}}$	–202.154***	–0.027
	(56.815)	(0.097)
$\text{ISPARK}_{\text{more than twelve months}}$	–305.514***	–0.373***
	(32.295)	(0.087)
R^2	0.962	0.964
N	13,740	13,740

Notes: $\text{ISPARK}_{\text{six months before}}$ is an indicator variable that equals one if a housing price or rent observation is 6 months before ISPARK's establishment of a parking location in a neighborhood. The other indicator variables are defined analogously. The dependent variables are housing prices per square meter and rents per square meter. All population variables, except the average household size, are recorded in thousands and have been controlled for as well. The Huber–White standard errors are reported in parentheses. Neighborhood and time dummies are included in all specifications.

*Significant at the 10% level, **significant at the 5% level, ***significant at the 1% level.

References

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

Arnott, R., Inci, E. (2010) The stability of downtown parking and traffic congestion. *Journal of Urban Economics*, 68: 260–276.

Arnott, R., Inci, E., Rowse, J. (2015) Downtown curbside parking capacity. *Journal of Urban Economics*, 86: 83–97.

Autor, D. H. (2003) Outsourcing at will: the contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of Labor Economics*, 21: 1–42.

Aysoy, C., Aysoy, C., Tumen, S. (2014) Quantifying and explaining stickiness in housing rents: a Turkish case study with micro-level data. *Journal of Housing Economics*, 25: 62–74.

Bertrand, M., Duflo, E., Mullainathan, S. (2004) How much should we trust differences-in-differences estimates? *Quarterly Journal of Economics*, 119: 249–275.

Cassel, E., Mendelsohn, R. (1985) The choice of functional forms for hedonic price equations: comment. *Journal of Urban Economics*, 18: 135–142.

Cropper, M. L., Deck, L. B., McConnell, K. E. (1988) On the choice of functional form for hedonic price functions. *Review of Economics and Statistics*, 70: 668–675.

De Borger, B., Russo, A. (2017) The political economy of pricing car access to downtown commercial districts. *Transportation Research Part B: Methodological*, 98: 76–93.
De Groote, J., van Ommeren, J., Koster, H. R. (2016) Car ownership and residential parking subsidies: evidence from Amsterdam. *Economics of Transportation*, 6: 25–37.
Dehejia, R. H., Wahba, S. (2002) Propensity score-matching methods for nonexperimental causal studies. *Review of Economics and Statistics*, 84: 151–161.
Dokmeci, V., Onder, Z., Yavas, A. (2003) External factors, housing values, and rents: evidence from survey data. *Journal of Housing Research*, 14: 83–99.
Dorsey, R. E., Hu, H., Mayer, W. J., Wang, H. C. (2010) Hedonic versus repeat-sales housing price indexes for measuring the recent boom-bust cycle. *Journal of Housing Economics*, 19: 75–93.
Duranton, G. (2015) Growing through cities in developing countries. *World Bank Research Observer*, 39: 39–73.
Ersoy, F., Hasker, K., Inci, E. (2016) Parking as a loss leader at shopping malls. *Transportation Research Part B: Methodological*, 91: 98–112.
Genesove, D. (2003) The nominal rigidity of apartment rents. *Review of Economics and Statistics*, 85: 844–853.
Gercek, H., Sengul, S. (2007) Istanbul'da yolculuk hareketlerindeki son on yildaki degismelerin arazi kullanimi-ulastirma iliskisi cercevesinde degerlendirilmesi. 09/2007, s. 82-93, 7. Ulastirma Kongresi, TMMOB, IMO Istanbul Subesi, Istanbul, 19–21 September 2007.
Glaeser, E. L., Gyourko, J. (2007) *Arbitrage in Housing Markets*. National Bureau of Economic Research Working Paper No. w13704.
Glazer, A., Niskanen, E. (1992) Parking fees and congestion. *Regional Science and Urban Economics*, 22: 123–132.
Halvorsen, R., Pollakowski, H. O. (1981) Choice of functional form for hedonic price equations. *Journal of Urban Economics*, 10: 37–49.
Hansen, C. (2007) Generalized least squares inference in panel and multilevel models with serial correlation and fixed effects. *Journal of Econometrics*, 140: 670–694.
Hasker, K., Inci, E. (2014) Free parking for all in shopping malls. *International Economic Review*, 55: 1281–1304.
Hirano, K., Imbens, G., Ridder, G. (2003) Efficient estimation of average treatment effects using the estimated propensity score. *Econometrica*, 71: 1161–1189.
IBB (2016) *Istanbul Parking Master Plan*. Istanbul: Istanbul Metropolitan Municipality (IBB).
Inci, E. (2015) A review of the economics of parking. *Economics of Transportation*, 4: 50–63.
Inci, E., van Ommeren, J., Kobus, M. (2017) The external cruising costs of parking. *Journal of Economic Geography*, 17: 1301–1323.
Jia, W., Wachs, M. (1999) Parking requirements and housing affordability: a case study of San Francisco. *Transportation Research Record*, 1685: 156–160.
Lai, R. N., Wang, K., Yang, J. (2007) Stickiness of rental rates and developers' option exercise strategies. *Journal of Real Estate Finance and Economics*, 34: 159–188.
Manville, M. (2013) Parking requirements and housing development. *Journal of the American Planning Association*, 79: 49–66.
Parry, I., Small, K. (2009) Should urban transit subsidies be reduced? *American Economic Review*, 99: 700–724.
Russo, A. (2013) Voting on road congestion policy. *Regional Science and Urban Economics*, 43: 707–724.
Shoup, D. C. (2005) *The High Cost of Free Parking*. Chicago: American Planning Association.
TUIK (2011) *Population and Housing Census*. Ankara: Turkish Statistical Institute,.
TUIK (2012) *Address-Based Population Registration System*. Ankara: Turkish Statistical Institute.
van Ommeren, J., Wentink, D. (2012). The (hidden) cost of employer parking policies. *International Economic Review*, 53: 965–977.
van Ommeren, J., Wentink, D., Dekkers, J. (2011) The real price of parking policy. *Journal of Urban Economics*, 70: 25–31.
Wang, K., Zhou, Y. (2000) Overbuilding: a game-theoretic approach. *Real Estate Economics*, 28: 493–522.
Wooldridge, J. (2006) *Cluster-Sample Methods in Applied Econometrics: An Extended Analysis*. Unpublished manuscript, Department of Economics, Michigan State University.