Cruising and On-Street Parking Pricing: A Difference-in-Difference Analysis of Measured
Parking Search Time and Distance in San Francisco

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ABSTRACT

The effect of a demand-responsive parking pilot program in San Francisco, known as SFpark, on cruising for parking is evaluated including both time and distance is evaluated with measured data in pilot and control areas before (2011) and after (2013) changes in on-street parking. A generalized mixed effects model is estimated and its specification controls for time effects, random area effects, time of day, and day of week. This study differs from previous evaluations of demand-responsive parking programs in that it (1) uses direct field measurements of parking search time and distance rather than simulated data or proxy variables such as parking availability, double parking, and illegal parking and (2) controls for time effects by using data from a separate control area as opposed to using variables such as block face parking price and employment. The results suggest that the SFpark may have, on average, reduced parking search times by 12% and by 10% for distance in the pilot areas relative to the control areas.

Key words: Cruising for On-street Parking, Parking Search Time, Parking Search Distance, Difference-in-Differences
1. INTRODUCTION

When on-street parking is scarce, the cost of parking is not just the metered rate, if in fact the space is metered; it also includes the extra time and fuel costs spent searching for parking. The cruising driver not only incurs costs, but also imposes costs on others by unnecessarily contributing to local congestion, noise, and vehicle emissions. In core urban areas, these costs may not be insignificant: average parking search times can range from 3.5 minutes to 14 minutes and as much as 8% to 74% of traffic can be attributed to cruising (1).

Not surprisingly, cities are increasingly considering parking programs to reduce cruising by setting on-street parking prices at a level that ensures that at least one parking space per block will be available continuously throughout the day. Such programs are frequently called demand-responsive parking pricing, because, ideally, prices are set to control parking demand by location and time of day using a parking availability performance metric.

The cities of San Francisco and Seattle have both implemented a large scale program piloting demand-responsive curbside parking in 2011. These pilots allow researchers, for the first time, to empirically evaluate changes in parking demand and related behavior from an actual implemented program. Previously, the literature had been dominated by theoretical modeling studies of on-street parking behavior (2) and, when data were used to develop these models, it was largely from stated preference surveys (3). The exceptions are more recent studies of non-demand responsive curbside parking pricing studies in Dublin, Ireland (4) and the Netherlands (2).

The subject of this study is the effect of demand-responsive parking pilot program in San Francisco, known as SFpark, on cruising for parking, including both time and distance. The effect is evaluated with measured data in pilot and control areas before (2011) and after (2013) changes in on-street parking prices. A generalized mixed effects model and its specification controls for time effects, random area effects, time of day, and day of week. This study differs from previous evaluations of demand-responsive parking programs in that it (1) uses direct field measurements of parking search time and distance rather than simulated data or proxy variables such as parking availability, double parking, and illegal parking; (2) controls for time effects by using data from a separate control area as opposed to using variables such as block face parking price and employment.

1.1 Background:

The SFpark tagline “circle less live move” emphasizes the significant user benefit anticipated from reduced parking search travel. The pilot includes eight pilot areas and two control areas (See Figure 1 below) that encompass approximately 6,000 on-street parking spaces (about 25 percent of the city’s total) and 12,250 parking spaces in 14 parking garages and one parking lot. Magnetic parking sensors were installed in on-street parking spaces. New parking meter technology allows payment by credit cards and remote payment (the previous meters required coins). The one to two hour parking time limits were also relaxed. Sensors and meters wirelessly transmit data to San Francisco Municipal Transportation Agency (SFMTA) enabling monitoring of occupancy levels. In the eight pilot areas, rates can change every six weeks by block (256 blocks in the pilot), time of day (morning, mid-day, and afternoon), and day of week (weekday or weekend). If average occupancy drops below 60%, then rates can be reduced by as much as 50 cents per hour and if average vehicle occupancy exceeded 80%, then rates can be increased.
by 25 cents per hour. The minimum hourly rate is 25 cents per hour and the maximum is 6
dollars per hour.

Figure 1 - Location of Pilot and Control Areas (Source: SFMTA)

The remainder of this paper is structured as follow: after a brief literature review, data
collection and methods of analysis are described, this is followed a discussion of results, and,
finally, conclusions are drawn.

2. LITERATURE REVIEW:

This literature review compares and contrasts published studies that evaluate implemented on-
street parking pricing programs. We are aware of six such studies published only within the last
five year. Key attributes of these studies and the current study are described in Table 1. Two
studies evaluate a fixed or flat on-street parking pricing program, one in Dublin, Ireland (4) and
another in the Netherlands (2). Five studies, including the current study, evaluate demand
responsive on-street parking programs, one in Seattle (5) and the rest in San Francisco (6–8).

Kelley and Clinch (4) collect parking meter transaction data before and after a 50% increase in on-street parking pricing in a central area of Dublin (six weeks in 2000 and 2001) to
estimate the aggregate price elasticity of demand for on-street parking in the test area by time of
day and day of the week. Parking availability is inferred from parking meter transaction data. In
the elasticity equation, change in average parking occupancy before and after the price change
represents parking demand and the change in parking price is adjusted for changes in income and
inflation over the one year period. The average aggregate price elasticity of demand is estimated
to be -0.29 and morning peak parking demand is found to be most responsive to changes in
parking prices.

The time spent cruising for parking is explored by van Ommeren et al. (2) in a country
with one of the highest shares of paid parking in the world, the Netherlands. The study uses data
on reported trip parking search time from the Dutch National Travel Survey (2005 to 2007),
which may be subject to recall and respondent bias. They “find that in about 30% of the trips
considered car drivers cruise for parking, and the average cruising time per trip is 36 seconds” (p.
128). The analysis excludes work and residential parking search time. The low level of cruising
is attributed to the high cost of parking in the Netherlands. A linear regression model is estimated
in which the dependent variable is parking search time for a specific trip, the independent
variables include area, destination, gender age, arrival time, and year activity type. The results
indicate that “cruising increases with car travel duration and with parking duration, but falls with
income” and “cruising is more common with shopping and leisure than for work-related
activities” (p. 128).

A new demand-responsive on-street parking program in Seattle, Washington, is evaluated
by Ottosson et al. (5). Like the Kelley and Clinch (4), parking meter transaction data is collected
before and after the implementation of the pricing program (four weeks in 2010 and 2011). Price
elasticity of demand for parking is estimated with a log-log regression model in which the
dependent variable is block-level average parking occupancy, independent variables are parking
price and neighborhood attributes, and fixed effect control variables include time of day, day of
week, unique block effects, and spatial correlation between blocks. Where on-street parking
prices increase, elasticities range from -0.7 to -0.37 and, where they decrease, parking price are
largely not found to be significantly related to block-level occupancy and often have counter-
intuitive signs. Price elasticities for demand vary by time of day and neighborhood
characteristics. Like Kelley and Clinch, they find that morning peak hour elasticities tended to be
higher than elasticities during other times of the day.

The first published evaluation of SFpark in San Francisco, California, is conducted by
Pierce and Shoup (6). This study uses parking sensor data sampled six weeks before a price
change and six week after a price change from 2011 to 2012. Parking sensor data may be a more
direct measure of parking occupancy than meter transaction data, but it can also be subject to
relatively high failure rates. Price elasticity for parking demand is calculated using block-level
change in average parking occupancy to represent parking demand and the associated change in
block-level price. The authors find that the average price elasticity of demand for parking is -0.4
and that it varies by time of day and location.

Millard-Ball et al. (7) also use parking sensor data to evaluate the SFpark pilot. However,
they use a continuous sample gathered before pilot implementation in 2011 and through 2013.
These data are used to calibrate theoretical models that simulated average vehicle occupancy and
cruising data. These simulated data are then used to estimate regression models (OLS and
negative binomial). Data from both the control and pilot areas are included in the analysis (see
discussion of control area below). The independent variables in these models are the number of
block-level rate changes and the dependent variables are the corresponding block-level percentage point change in average occupancy outside the 60% to 80% target and the number of blocks cruised. The models included fixed effect control variables for area, date, day of week, and time of day. The authors find that “on average, each rate change brings a block 0.1–0.2 percentage points closer to the 60–80% range, and thus the average impact is 1–2 percentage points after ten rate changes” (p. 87). For cruising, “each rate change reduces the average search distance for parking by 0.007–0.017 blocks or 0.07–0.17 blocks after the tenth rate change” (p. 87).

The effect of price change in SFpark on parking is also evaluated by Chatman and Manville (8). However, they use manually collected field data before the start of the pilot in May 2011 and after in October 2011 and in May 2012 on approximately 40 blocks (in Mission, the Financial District, Civic Center, and South of Market) and nine nearby control blocks where prices did not change. The blocks were selected by stratified random sampling to ensure a large number of blocks would experience price change. The following data were collected by the survey: average occupancy, parking availability, duration per vehicle, hourly turnover per space, occupants per vehicle, double parking, share of minutes unpaid, share of minutes illegal, and share of minutes by disabled placards. Linear and log-log regressions are estimated for separate time periods. Price is included as an independent variables and initial price, area, time of day, day of week, weather, and employment are fixed effect control variables. They find that positive parking prices are associated with reduced block-level occupancy, but not improvement in the “share of time at least one space on a block face was vacant” as well as “parking duration, vehicle turnover, and carpooling” (p. 52). Since the latter variables are an indirect measure of cruising, they conclude that SFpark may not have had a significant effect on cruising.

3. DATA COLLECTION AND METHODOLOGY

3.1 Experimental Design

A quasi-experimental design was employed for evaluation of SFpark. Independent data samples of cruising were collected in both the control and the pilot areas before and after the implementation of the pricing pilot in the spring of 2011 (presented in Figure 1 above). Figure 2 is a hypothetical illustration of possible time and intervention effects in the control and pilot areas and why data are collected in both control and pilot areas before and after the implementation of the pilot. In Figure 2, solid lines represent the observed data. Over time, the effect of the pilot on measured outcomes may be confounded by economic and demographic changes. This is presented as the “Time Effect” in Figure 2. Data are collected in a control area to measure changes over time that may confound the analysis. For example, an economic decline or sharp rise in gas prices may result in reduced traffic and congestion during the before and after data collection period. One can see in Figure 2 below that the effect of the pilot would be significantly overestimated if the time effect was not controlled. The opposite is also true. A significant improvement in the local economy may spur additional traffic and congestion, which may have been the case over the 2011 and 2013 period in San Francisco. If this time effect is not accounted for in the evaluation, then the positive effect on traffic and congestion may be masked.
<table>
<thead>
<tr>
<th>Location</th>
<th>Kelley and Clinch, 2009</th>
<th>van Ommeren et al., 2011</th>
<th>Ottosson et al., 2013</th>
<th>Pierce and Shoup, 2013</th>
<th>Millard-Ball et al., 2014</th>
<th>Chatman and Manville, 2014</th>
<th>Current Study</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parking Pricing</td>
<td>Flat</td>
<td>Flat</td>
<td>Demand-Responsive</td>
<td>Demand-Responsive</td>
<td>Demand-Responsive</td>
<td>Demand-Responsive</td>
<td>San Francisco</td>
</tr>
<tr>
<td>Experimental Design</td>
<td>Before &amp; after equivalent test groups</td>
<td>Repeated non-equivalent sample groups</td>
<td>Before &amp; after equivalent test groups</td>
<td>Before &amp; after equivalent test &amp; control groups</td>
<td>Before &amp; repeated after equivalent test and control groups</td>
<td>Before &amp; after equivalent test and control groups</td>
<td>San Francisco</td>
</tr>
<tr>
<td>Data Source</td>
<td>Meter</td>
<td>D Travel Survey</td>
<td>Meter transactions</td>
<td>Parking sensor</td>
<td>Parking sensor</td>
<td>Field survey</td>
<td>San Francisco</td>
</tr>
<tr>
<td>Sample Size</td>
<td>Not reported</td>
<td>11,425</td>
<td>Not reported</td>
<td>5,294</td>
<td>Not Reported</td>
<td>132</td>
<td>212</td>
</tr>
<tr>
<td>Method of Analysis</td>
<td>Price elasticity equation</td>
<td>Linear regression</td>
<td>Log-log regression</td>
<td>Price elasticity equation</td>
<td>Regression with simulated data</td>
<td>Linear and log-log regression</td>
<td>Generalized mixed effect</td>
</tr>
<tr>
<td>Unit of Analysis</td>
<td>Area</td>
<td>Individual</td>
<td>Block</td>
<td>Block</td>
<td>Block</td>
<td>Area</td>
<td>Area</td>
</tr>
<tr>
<td>Dependent Variable(s)</td>
<td>Average parking occupancy</td>
<td>Parking search time for specific trip</td>
<td>Average parking occupancy</td>
<td>Average parking occupancy</td>
<td>% point change average occupancy outside 60-80% &amp; blocks cruised</td>
<td>Average parking occupancy, availability, duration, turnover; double &amp; illegal</td>
<td>Average parking search time &amp; distance</td>
</tr>
<tr>
<td>Independent Variable(s)</td>
<td>Price</td>
<td>Income, parking duration, travel duration, &amp; passengers</td>
<td>Price &amp; neighborhood attributes</td>
<td>Price</td>
<td>Price change frequency</td>
<td>Price</td>
<td>Pilot</td>
</tr>
<tr>
<td>Control Variable(s)</td>
<td>Income &amp; inflation, elasticity by time of day &amp; day of week</td>
<td>Area, destination, gender, age, arrival time, year &amp; activity type</td>
<td>Time of day, day of week, unique block effects, &amp; spatial correlation between blocks</td>
<td>Elasticity by location, time of day, day of week, initial price, change size &amp; over time.</td>
<td>Area, date, day of week &amp; time of day</td>
<td>Initial price, time of day, day of week, area, weather, &amp; employment</td>
<td>Control; time of day, day of week &amp; area</td>
</tr>
<tr>
<td>Findings</td>
<td>Average price elasticity of demand is -0.29 &amp; morning peak most responsive</td>
<td>Low cruising times due its strong parking pricing program</td>
<td>Elasticities for price increase from -0.7 to -0.37; price decrease not significant; higher in am peak.</td>
<td>Average price elasticity is -0.4 &amp; varies by largely time of day and location</td>
<td>Block-level rate changes significantly related to average occupancy and blocks cruised.</td>
<td>Price improves average occupancy not parking availability, duration, turnover, or carpooling</td>
<td>15% reduction in parking search time and 12% reduction parking search distance due to pilot.</td>
</tr>
</tbody>
</table>
The pilot and the control areas were selected by SFMTA. As noted by Millard-Ball et al. (7), the control areas of Filmore and Union are characterized by a central commercial area surrounded by residential areas and may be more similar to the Marina and Richmond areas than central business districts of Civic Center, Downtown, and South Embaradero. As a result, they estimated their models with and without these central business districts, but found no significant differences in the results. In addition, the Union control area is close to the Marina pilot area. Control areas (as in this study) and control blocks (as δ) may be subject to spillover effects of the experiment.

![Hypothetical Illustration of Possible Time and Intervention Effect in the Control and Pilot Areas](image)

**Figure 2- Hypothetical Illustration of Possible Time and Intervention Effect in the Control and Pilot Areas**

### 3.2 Data Collection

Parking search time and distance data were collected manually in both control and pilot areas in the spring of 2011 before the implementation of SFpark and in the spring of 2013 after its implementation. Surveyors followed a predefined route in each of the pilot areas (Marina, Fillmore, Civic Center, Mission Downtown, and South Embarcadero) and control areas (Inner Richmond and Union), as shown in Figure 3. The data were collected by surveyors on bikes rather than in cars to avoid adding to congestion. After discussions with SFMTA, the research team decided to exclude the Mission pilot data. The implementation of SFpark was so minimal due to construction in that area that it cannot be considered a true treatment case.

The parking search routes included 62 blocks and 1,150 spaces (excluding Mission) of the 256 blocks and 6,000 on street parking spaces included in the SFpark program. Table 2 describes the share of the parking spaces included in the parking search routes of the total parking spaces in the control and the pilot areas, which ranges from 11% to 60%. Surveyors biked along each of the routes, recording the elapsed time for each run. Surveys were not scheduled in locations with special events that could distort parking search time data (e.g., parades, street fairs, street cleaning, or major sporting events). Data were collected in each pilot and control area on weekdays (Tuesday, Wednesday, or Thursday) and on both Saturday and Sunday for four time periods subject to parking fee changes: 8:00 to 10:00 a.m., noon to 2:00
p.m., 4:00 to 6:00 p.m., 8:00 to 10:00 p.m., and where meter operating hours extended into the evening from 10:00 p.m. to 12:00 a.m. Table 3 describes the change in parking prices in the pilot areas from 2011 to 2013.

A total of 6,466 usable data points were available after SFMTA completed their initial data screening process. Parking search distances were calculated as follows: “Each survey run includes the meter post ID where parking was found as well as the number of laps completed. Distance is measured in feet and is measured to each meter post ID, accounting for the number of completed laps for each survey run.”

Table 2-Percent of Parking Spaces Sampled for the Parking Search Routes of the Total Parking Spaces in the Pilot and Control Areas

<table>
<thead>
<tr>
<th>Area</th>
<th>Percentage of total parking spaces in the area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Civic center</td>
<td>17%</td>
</tr>
<tr>
<td>Downtown</td>
<td>37%</td>
</tr>
<tr>
<td>Fillmore</td>
<td>18%</td>
</tr>
<tr>
<td>Marina</td>
<td>16%</td>
</tr>
<tr>
<td>Richmond</td>
<td>60%</td>
</tr>
<tr>
<td>South Embarcadero</td>
<td>11%</td>
</tr>
<tr>
<td>Union</td>
<td>40%</td>
</tr>
</tbody>
</table>

*Control areas in italics.

Table 3-Average Meter Hourly Changes in Pilot Areas from 2011 (Before) to 2013 (After)

<table>
<thead>
<tr>
<th>Weekday</th>
<th>Civic Center</th>
<th>Downtown</th>
<th>Fillmore</th>
<th>Marina</th>
<th>South Embarcadero</th>
</tr>
</thead>
<tbody>
<tr>
<td>Morning</td>
<td>-$0.78</td>
<td>$1.19</td>
<td>-$0.09</td>
<td>$0.08</td>
<td>-$0.35</td>
</tr>
<tr>
<td>Mid-day</td>
<td>$0.42</td>
<td>$1.92</td>
<td>$0.71</td>
<td>$1.15</td>
<td>$0.70</td>
</tr>
<tr>
<td>Afternoon</td>
<td>$0.13</td>
<td>$1.77</td>
<td>$0.42</td>
<td>$1.08</td>
<td>$0.17</td>
</tr>
<tr>
<td>Weekend</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Morning</td>
<td>-$1.58</td>
<td>-$0.60</td>
<td>-$0.37</td>
<td>$1.20</td>
<td>-$1.54</td>
</tr>
<tr>
<td>Mid-day</td>
<td>-$0.69</td>
<td>$0.29</td>
<td>$1.13</td>
<td>$2.01</td>
<td>-$0.70</td>
</tr>
<tr>
<td>Afternoon</td>
<td>-$0.91</td>
<td>$0.05</td>
<td>$1.02</td>
<td>$1.99</td>
<td>-$0.59</td>
</tr>
</tbody>
</table>

While the realism of directly measuring change in parking search time and distance is appealing, it is also very difficult. As a result, previous studies use proxy measures that are easier to collect such as average parking occupancy, availability, duration, turnover, double, and illegal parking (8) or simulate cruising data with theoretical models calibrated with observed parking occupancy data (7). The cost of manual surveys limits the number of blocks and perhaps how well the blocks represent an area as a whole. The data may also be subject to surveyor error and bias. Meter transaction and sensor is less costly to gather and thus should provide a more comprehensive representation of parking events both temporally and spatially; however, the quality of the data is subject to operational failures. Simulated data lacks the realism of observed data but can be a very effective way to derive secondary outcomes from data that are available. Parking search data will vary type (stated and observed) and by procedures that define the actual measurement of the data. In this study we assume a fixed parking start location and restrict the area by which parking can be found, which is likely not truly represent actual parking search behavior, but it does allow for consistent measures to be collected over time.

3.3 Methods of Analysis

Although there were many thousands of measurements from cruising surveys, the individual searches are not meaningful measures for statistical analysis. Time and distance measures in the parking search survey are not independent random variables, they are a function of the time or distance to find the parking space and the time and distance to find the next parking space. Longer search trips are less likely to be represented in the data because it takes longer to find spaces on those trips and, thus, get back to them within the scheduled time window. As a result, parking searches are over-represented during non-congested time periods. The reverse is true for congested time periods. For example, within a two-hour time period there could have been four, 20-minute search trips in time period 1 (more congested) and eight, 10-minute trips in time period 2 (less congested). The observations are reduced by half in the more congested conditions, because of the two-hour time period restrictions. Moreover, surveying did not always include the full survey time period because surveyors may have started late and/or ended early.

As a result, the total number of successful searches (y in equation 1 below) during one time period in each area is adjusted for the actual time searched or the actual distance search (t in equation 1 below) and the results enables a statistical model that is easily implemented. It does not require untestable assumptions about the correlation structure of the search times and distances associated with each newly started route. Thus, our outcomes consist of, for example, the total number of parking spaces found from 10 a.m. to noon on Tuesday May 3, 2011 divided...
by the total parking search time between 10 a.m. and noon. Two models were estimated (as
described below in equation 1), one for the number of parking spaces found by actual time
searched and one for the number of parking spaces found by actual distance searched.

Figure 4 are box-plots describing changes in average parking search time and distance
(the inverse of y/t) from 2011 to 2013 for different control and pilot areas. Because of the
variation in average search time and search distance by area, we plot the average search time and
search distance on a logarithms scale. As indicated in both graphs (left and right panel), median
average parking search time and parking search distance has been decreased form 2011 to 2013
in almost all areas, except Richmond and Civic Center.

The model described in equation (1) below is a generalized mixed effects model in which the
dependent variable was assumed to have a Poisson distribution:

\[
\log[y_{ij}/t_{ij}] = \beta_0 + b_0 + \beta_p d_p + \beta_{wp} d_{wp} + \beta_{wc} d_{wc} + \beta_1 x
\]

where \(d_p = \begin{cases} 1 & \text{if pilot area} \\ 0 & \text{otherwise} \end{cases}\), \(d_{wp} = \begin{cases} 1 & \text{if 2013 pilot area} \\ 0 & \text{otherwise} \end{cases}\), and \(d_{wc} = \begin{cases} 1 & \text{if 2013 control area} \\ 0 & \text{otherwise} \end{cases}\).

For this model, the effects related to the pilot program are \(\beta_p\), \(\beta_{wp}\) and \(\beta_{wc}\). Confounding variables
or covariates (x) include the time of day and the day of the week (i.e., weekday versus weekend).
The intercept is \(\beta_0\) and the random parking area effect is \(b_0\). Making area a random effect adjusts
for heterogeneity between areas and accounts for the fact that observations within area are
typically more similar than observations from different areas and thus are likely correlated. The
time effect in the pilot areas is measured by $\beta_{wp}$ and in the control areas by $\beta_{wc}$. Thus, $\beta_{wp} - \beta_{wc}$ measures the effect of the pricing program. The pilot area effect is $\beta_p$ and it models differences that might exist between pilot and control areas. If $\beta_p$ is significant, then measured outcomes were different before implementation of the pricing program. Interpretation of this coefficient only makes sense if $\beta_{wp} - \beta_{wc} = 0$.

Poisson and negative binomial are approaches typically used for the analysis of count data. The Poisson model requires that mean and variance are equal. This assumption did not hold, and thus a negative binomial model was also fit, but the results did not differ significantly from the Poisson model. Deviation from the Poisson distribution would not tend to bias parameter estimates, but it would typically underestimate the variance resulting in standard errors that are too small and confidence intervals that are too narrow. The negative binomial model allows for variation that is larger than would be expected from a Poisson model.

4. RESULTS

The estimated model results are provided in Table 3. The coefficient estimates are presented as odds ratios. The coefficients for the pilot and control are significant at the 0.05 level. We can see that parking search time and distance improve over time in both the pilot and control, but more so in the pilot. The difference between the coefficient of the pilot and control is significant ($p = 0.03$) for parking search time and nearly significant ($p = 0.07$) for parking search distance comparing pilot and control areas based on the Wald test.

Table 4—Changes in the Rate of Parking Spaces Found by Time and Distance in Pilot and Control Areas (P-values are Reported in Parentheses)

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Changes in Pilot Areas</th>
<th>Changes in Control Areas</th>
<th>Changes caused by SFpark (dif-in-dif)</th>
<th>Number of observation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parking Events by Time Searched</td>
<td>1.42</td>
<td>1.21</td>
<td>1.17</td>
<td>221</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.03)</td>
<td></td>
</tr>
<tr>
<td>Parking Events by Distance Searched</td>
<td>1.37</td>
<td>1.21</td>
<td>1.14</td>
<td>221</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.07)</td>
<td></td>
</tr>
</tbody>
</table>

* Changes are reported as odd ratio.

* The bold values are statistically significant at 95% confidence interval.

In Table 5, the inverse of the pilot and control coefficients presented in Table 4 are applied to generate the average percentage change in search time and distance in the pilot and the control areas, which is -12% for search time and -10% for search distance.

Table 5—Average Change in Parking Search Time and Distance in Pilot and Control Areas

<table>
<thead>
<tr>
<th>Area</th>
<th>Average changes from 2011 to 2013</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Parking Search time</td>
</tr>
<tr>
<td>Pilot Areas</td>
<td>-29.37%</td>
</tr>
<tr>
<td>Control Areas</td>
<td>-17.26%</td>
</tr>
<tr>
<td>Pilot- Control (Dif-in-Dif)</td>
<td>-12.11%</td>
</tr>
</tbody>
</table>

The results of the model estimates used to estimate total change in 2013 with and without the pilot. Table 6 shows the results of average search time and distance (using the inverse of the
estimated coefficients for the pilot and control), respectively, in 2013 with and without variable
pricing in the pilot area by time period and day type. Search time range from about half a minute
to two minutes. These are lower than those reported by Shoup (1); however, Shoup notes that the
3.5 to 14 minute from identified surveys of cruising maybe biased upward because “researchers
study cruising only where they expect to find it” (p. 479). The morning average search time is
close to the van Ommeren et al.’s (2) 36 seconds. The share and cost of car parking for workers
who most typically arrive in the morning is very high in San Francisco. On the other hand,
the design of the survey may have a conservative bias on the total travel time and distance, as
described above, in exchange for a measures that could be replicated over time. The absolute
difference ranges by time period and day of the week and ranges from 3.2 seconds to 10.6
seconds for average parking search time and 50 to 200 feet for average parking search distance.

<table>
<thead>
<tr>
<th>Time</th>
<th>2013 without SFpark</th>
<th>2013 with SFpark</th>
<th>Total Change</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time</td>
<td>Distance</td>
<td>Time</td>
</tr>
<tr>
<td><strong>Weekday</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8-10 AM</td>
<td>35.40</td>
<td>340.36</td>
<td>32.20</td>
</tr>
<tr>
<td>12-2 PM</td>
<td>116.69</td>
<td>1267.14</td>
<td>106.37</td>
</tr>
<tr>
<td>4-6 PM</td>
<td>74.17</td>
<td>762.95</td>
<td>67.59</td>
</tr>
<tr>
<td>8-10 PM</td>
<td>92.95</td>
<td>1147.07</td>
<td>84.72</td>
</tr>
<tr>
<td><strong>Weekend</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8-10 AM</td>
<td>36.28</td>
<td>313.55</td>
<td>33.01</td>
</tr>
<tr>
<td>12-2 PM</td>
<td>119.61</td>
<td>1167.31</td>
<td>109.02</td>
</tr>
<tr>
<td>4-6 PM</td>
<td>76.02</td>
<td>702.85</td>
<td>69.28</td>
</tr>
<tr>
<td>8-10 PM</td>
<td>95.27</td>
<td>1056.70</td>
<td>86.83</td>
</tr>
</tbody>
</table>

*Average search time and distance are reported in seconds and feet.

5. CONCLUSIONS

In this study, the effect of demand-response parking pilot program in San Francisco, known as
SFpark, on cruising for parking including both time and distance is evaluated. The effect is
evaluated with measured data in pilot and control areas before (2011) and after (2013) the
implementation of the pilot. A generalized mixed effects model is estimated using this data and
its specification controls for time effects, random area effects, time of day, and day of week. This
study differs from previous evaluations of demand-responsive parking programs in that it (1)
directly takes measurements of parking search time and distance rather than simulating data or
proxy variables such as parking availability, double parking, and illegal parking and (2) controls
for time effects by using data from a separate control area as opposed to using variables such as
block face parking price and employment. The results show that the average percentage change
in search time and distance between the pilot and the control is -12% for search time and -10%.
The design of the cruising survey may have a conservative bias on the total parking search travel
time and distance to allow for measurements that could feasibly be replicated over time. The
absolute difference ranges change by time period and day of the week from 3.2 seconds to 10.6
seconds for parking search time and 50 to 200 feet for parking search distance.
REFERENCES:


