Is the curb 80% full or 20% empty? Assessing the efficacy of San Francisco's parking experiment

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ABSTRACT

The San Francisco Municipal Transportation Agency has adopted a performance goal of 60% to 80% occupancy for their metered parking. The rule represents an heuristic performance measure intended to reduce double parking and cruising for parking, and improve the driver experience. In this paper, we study the data collected as part of the SFpark pilot and evaluate that rule against other possible measures. We confirm the finding of others indicating that the probability a driver finds available parking on the block where s/he is destined tracks with average occupancy until about 85%-90%, after which the system breaks down and the chances of finding a spot deteriorate rapidly. We also find that the relationship between occupancy and the probability of finding a space is sensitive to the duration of the averaging period, i.e. the hourly average occupancy is a better predictor of finding a spot than is occupancy averaged over a longer period such as a few weeks. In addition, using occupancy data for five minute time periods, we develop a lower bound on the arrival rate for each block. For blocks that are full, we develop a refill rate which measures the time from full to space available and back to full again. Using the refill rates and the arrival rate we run simulations to estimate the expected number of blocks a driver must cruise before finding a space, and some preliminary evidence for impacts of SFpark over one year.
INTRODUCTION

Parking management has been a vexing problem for cities since the invention of the automobile. One concern is excess travel, congestion, air pollution and greenhouse gas (GHG) emissions that are caused by drivers searching for available parking – an activity colloquially known as cruising. Studies of cruising date to 1927 [1], and some researchers have estimated that upwards of 30%, and maybe as much as 50%, of traffic on a given downtown street is comprised of people searching for a parking spot [1] [2] [3]. Shoup estimated that cruising in one small area of Los Angeles produced 3,500 miles of excess travel each day [1]. That is enough to cover the distance from Los Angeles to New York City and back to Chicago. In 1935, the City Council of Oklahoma City introduced parking meters, the first city to do so, so that customers to a commercial area would be able to find a space more easily. A 1956 book by the United States Bureau of Public Roads recommends maintaining a curb occupancy rate of no more than 85%-90% in order to mitigate cruising [4].

A typical response by cities has been to require off-street parking in areas where these curb standards are exceeded. The theory is that off-street spaces will accommodate the excess demand. Many cities had introduced off-street parking requirements for new development by the mid 1960s, but lack of coordination between pricing of curb parking and off-street parking and the requirement that off-street parking – by and large—remains preserved for the exclusive use by users of the particular building have not solved the cruising problem. Increasingly cities such as San Francisco, Seattle, Pasadena, New York City, and Mexico, D.F. have set parking occupancy performance standards and used pricing to meet the performance goals. The primary objective is elimination of cruising.

In this paper we analyze data from San Francisco, a city that has piloted and carefully documented an extensive program – SFpark – to reduce cruising and improve the experience of parkers in the city. One expectation from the program is that reduction of cruising will represent an improvement in livability that benefits all users of the transportation system and the city, whether they are drivers or not. In this paper we focus on two key questions. First, we examine the 80% rule – the occupancy threshold above which SFpark increases meter rates – and develop a simulation model to examine how different occupancy levels affect the extent of cruising.

Second, we are interested in how the driver experiences the policy outcome. We argue that a driver is not interested in the occupancy rate on a block. Rather, s/he is only interested in whether or not there is available parking. Because more people will be trying to park at high-demand times, more people will experience the full curb. While the occupancy target may thus be met, the user experience may still leave something to be desired. The problem is best illustrated by the case where a block is empty for half the time and full for the other half. Objectively, this block has an average occupancy rate of 50% yet, since it is empty half the time, only the first user experiences it as empty. Moreover, very few users (only those who are present as the block fills and empties) experience it as 50% full. Since, by definition the block is full at the times of high demand, the vast majority of parkers experience it at 100% occupancy and they are forced to seek parking elsewhere.

In the remainder of this introduction we provide a brief summary of SFpark, we describe our research questions, and summarize the contributions. In subsequent sections we discuss previous research that
bears on the work we represent here. We continue with a discussion of the data and methodology followed by a discussion of our results. We conclude with a summary of our research and with some thoughts for future research and practice.

Overview of SFpark

The stated goal of smart parking initiatives, such as SFpark, is to reduce the number of drivers cruising for an on-street parking space. This is evidenced by the program’s slogan, “Circle Less, Live More.” Decreasing the number of cruising drivers is directly connected to the primary public policy goals of interest: reduced traffic congestion and pollution. Several other public policy goals of smart parking initiatives follow from reduced traffic congestion, they include: safer streets for bikers and pedestrians, and more reliable public transit schedule adherence.

To achieve these goals, smart parking initiatives deploy three main tools: parking information systems, payment technologies, and pricing schemes. The underlying theory of many smart parking initiatives, including SFpark, depends on using pricing and information to balance supply and demand for parking. The expectation is that the resulting equilibrium is one with a reduced level of cruising and double parking.

As a step toward implementing this vision, many cities, including San Francisco, are setting parking occupancy targets as an heuristic to guide their pricing schemes. The heuristic seeks to maintain target hourly occupancy levels for each block throughout the day. Shoup [1] has advocated for an 85% hourly occupancy target for all blocks. The SFpark program has adopted the slightly lower target of 80%, given that some spaces will be unavailable while technically vacant, as vehicles enter and exit. SFpark has set a lower target as well, below which meter price is reduced. The pricing scheme employed by SFpark intimately depends on this hourly occupancy target range.

While SFpark is administered by the San Francisco Municipal Transportation Agency (SFMTA), the United States Department of Transportation (USDOT) has been an important partner. USDOT has helped finance state-of-the-art technology with new parking meters and in-street sensors that communicate data regularly to a data management system. The system includes two new ways to accept payment, credit card and pay-by-phone; these are in addition to the previous payment options of cash and parking cards. The mantra of SFpark has been to improve the parker experience and that philosophy undergirds many of their decisions.

During the first year of SFpark operations, there were four rate changes. There has been some variation but, by and large parking rates have changed monotonically. Two hundred and forty-eight on-street blocks (i.e., pairs of opposing block faces or street segments) were included in the pilot, in addition to one surface lot and 14 parking garages (which are not considered in this paper). There are three time bands: meter opening time to noon; noon to 3pm; 3pm to close, over two day types: weekday and weekend, allowing for six possible price regimes. These different block, day-type and time band combinations create nearly 1,500 possible on-street price adjustments at each rate change. In 8% of cases the meter rate was never adjusted indicating that average occupancy was in the target range. In 46% of cases the meter

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1 The information in this section is derived from the policy and evaluation reports on the SFpark website (www.sfpark.org), and personal communications with staff at the San Francisco Municipal Transportation Agency.
prices were adjusted upward or stayed the same at each adjustment. These segments experienced average occupancy above the target level during at least one rate change period. In 37% of cases the meter price was adjusted downwards or stayed the same, indicating segments that were under the target occupancy during at least one rate change period. Finally, it is worth noting that 9% of the segments were adjusted up at least once and down at least once. These fluctuating segments may merit additional attention.

LITERATURE REVIEW

Shoup [1] identifies 16 empirical cruising studies conducted between 1927 and 2001. In more recent years, there have been numerous studies of cruising added to this collection. Empirical studies rely on some kind of driver survey [2] [5], videotaping [6], or driving and searching by car [1]. This last technique has been criticized as adding to cruising, thus changing the fundamental terrain of the study. Some have tried to address that criticism by using bicycles. Driver surveys generally stop people at intersections or when they have come out of their cars to ask about the purpose of their travel (people stopped during their journey are asked if they are seeking parking) or their experience finding a parking place (people who have parked). Studies that rely on video – or other visual technique—may be the most robust. They count vehicles passing an open space and infer that the inverse of the number of vehicles to pass an open space is equal to the proportion of traffic that is looking for parking.

The other class of cruising studies is theoretical; this work is well represented in the economics literature. Most analyses conclude that cruising is due to misallocation of resources and should be eliminated [7] [8]. An extension of [7] is due to Arnott and Rowse [9] who look specifically at spatial competition between curb parking and garages. One study suggests that street parking should be priced equivalent to the marginal cost of providing an additional off-street space [10].

In spite of widespread acceptance of the 85% occupancy standard, very few studies have sought to analyze the heuristic. Two studies using simulation models do look at the threshold and in particular focus on the important non-linearities in occupancy and cruising [11] [12]. In the latter study, an agent-based model is employed. The authors identify changes in the system dynamics at about 85% but find a much greater impact above 92% [12].

While the body of knowledge in this area is growing, until now there has been little opportunity to model and analyze an empirical case as complex as San Francisco. That is the gap in research we address here.

Research Questions

This study is motivated by two main research questions. The first research question deals with how average occupancy relates to the probability that a driver finds available on-street parking, and the expected number of blocks a driver would cruise for parking. This question is important given that the desired policy outcomes are directly related to the driver experience metrics, i.e. probability of available parking and expected cruising time, not the occupancy of parking spaces. For example, it is evident that a high average occupancy at 2am has no impact on cruising if there is no demand for parking at that time. Also, it is our contention that there is a nonlinear relationship between the average occupancy and the
probability of finding a full block. This view is supported by fundamental results in queueing theory (see [13]). The queueing literature establishes that the probability of an arriving customer finding a system full is not the same as the time-averaged number of unavailable resources. In fact, the relationship between the time average number of unavailable resources and the probability of an arriving customer finding the system full is an increasing convex function. For example, an increase in average occupancy from 30% to 40% likely has no impact on the probability of finding a space, in sharp contrast to an increase from 90% to 100%. This implies that the marginal change in the probability of finding a block full as a function of average utilization grows at an increasing rate.

Furthermore, the pricing scheme employed by SFpark uses occupancy per time band averaged over a two-week period as the basis for changing rates. As the period over which occupancy is averaged grows longer, it converges to expected occupancy. Since the relationship between average occupancy and the probability of a full block is convex, by Jensen’s inequality [14], we would expect the probability of a full block under the two-week average metric (i.e., expected occupancy) to be higher than under the hourly average metric. This phenomenon is illustrated in Figure 2. This sub-question is important because it highlights the impact of the time scale of setting occupancy targets on cruising.

After exploring the relationship between average occupancy and driver experience, at both the hourly and two-week aggregations, we tackle the second main research question – whether SFpark has reduced the total amount of cruising in the pilot areas during its first year. The existing literature – based on theory, limited empirical observations and simulation models – suggest that the total amount of cruising should decrease as prices adjust to achieve the target occupancy. However, it is also possible that rate changes have merely displaced cruising drivers to other blocks, leaving total cruising constant, or even had a perverse effect and increased cruising. This question is fundamental to the evaluation of SFpark specifically and performance-based parking pricing interventions more generally.

DESCRIPTION OF DATA SOURCES
The data used for this study comprise variations on the in-road parking sensor data collected by SFMTA. Some of the analysis is based on hourly average occupancy rates on each block. These hourly data, provided by SFMTA, span the period March 1, 2011 to February 29, 2012. In addition we have captured occupancy data from the SFMTA website every five minutes. The website data were captured using an application programming interface (API), made available by SFMTA to mobile phone and web application designers as well as any other interested party.

SFMTA Hourly Data
The hourly data contains information for metered on-street spaces on 398 blocks, plus one off-street lot which we do not consider in this paper. Of the 398 blocks, 55 are in the study control group, i.e. the meter prices were held fixed throughout the period, and 343 form part of the SFpark pilot where meter prices are changed in response to parking demand.
Each data point specifies the date, the hour, the number of metered and commercial spaces on the block, and the parking rate in effect. Most important for this analysis, the SFMTA hourly data set also includes parking occupancy averaged over the hour, from which we infer availability for each block in the analysis. Each data point combines parking occupancy of both sides of the street, which makes most sense for one-way streets and represents a minor data limitation for our analysis with respect to two-way streets (discussed in more detail below). The entire data set comprises 3,307,419 data points over a one-year period. For this study, we only consider on-street data during metered hours. This reduces the number of data points to 1,120,120.

**Web API Snapshots**

The second data variant was collected by developing a web application that interacts with the SFpark API. The data collected from the API provide snapshots of parking availability and capacity for each side of the street (i.e., block faces) which we aggregate to both sides of the street (i.e., blocks) in order to match the hourly data. Here, we use data for 225 blocks in the SFpark pilot area, collected at approximately 5-minute intervals.

The two data sets contain overlapping periods of observations from January 1, 2012 to February 14, 2012. The API data set comprises 3,070,252 block-level data points during this period, which reduces to 1,077,931 when we discard observations outside metered hours. The API snapshot data set was joined to replicates of the hourly data set using the unique block IDs and the date and time. The two data sets were further checked and cross-validated with each other for consistency. During this validation process, 3.4% of observations from the API snapshot data were discarded due to inconsistencies in hourly average occupancy. In most cases, these inconsistencies simply reflect sampling error given that the API provides about 12 snapshots per hour while the hourly data averages the minute-by-minute occupancy data from the sensors.

**METHODOLOGY**

In order to investigate our two research questions, we employ two main methodologies: simulation and queueing theory. The goal of the simulation methods is to relate the average occupancy levels with the probability that a person looking for parking will find an open space. These simulations are calibrated using the two data sources described in the previous section. Queueing theory provides the methodological foundation to compute performance measures from the perspective of the driver. In order to compute the performance metrics as the driver experiences them, an additional demand estimation metric, the refill rate, is introduced. Additionally, the underlying queueing model for the system is a Markovian multiserver queue. [13].

**Simulation of Parking Availability**

This section presents the methods used to estimate cruising in the area covered by SFpark. It takes advantage of the high-fidelity sensor data obtained through the API, coupled with the hourly data provided by SFMTA.
First, the relationship between the probability of a block being full (Pr[full]) and hourly average occupancy is calibrated from the joined hourly occupancy and five-minute API data. The SFMTA hourly data cover a full year, but provide only hourly averages rather than snapshots of occupancy, and so are ill-suited to assessing whether a block is full. Pr[full] is calculated for each hourly period as the proportion of API observations where the block is full, allowing the following regression model to be estimated:

$$\log(\text{percent\_full}_i) = \alpha + \beta_1 n_i + \beta_2 \text{occ}_i + \beta_3 \log(\text{occ}_i) + \epsilon_i,$$

where: $n_i$ is the number of spaces during each hourly block-level data point $i$; $\text{occ}_i$ is occupancy on that block averaged over that hour; $\text{percent\_full}_i$ is the percentage of API observations on the block during that hour where no space is available; and $\alpha, \beta_1, \beta_2, \beta_3$ are coefficients estimated via iteratively reweighted least squares.

The log-linear functional form is loosely derived from queuing theory, but is estimated using a general parametric model since many of the assumptions inherent in standard queuing theory models (particularly, independence and a uniform arrival rate and length of stay) are likely to be violated here. Table 1 shows the coefficients of the regression model, and Figure 1 shows the fit of the regression model predictions against the actual data. As can be seen, the fit is very close across multiple block sizes.

The relationship between block size (number of spaces) and Pr[full] can also be seen in Figure 1. For any given hourly average occupancy, Pr[full] decreases as the number of spaces increases. This makes intuitive sense. On a block with only one space, the hourly average occupancy is the same as Pr[full] — the relationship is a 45 degree line. For very large blocks, a parker has a good chance of finding a space even at an occupancy level of 90% or more.

| Table 1 Predictive Model to Estimate Probability that Block is Full |
|---|---|---|
| $\alpha$ (intercept) | -0.0298 | 0.0238 |
| $\beta_1$ (number of spaces) | $5.68 \times 10^{-5}$ | $1.67 \times 10^{-4}$ |
| $\beta_2$ (hourly average occupancy) | $5.68 \times 10^{-4}$ | $2.44 \times 10^{-4}$ |
| $\beta_3$ (no. of spaces x log(hourly average occupancy)) | 1.365 | 0.00461 |
| $n=87361$ | | |
Second, the predictive model is used to estimate \( Pr[\text{full}] \) for each data point in the hourly occupancy data set – including data points which do not overlap with the API data. In other words, \( Pr[\text{full}] \) is estimated as a function of the number of spaces on a block and the hourly average occupancy.

Third, for each hourly observation in the SFMTA dataset, a single cruising simulation is run. A parker ‘arrives’ at each block within each hourly period, and finds a space on that block with probability \( 1 – Pr[\text{full}] \). If a space is found, then the number of blocks cruised is recorded as zero. Otherwise, the parker randomly selects an intersecting block, and finds a space on that block with \( 1 – Pr[\text{full}] \). Thus, the parker

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2 Multiple simulations could be run and the average number of blocks cruised taken. However, we do not report results for individual hours on individual blocks, and so the law of large numbers will apply at the level of all blocks within a given time period. Our approach also preserves the full range of the distribution.

3 Some blocks on the fringes of a pilot or control area have few intersecting blocks. In these instances, the block’s nearest neighbors (e.g. parallel blocks) are added to ensure that at least four blocks are available to be chosen at random as the parker cruises. Also note that the randomly selected block is constrained to be within 400m (~1/2 mile) of the original block, ensuring that the parker cannot cruise too far from his or her presumed destination.
proceeds via a random walk through the neighborhood until either a space is found, or the cap of 3 blocks
cruised is reached (and by assumption, the parker gives up or parks off-street). Note that blocks (including
the original block) can be visited multiple times.

This approach has several advantages over alternative methods of assessing cruising. Most importantly, it
allows cruising to be estimated for every hour on every block, rather than the small sample possible with
manual methods. It also avoids potential selection bias whereby cruising surveys may focus on busy blocks
at busy times. The downsides are primarily as follows:

1. Blocks are chosen at random from the set of blocks that intersect the parker’s current location. Refinements
to this process could take account of the direction of travel, one-way streets and other restrictions. Alternatively, allowing parking search to follow a Markov chain model could eliminate the need for a simulation, and obtain analytic P[full] and cruising results.

2. Intra-hour correlations between neighboring blocks are not considered. The simulation only considers blocks within the same hourly observation period (e.g. 10-11AM on June 22, 2011). However, it is likely that Pr[full] is spatially correlated within each hour. For example, if at 10:10AM a particular block is full, the neighboring block is more likely to be full at that precise time than would be expected from the occupancy averaged over the hour.

3. Only streets with sensor data and general metered parking are included. Thus, cruising on residential side streets that are not equipped with sensors, or on other blocks with no general metered parking in that hour are not accounted for.

4. The simulation assumes that a parker can take advantage of available spaces on either side of the street. On a one-way street, this is realistic (except on wide streets at times of heavy traffic volume). On two-way streets, this may require illegal U-turns. In practice, many motorists do make U-turns to secure a vacant space on the opposite side of the street, particularly if available parking is scarce. However, the assumption will underestimate cruising from more law-abiding drivers.

Points 2 and 4 and, to the extent that residential streets with free 2-hour parking have higher occupancy
rates, Point 3 are likely to mean that our estimates of cruising under count and are, therefore, a lower bound on cruising. When estimates from SFpark’s own cruising surveys are available, it will be instructive to compare the results.

Parking Availability as the Drivers Sees It

Using time-averaged measures, such as hourly average occupancy, to summarize the driver experience
may lead to misguided conclusions. As noted earlier, the connection between time averages and customer
averages is well studied in the field of queueing theory. There are established results specifying the
conditions under which time averages equal customer averages (see [15] and [16]). The time-average and
customer-average perspective of the system diverge when the demand for the resource varies over time,
and the system has finite capacity. Imagine a simplified example of this property, where a bus is full 50
percent of the day, and half full 50 percent of the day. Because a typical passenger is twice as likely to
have ridden on a bus that is completely full, the expected passenger experienced occupancy does not
equal the expected bus occupancy. From a passenger perspective, 2/3 of the passengers experience the
bus as full, and 1/3 of the passengers experience the bus as half full. By analogy, more drivers arrive to
park during times when parking occupancy is high, therefore they experience a parking occupancy level
higher than hourly averaged occupancy.

To formalize the experience of the typical driver, assume that drivers arrive randomly to park at a block
according to a non-stationary Poisson process, N= \{N(t), t > 0\} with an arrival rate function, \( \lambda(t) \), which is
a function of the time of day. The number of arriving drivers up to time \( T \) is denoted by the random
variable \( N(T) \), and denote the random arrival time of the \( i \)th driver by \( T_i \). Let \( X_i \) be Bernoulli a random
variable denoting the parking occupancy of the block at time \( t \). In this stylized setting, a block at time \( t \) can
be either full, \( X_i=1 \), or not full, \( X_i=0 \). The driver average (shown below on the left) and time average of the
system state are:

\[
E\left[ \frac{1}{N(T)} \sum_{i=1}^{N(T)} 1\{X_{T_i} = 1\}\Big| N(T) > 0 \right] \quad \text{and} \quad \frac{E\int_0^T \{X_s = 1\} ds}{T}.
\]

These two quantities need not be equal.

Since the policy outcomes are linked to the driver experience, we focus on the driver average. The
expected parking occupancy, as experienced by the typical driver is computed using conditioning and the
definition of a non-homogeneous Poisson process [17],

\[
E\left[ \frac{1}{N(T)} \sum_{i=1}^{N(T)} 1\{X_{T_i} = 1\}\Big| N(T) > 0 \right] = \frac{\int_0^T P\{X_s = 1\} \cdot \lambda(s) ds}{\int_0^T \lambda(s) ds}.
\]

This equation also has the interpretation as the average fraction of arriving drivers that find the block full.

**Estimating Parking Demand and Refill Rates**

In order to compute the performance measures for the typical customer, we need an estimate of the
arrival rate of drivers to each block over time. This task is complicated by two factors: discrete
observations and censoring. First, we were able to capture the web API snapshot data only at 5-minute
intervals. Hence, we are unable to observe parking activity in smaller time increments; it is conceivable
that a spot is vacated and then filled in less than five minutes. Such parking events unfortunately must go
unobserved. However, we can compute upper and lower bounds on the arrival rates using the API
snapshots. The observed arrival rate is estimated by the positive change in parking occupancy across
consecutive observations. \((N2-N1)/(t2-t1)\). There could be many arrival and departure scenarios which
lead to the same observed difference \(N2-N1\). A lower bound on the number of arrivals, \(N2-N1\), is obtained
by assuming that no departures occur in the interval \([t_1,t_2]\). An upper bound on arrival rate is all of the parked cars depart, \(D=N_1\), and \(A=N_2\). The number of arrivals is bounded by \(N_2-N_1 \leq A \leq N_2\). Improved estimates of the arrival rate may be obtained by imposing a queueing model based on Poisson process assumptions. However, this is beyond the scope of this paper.

The second challenge in estimating the arrival rate is that observations are censored when parking availability is zero. In other words, when a block is full there is no way to observe or infer how many vehicles arrive looking for parking but have to proceed to the next block since no spaces are available. The arrival rate for a specific hour, say 1pm, is computed by averaging over all of the days in the data set. Presumably, parking availability is zero on some of those days and not the others. Thus censoring causes the estimated arrival rate to be smaller than it would otherwise be.

To address the censoring of demand, we introduce a measure of the censored parking demand, the refill rate. First, we define a busy period. A contiguous block of time when all spaces are occupied is called a busy period. A refill time is the amount time between consecutive busy periods. If a block is full and a parked car leaves, the time until the block becomes full again is an indication of latent demand for parking and the number of cruising drivers. The refill rate is the reciprocal of the refill time. Larson, [18] develops the refill rate to estimate queue length in systems where it is unobserved. Note that a high-occupancy block does not necessary have a high refill rate. If parking durations are long (perhaps because of disabled placard use), then latent demand as measured by the refill rate may be low even when the block is fully occupied.

For the remainder of the paper, we compute the driver performance measures by following the logic of equation (1.1). Our estimate of the true arrival rate is taken as the sum of the observed arrival rate and the refill rate. We then weight each data point by the estimate of the true arrival rate, meaning that busy blocks and/or busy hours receive more weight in our estimates of total cruising. Unless otherwise stated, all results in the remainder of the paper use the weighted data. Note that the weighting system used here is preliminary and represents a lower bound. In future work, we plan to revise the weights, which is likely to give a higher weight to the blocks with the highest occupancies. This is primarily because we only partially address the censoring issue. Given the five-minute discretization of the data, we only observe ‘refill’ events that span one of our five-minute observation periods.

RESULTS

Evaluating SFpark Average Occupancy Targets

SFpark uses average occupancy as a parking performance measure. When average occupancy in the evaluation period\(^4\) on a given block in a given timeband (e.g. weekdays 7am to noon) exceeds 80%, the

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\(^4\) The length and nature of the evaluation period has been refined during the SFpark pilot. Initially, two weeks of data were used to compute a separate average by timeband, giving an average of 10 days of data for weekdays and 2-4 days of data for weekends (depending on whether meters operate on Sundays in a given area). More recently,
hourly cost to park is increased by 25 cents. When average occupancy is below 60%, the rate is reduced by 25 cents (50 cents if it is below 30%). As noted earlier, however, average occupancy is only an approximate proxy for two policy metrics of direct interest to a city – the probability that a block is full, and the amount of cruising. Both of these metrics directly affect the driver experience, and the second directly affects congestion and air pollution outcomes.

Figure 2 plots the relationship between average occupancy and two related metrics: the probability that a block is full (blue lines), and the average number of blocks cruised per parking attempt (red lines). The first metric is calculated from the regression model. The second metric is calculated from the cruising simulations. The average number of blocks cruised is a function of Pr[full], but also depends on the probability of finding a space on neighboring blocks.

There are two points of particular note from the chart. First, both the probability that a block is full and cruising have highly nonlinear relationships to average occupancy. Below 95% occupancy, there is almost no cruising – even if no space is available on a particular block, a driver is likely to find space on the next block visited. Above 95% occupancy, however, the expected cruising distance increases dramatically. The probability of a block being full also increases more rapidly at higher average occupancies. Moving from 85% to 90% average occupancy has much more impact than moving from 80% to 85%.

Second, it matters how average occupancy is computed. For any given average occupancy, further aggregation (solid lines) results in a higher probability that a block is full and implies more cruising than a lower aggregation would indicate (dotted lines). This occurs because of the nonlinear (convex) shape of the curves in Figure 2. Intuitively, a longer averaging period will include more observations with higher-than-average occupancies where both cruising and Pr[full] are much higher, as well as lower-than-average occupancies where cruising and Pr[full] are more similar to those at the mean. For example, an hourly average occupancy of 85% might not include any instances when the block was full, meaning that cruising will be zero. In contrast, a two-week average occupancy of 85% will include many instances when the block was full (and thus cruising occurs), as well as many when the block was almost empty.

The direct implication of this second finding is that average occupancy targets should not be set without reference to the period over which the average is calculated. If a two-week period of averaging is used, as by timeband in SFpark, then a lower occupancy target may be appropriate to achieve a given level of cruising. If a day or two of data are used (perhaps as in a small town with fewer data collection resources and fewer parking spaces), then a higher occupancy target may be appropriate.

We do not attempt to calculate the optimum occupancy level in this paper. However, any calculation would need to balance the costs of either increasing supply or reducing demand to reduce average occupancy, against the benefits of time savings for drivers looking for parking, along with air pollution and congestion externalities saved. Moreover, the nonlinearities shown in Figure 2 indicate that the real gains

Mondays and Fridays have been excluded from the data, meaning that the weekday average uses six days of data. Holidays and special events are also excluded.
come from reducing demand on the blocks with the very highest demand (more than 95% average occupancy), rather than those with more moderate occupancy levels.

Changes Over Time in Occupancy and Cruising

An initial assessment of the impacts of SFpark on occupancy and cruising can be made through plotting changes over time for both pilot areas (where rates have been adjusted) and control areas (where sensor data exists but no rate changes have been made). This is not intended to provide a definitive evaluation of the initial impacts of SFpark after the first four rate changes. Rather, it is intended to illustrate the application of the metrics developed earlier in this paper, and provide some descriptive evidence of how these have changed over time.

Figure 3 plots the changes in the distribution of hourly average occupancy for four periods: before the advent of any rate changes (March to July 2011), and three subsequent periods. The most surprising finding is that there has been almost no change in the distribution over time, with the (perhaps important) exception of a slight drop in the proportion of blocks at 100% occupancy. Despite significant rate changes on some blocks, both upwards and downwards, hourly average occupancy has hardly budged. While the seasonality of the data might affect the results, as we report only the first year of data, there are no seasonal trends evident in the control areas.
The plot of the distribution also shows that parking availability is generally good within the SFpark study area. Very few blocks are fully occupied, and the majority of the system operates at less than 80% occupancy. These data are shown in Table 2 where it is easy to see that the control areas have more blocks with average occupancies of 81% to 90% while the pilot areas are more likely to have blocks in the 96% to 100% occupancy range.

To ensure a robust analysis, SFMTA designated pilot areas and control areas and collected data for several months before beginning the price adjustments. However, occupancy is generally lower in the control neighborhoods than the pilot neighborhoods, suggesting that caution is needed when using the controls to help establish the causal impacts of SFpark rate changes.

<table>
<thead>
<tr>
<th>Occupancy Range</th>
<th>March –July 2011 %</th>
<th>Aug-Oct ’11 %</th>
<th>Oct-Dec ’11 %</th>
<th>Dec ’11-Feb ’12</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 to 80%</td>
<td>61.7%</td>
<td>62.7%</td>
<td>60.3%</td>
<td>59.0%</td>
</tr>
<tr>
<td>81 to 85%</td>
<td>14.0%</td>
<td>13.3%</td>
<td>13.5%</td>
<td>13.8%</td>
</tr>
<tr>
<td>86 to 90%</td>
<td>12.3%</td>
<td>12.0%</td>
<td>13.3%</td>
<td>13.4%</td>
</tr>
<tr>
<td>91 to 95%</td>
<td>7.1%</td>
<td>7.4%</td>
<td>7.7%</td>
<td>8.4%</td>
</tr>
<tr>
<td>96 to 99%</td>
<td>3.7%</td>
<td>3.5%</td>
<td>4.1%</td>
<td>4.3%</td>
</tr>
<tr>
<td>100%</td>
<td>1.2%</td>
<td>1.1%</td>
<td>1.2%</td>
<td>1.2%</td>
</tr>
</tbody>
</table>

Table 2 Distribution of occupancies
Figure 3 Changes over time in distribution of average hourly occupancy (unweighted)

Figure 4 shows the changes in four metrics — hourly average occupancy, the probability that a block is full and average blocks cruised (left axis) and average rate per hour (right axis) — for weekdays from March 2011 through February 2012. Observations are weighted by the arrival and refill rates as discussed above, so that blocks that have more arrivals and more latent demand are weighted more highly. Results for the pilot areas are shown with solid lines, and the control areas with dashed lines.

As would be expected given that there has been little change in the distribution of hourly average occupancy, there are few clear trends evident from the charts. Moreover, analysis is complicated by seasonal variations. Parking rates (red lines) have come down in the morning period, and increased in other periods. However, these rate changes have had little discernible impact on cruising, hourly average occupancy or the probability that a given block is full. Average hourly occupancy and the probability that a block is full have remained almost constant since May 2011. Cruising was increasing gradually in the pilot areas prior to the August 2011 start of the SFpark rate changes and has since leveled off.

Table 3 shows the overall distribution of cruising. Recall that the simulations assume that parkers can take advantage of vacant spaces on either side of the street. If parkers are restricted to one side of the street, the mean number of blocks cruised nearly doubles to 0.38, as the effective capacity of each block is cut in half. Note that because of the highly nonlinear relationship between occupancy and cruising, the number of blocks cruised will usually be a more volatile metric, as it is highly dependent on the number of blocks that are full at a given time and their spatial correlation.
The data in Table 3 suggest that cruising is limited during metered hours. It is important to stress that this represents a lower bound on cruising for several reasons. First, as noted above, cruising would be nearly doubled if parkers could only take advantage of vacant spaces on one side of the street. Second, even if a vacant space is available, it may not be taken by a parker – perhaps due to an impending tow-away restriction or a 30-minute time limit. Third, our simulation assumes that drivers follow a random path and are unimpeded by one-way streets and turn restrictions. Fourth, our weighting scheme is preliminary and may be revised to give greater weight to higher-occupancy blocks. However, the overall message in qualitative terms is that cruising is perhaps primarily a perception problem, or on unmetered streets or at unmetered times. Indeed, SFpark has begun to address these issues through improved driver information and through installing new meters.

Table 3  Distribution of Cruising

<table>
<thead>
<tr>
<th>Blocks Cruised</th>
<th>Pilot Areas</th>
<th>Control Areas</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 (parking found on initial block)</td>
<td>87.2%</td>
<td>89.8%</td>
</tr>
<tr>
<td>1</td>
<td>8.7%</td>
<td>8.0%</td>
</tr>
<tr>
<td>2</td>
<td>2.4%</td>
<td>1.6%</td>
</tr>
<tr>
<td>3</td>
<td>0.9%</td>
<td>0.4%</td>
</tr>
<tr>
<td>4</td>
<td>0.4%</td>
<td>0.1%</td>
</tr>
<tr>
<td>5</td>
<td>0.2%</td>
<td>0.0%</td>
</tr>
<tr>
<td>6 or more</td>
<td>0.2%</td>
<td>0.0%</td>
</tr>
<tr>
<td>Mean blocks cruised</td>
<td>0.21</td>
<td>0.13</td>
</tr>
</tbody>
</table>
One further measure of changes over time is shown in Figure 5, which plots cruising over time by the average occupancy on a given block. This suggests that cruising has fallen since the advent of SFPark's rate changes, but only for motorists seeking parking on the most highly utilized blocks (blue line). The interpretation here is that while it is still difficult to find parking on a block that has an hourly average occupancy of 95% or more, it is becoming easier to find parking on adjacent blocks. Because such highly utilized blocks are such a small fraction of the total parking supply, these trends are not apparent when results are aggregated to the level of the city as a whole.

Figure 4 Changes over time (note: blocks weighted by arrival/refill rate)
Figure 5  Changes in cruising over time by hourly average occupancy

Finally, it is worth noting another important implication of the non-linearities in occupancy, probability of a block being full and the related cruising. We showed in Table 2 and in the figures that the distribution of occupancies has changed very little. It is further the case that a very small number of streets are highly problematic and likely contribute disproportionately to cruising in San Francisco. While a small percentage of the sample at about 2.5% the incidence of fully occupied blocks is relatively small. At the same time, it is close to 94,000 times that blocks had an average occupancy of 100%. The map below indicates 40 blocks that account for 50% (47,000 hours) of the full blocks and, in turn, very likely a similar share of cruising.
DISCUSSION OF RESULTS AND CONCLUSION

It is too soon to provide a definitive evaluation of SFpark. While there appear to have been limited impacts on cruising and occupancy to date, there are a number of potential explanations. One possibility is that it takes considerable time for parkers to adjust to rate changes and to learn where to find blocks with cheaper parking. Another is that SFpark’s rate changes have enabled occupancy and cruising to remain stable, while relaxing time limits, providing more information to users and improving other aspects of the parker experience – changes that would normally be expected to increase demand and reduce availability. A third possibility is that demand for on-street parking is sufficiently inelastic that more dramatic rate changes are needed before large impacts are revealed. A fourth is that the initial effects of improved availability are felt first through reduced double parking, and only subsequently on occupancy and cruising.

However, the SFpark experiment is already providing a large volume of useful data that allows the merits of different performance metrics to be tested, and the relationships between different metrics to be examined. As we discuss in the literature review, 85% occupancy has been widely promoted as a performance standard. Our analysis, consistent with that of others, shows this to be a reasonable threshold considering that average occupancies below that threshold track well with probability that a driver will find a parking space and probability of finding a space on streets with occupancies above that threshold go quickly to zero (Figure 3). However, the precise impacts of the performance standard will vary with the size of the block and the length of time over which occupancy is averaged. The fewer spaces on the block and the longer the period of averaging, the lower the occupancy standard needed to achieve a given availability to the parker and a given level of cruising.
A simple rule of thumb such as 80% or 85% may be useful in data-poor settings (i.e., almost everywhere except San Francisco at present). However, policy makers should remember that average occupancy is not the metric of interest when determining impacts on congestion and air pollution. Similarly, drivers are interested in finding a space and are also indifferent to average occupancies. If SFMTA and USDOT are interested in reducing cruising rather than occupancy rates per se, it would be worth investigating using different performance standards, such as the percent of time a block is full or the refill rate as we discuss above, as the basis for changing rates.

Works Cited


