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# Cruising for parking around a circle

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ABSTRACT

Several recent papers have used the approximation that the number of curbside parking spaces searched before finding a vacant space equals the reciprocal of the expected curbside vacancy rate. The implied expected cruising-for-parking times are significantly lower than those that have been obtained through observation and simulation. Through computer simulation of cars cruising for parking around a circle in stochastic steady state, this paper shows that the approximation leads to underestimation of expected cruising-for-parking time and, at high occupancy rates, considerable underestimation. The paper also identifies several "effects" that contribute to the approximation being an increasingly poor one as the occupancy rate increases.



## 1. Introduction

The pioneering work of Shoup (2005) has stimulated considerable discussion of cruising for curbside parking as a major contributor to traffic congestion in the downtown areas of major cities. The literature contains estimates that the proportion of cars traveling on downtown city streets during the business day that are cruising for parking is 30% or even higher. Such estimates are not obtained from sidewalk observation since cars that are cruising for parking cannot be distinguished from cars in transit, but are instead obtained either by following a sample of cars or through model-based inference.

The density of cars cruising for parking in the downtown area is related to the rate at which cars in transit in the downtown area start cruising for parking and the expected search time of a car that searches for parking. This paper focuses on this expected search time. The literature has employed two main approaches to estimate expected cruising-for-parking time: direct measurement, and inference based on an assumed statistical relationship between expected cruising-for-parking time and the curbside parking occupancy rate.

Most of the studies that employ direct measurement of cruising for parking are reviewed in Shoup (2005, Chapter 11). There are three reasons to be skeptical of the results. First, it is difficult to identify cars that are cruising for parking. One approach is to delineate a study area, follow random cars that enter the study area, identify them as searching for parking if they park curbside in the study area, and measure their travel times within the study area. This approach fails to identify cars that are indeed searching for curbside parking in the study area but end up parking either outside the study area or in a parking garage. It also fails to identify when cars that park curbside in the study area initiate cruising for parking. Second, the study areas were not randomly selected, but were chosen instead because cruising for parking was perceived to be a severe problem there. And third, some very recent work that applies GPS tracking techniques (Weinberger et al., 2017) suggests that, on average, the proportion of cars in downtown traffic that is cruising for parking is modest.

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The second approach considers a situation in which curbside parking is described by an expected occupancy rate. The central assumption is that the probability that each curbside parking space is occupied equals the expected occupancy rate, independent of history and of the occupancy status of neighboring curbside parking spaces. We term this the *binomial approximation*. It generates a geometric distribution for the number of parking spaces searched before finding a vacant space (including the vacant space). The number of parking spaces searched corresponds to the number of balls drawn from an urn with replacement (or with an infinitely large number of balls) before a "vacant" ball is drawn. Let $q$ denote the probability that a ball is labeled "occupied", so that $1-q$ is the probability that a ball is labeled "vacant". The probability of finding the first vacant space on the first draw (i.e., the first parking space searched) is $1-q$; the probability of finding the first vacant space on the second draw is $q(1-q)$, which is the probability that the first space searched is occupied times the probability that the second space searched is vacant, etc. Thus, *the binomial approximation is that the expected number of parking spaces searched before finding a vacant space (including the vacant space) is* $1/(1-q)$.[1] The expected numbers of parking spaces searched (including the vacant space) with curbside parking vacancy rates of 20%, 10%, 5%, and 1% are therefore 5, 10, 20, and 100, respectively. Expected cruising-for-parking time can then be obtained by applying estimates of the average distance between parking spaces and of cruising-for-parking speed. As an example, assume that the distance between curbside parking spaces is 21.12 ft (1/250 ml) and that cruising-for-parking speed is 8.000 mph. Then the average cruising-for-parking time between parking spaces is 1/2000 h or 1.800 s. Shoup (2006) proposed that curbside meter rates be set to achieve a curbside occupancy rate of 85%.[2] Under the binomial approximation and the above parameter assumptions, applying the Shoup rule would generate expected cruising-for-parking time of only 12.00 s $(1.800 \times 1/(1-0.8500))$.[3]

All the recent papers that derive the expected cruising-for-parking time from the occupancy rate, including Arnott and Rowse (1999), Anderson and de Palma (2004), Geroliminis (2015), and Du and Gong (2016), have employed the binomial approximation.

Levy et al. (2013) simulate a situation in which drivers search for parking in a residential neighborhood on their return from work, and in which therefore the occupancy rate increases as the evening proceeds. They compare the average realized number of parking spaces searched in their simulation model, PARKAGENT, as a function of the realized occupancy rate, to the expected number of parking spaces searched under the binomial approximation, as a function of the occupancy rate. When the realized occupancy rate in their simulation model is above 85%, the simulated average number of parking spaces searched is considerably higher than the expected number under the binomial approximation with that occupancy rate. Though their analysis is not steady state, and though their conclusions rest on the soundness of their simulation model, the discrepancy between their simulated numbers and those obtained under the binomial approximation is sufficiently large to cast doubt on the accuracy of the binomial approximation.

There are further reasons to doubt the accuracy of the binomial approximation. The following four apply even if entry to the parking search area is indeed generated by a time- and space-independent Poisson process.

1. The binomial approximation takes the occupancy rate over the parking area as being constant over time. But with a finite parking area, which we assume and is realistic, stochasticity results in fluctuations in the realized occupancy rate. We shall show that taking this into account results in an expected cruising-for parking time that exceeds that obtained under the binomial approximation.

2. The binomial approximation is based on the assumption that the occupancy probabilities of adjacent parking spaces are statistically independent. But since parking spaces are spatially ordered, the probability that a particular parking space is occupied is higher if its upstream neighbor is occupied.[4] This positive spatial autocorrelation leads to more concentrated bunching of occupied parking spaces than would occur under the binomial approximation.

3. The binomial approximation does not account for competition between cars cruising for parking.

4. Since the parking area is finite, a car may have to circle the block to find a vacant parking space. If it does so, then the probability of its finding a vacant parking space on its second circuit is lower than the unconditional probability of its finding a vacant parking space on its first circuit.

There are also good, practical reasons to doubt that entry into a parking search area is well described by a time- and space-independent Poisson process.

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[1] Let the expected number of draws before drawing a vacant ball (including the draw with the vacant ball) be $S$. $S = (1)(1-q) + (2)[q(1-q)] + (3)[q^2(1-q) + \cdots] = (1-q)(1+2q+3q^2+\cdots)$. Multiplying both sides by $q$ yields $qS = (1-q)\left(q+2q^2+3q^3+\cdots\right)$. Subtracting $qS$ from $S$ yields $(1-q)S = (1-q)\left(1+q+q^2+\cdots\right)$. Since the value of the infinite sum in the curly brackets is $1/(1-q)$, $S = 1/(1-q)$.

The variance, skewness, and Fisher kurtosis of the geometric distribution are $q/(1-q)^2$, $(1+q)/q^{1/2}$, and $6+(1-q)^2/q$ (Wikipedia: Geometric distribution).

[2] Shoup's work has stimulated a number of downtown parking experiments. The best known is SFpark. The City of San Francisco has been adjusting curbside meter rates by block and by time of day to achieve a target curbside parking occupancy rate. Shoup (2006) originally proposed a target curbside parking occupancy rate of 85%. The City has been adjusting this rate by block and time of day to achieve what it judges to be optimal rates. They vary substantially but the average is considerably lower than 85% (Pierce and Shoup, 2013).

[3] Arnott and Rowse (2009); 2013) apply a third approach that applies only when both curbside and garage parking are available, and when curbside parking is saturated.

[4] If a parking space is vacant, then the probability that it is occupied during time unit t equals the probability that a car enters the track adjacent to the parking space during time unit $t$, plus the probability that a car entered the track adjacent to the immediately upstream parking space during the time unit $t-1$ and found it occupied, plus the probability that a car entered the track adjacent to the next upstream unit in time unit $t-2$ and found it occupied at time unit $t-2$ and then found the parking space downstream from it occupied at time unit $t-1$, and so on.