

Parking behavior: The curious lack of cruising for parking in San Francisco

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ABSTRACT

Cruising for parking has long been perceived as a major source of congestion and emissions in urban areas, but recent empirical work has suggested that parking may not be as onerous as folklore suggests, and that the amount of vehicle travel attributable to cruising is minimal. In this paper, we reconcile these perspectives through a dynamic programming model of parking search, and empirical insights from a large-scale GPS dataset in San Francisco and the California Household Travel Survey. We first draw a conceptual distinction between parking *search*, the time between the driver's decision to park and when a parking space is taken; and *cruising*, defined as excess vehicle travel from parking search. In places with little or no through traffic, up to half of traffic can be searching for parking, but cruising can be zero. We then operationalize this distinction through a dynamic programming model. The model predicts that when parking is perceived to be scarce, drivers are more willing to take a convenient available space, even if it is some distance from their destination. Counter-intuitively, scarce parking can even suppress vehicle travel as perceived parking scarcity leads drivers to stop short of their destinations and accept a longer walk to their destinations. Empirical data from California indicate that neighborhood density (a proxy for parking availability) has little impact on cruising for parking, but increases walk distances from parking locations to final destinations. We conclude that cruising for parking is self-regulating, and that in certain circumstances parking scarcity can even reduce vehicle travel.

INTRODUCTION

Cruising for parking has long been the subject of dinner party and watercooler gripes in urban centers. The scarcity of parking—and the consequent need to drive around in search of a vacant space—provides ample fodder for horror stories about the difficulty of parking.

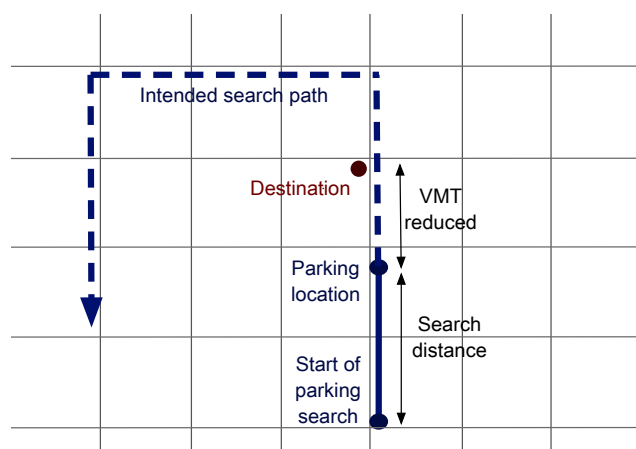
Given that on-street parking is often priced lower than off-street garages, cruising for a lower-cost or free on-street space can be a rational decision for a traveler who trades the monetary savings against the time cost of cruising. Shoup (2006) presents a model that formalizes the tradeoff, and finds a \$4.71 per hour gap between on- and off-street parking costs in US central cities. Given this gap, a traveler parking for two hours, who values the monetary and time costs of cruising at \$20 per hour, would find it rational to cruise for up to 28 minutes.¹

It is surprising, then, that some empirical studies of cruising (reviewed in more detail in the following section) have found cruising to be less prevalent than would be expected from either folkloric accounts or Shoup’s rational-behavior model. For example, our earlier work in San Francisco and Ann Arbor (Weinberger et al. 2017) found that fewer than 5% of vehicle trips involved excess travel from cruising for parking, with a median cruising distance of less than 500m.

In this paper, we present a new theory that can explain why on-street parking scarcity is unlikely to lead to much additional vehicle travel or congestion. On the contrary, scarce parking may serve to reduce traffic. The intuition is simple: when traveling to an area where on-street parking availability is known to be very low, drivers will start their search earlier and be willing to walk further to their destination. They are likely to take the first acceptable space, even if their destination lies several blocks ahead—thus cutting their vehicle trip short, as illustrated in Figure 1. Moreover, we show that in such a situation, up to half of traffic can be *searching* for parking in the sense that a driver is looking for a parking and will take the first reasonable space, but excess travel from *parking search* what is often called “cruising” can be zero or negative. Figure 1 shows that even if cruising is negative, the search distance is still positive.

The first section of this paper briefly reviews the literature on cruising, drawing a closer distinction between *searching* and *cruising* for parking. We then elaborate our formal theoretical model, before presenting some suggestive empirical evidence using GPS traces in San Francisco and a household travel survey in California.

Figure 1 Schematic impacts of vehicle travel on cruising



¹ At 28 minutes, the cost of cruising ($\$20 \times 28 / 60$) is still less than the monetary savings ($\$4.71$ per hour \times 2 hours).

ANALYZING CRUISING

Previous Studies

Cruising is difficult and expensive to quantify empirically, and so most studies of cruising have used an analytical or simulation approach (for a comprehensive review, see Inci 2014). For example, several studies use idealized (Arnott & Williams 2017) or real-world (Gallo et al. 2011; Levy et al. 2013) street networks to simulate the relationship between vacancy rates and cruising. Millard-Ball et al. (2014) use a queuing theory model and observed occupancy data to simulate how cruising changed following San Francisco's parking price reforms. In a similar vein, a range of other studies do not directly observe cruising, but infer it from a model calibrated with occupancy or traffic data (Horni et al. 2013; Inci et al. 2017; Cao et al. 2017).

Empirically, a wide range of methods have been employed to study cruising in the field (Brooke et al. 2014; Hampshire & Shoup 2018). Household travel surveys (van Ommeren et al. 2012) or intercept surveys (e.g. Lee et al. 2017) can ask drivers about how long it took to find parking. Alternatively, researchers can use direct observation and avoid the recall bias inherent in surveys. They can observe how many cars pass a vacant space until a driver parks (Hampshire & Shoup 2018), follow vehicles (e.g. Shoup 2005); or conduct park-and-visit tests (Alemi et al. 2018). More recent work uses evidence from in-car video (Hampshire et al. 2016) and GPS traces (Weinberger et al. 2017) to quantify cruising.

However, empirical studies do not paint a consistent picture. In the 16 studies compiled by Shoup (2006), which date back to 1927, the proportion of traffic accounted for by supposed cruising ranges from 8% to 74%, and average search time ranges from 3.5 to 13.9 minutes. It is highly likely that many respondents were simply searching for parking and may not, in fact, have been cruising. More recent studies have provided even more mixed results. In the Netherlands, van Ommeren et al. (2012) find that cruising averages just 36 seconds per car trip, while Alemi et al. (2018) find mean search times in San Francisco range from 32 seconds to 120 seconds, depending on time period and neighborhood. At the other extreme, Lee et al. (2017) report a mean cruising time of 15 minutes in one neighborhood of Brisbane, Australia. Recent studies that estimate the proportion of traffic cruising for parking have yielded similarly varied results, from less than 1% in San Francisco (Weinberger et al. 2017) to 15% in central Stuttgart (Hampshire & Shoup 2018) and 64% of local traffic in a neighborhood of New York City (Transportation Alternatives 2007).

Partly, the wide gulf between different studies can be explained by selection effects. Studies that focus on a particular neighborhood where parking is known to be scarce generate much higher estimates of cruising than studies at a wider spatial scale. Likewise, the proportion of vehicles searching for parking is a function of the proportion of traffic that is destined for the area as opposed to the proportion passing through on the way to a different destination. van Ommeren et al. (2012), for example, consider the entire Netherlands, which may partly explain their low cruising estimates.

Distinguishing Parking Search and Cruising

Differences in empirical findings between different studies can also be attributed to the distinction—highlighted in the Introduction—between time spent searching for parking and excess travel from cruising. Take, for example, a neighborhood that sees only origin/destination traffic, perhaps because it lies at the end of a peninsula, or because adjacent freeways or arterials

provide a faster route for through vehicles. Suppose that vehicles entering the neighborhood take the first space that is available. Most “cruising” methodologies will find that 50% of traffic—all vehicles that are entering the neighborhood, but not those that are leaving—is cruising for parking. Such a statistic, however, reveals nothing about excess vehicle travel, pollution or congestion. The “cruising” in places such as Westwood Village highlighted by Shoup (2005) is likely to reflect the lack of through traffic as much as the scarcity of parking.

A related problem is that theoretical and empirical studies of cruising almost always ignore the potential of drivers to reduce their travel by accepting a parking space short of their destination. Park-and-visit tests, for example, typically begin at the destination; test drivers (or cyclists) then cruise in search of a parking space. In reality, however, the search for parking is likely to begin before the destination is reached.

The most common explanation for cruising is the price differential between on- and off-street parking (Shoup 2006; Inci 2014; Lee et al. 2017; Inci et al. 2017; van Ommeren et al. 2012). But while most studies take care to capture the driver’s choice between cruising for an on-street space and parking off-street immediately, they do not consider the ability of a driver to reduce their cruising time through longer walking distances. There is considerable evidence outside the cruising literature that drivers will trade off greater walking distances for lower prices (Harmatuck 2007), and so it is reasonable to expect drivers to make a similar tradeoff of greater walking distances for less cruising.

The only empirical study to examine the impact of parking occupancy on walking distances (de Vos & van Ommeren 2018) treats walking as an externality. Using license plate data from Amsterdam, the authors examine how above an occupancy level of 85%, each parker imposes external costs (increased walking) on subsequent arrivals. However, because the authors observe occupancy and distance walked but not cruising, they cannot determine whether longer walking distances are due to drivers stopping short of their destination (i.e., negative cruising), or searching for parking after reaching their destination (positive cruising). In the remainder of this paper, we define parking *search* as the time between the driver’s decision to park and when a parking space is taken; and *cruising* as excess vehicle travel from parking search.

A MODEL OF CRUISING

We consider a setting where drivers are limited to on-street parking. They choose whether to accept a parking space based on minimizing the expected time to get to their destination (cruising time + walking time). The purpose of the model is to explore systematically the relationship between cruising, walking and the perceived scarcity of parking. We focus on a setting where drivers aim to get to their destinations as quickly as possible, and do not address cases such as visitors who simply wish to explore an area of a city, or people who enjoy a walk and aim to park at more distant locations.

In the model, the driver takes a straight-line path toward the destination, and can choose to park before reaching the destination and walk, as in Figure 1. If the driver reaches the destination before parking, then he searches for parking by following a concentric circle strategy – circling the destination with an increasing search radius.

Suppose that all blocks in a neighborhood have a probability λ that a space is available on that block. Let V_k be the expected time to reach the destination (cruising time + walking time) when the driver is k blocks away from the destination. At each block, conditioned on parking space availability, the driver must decide whether to park and walk to the destination, or to

continue the search by driving to the next block where he will be confronted with the same decision. If the driver is k blocks away from the destination, then the expected time to the destination satisfies the dynamic programming equation,

$$V_k = \lambda \cdot \min(w \cdot k, 1 + V_{k-1}) + (1 - \lambda) \cdot (1 + V_{k-1}) \quad k = 1, 2, \dots, K \quad (1)$$

where w is the time it takes to walk each block, expressed as a multiple of time it takes to drive. The driving time is normalized to 1. The first term on the right side of Equation (1) corresponds to finding an available space on block k . The walking cost from block k is $w \cdot k$. The cost to continue the search is the driving time plus the expected time to the destination from $k-1$ blocks away. The second term corresponds to finding no available space on block k . The driver has no choice, but to continue the search.

The dynamic programming equation is solved backwards starting from the destination, i.e. V_0 . Having arrived at the destination without parking, the driver commences a concentric circular search strategy. For the sake of simplicity we approximate V_0 . We assume that there is available parking on the destination block with probability λ , in which case the walking distance is zero. Otherwise, the driver use a concentric circles search strategy with an R -block radius, yielding the approximation

$$V_0 \approx (1 - \lambda) \cdot \left(\frac{1}{\lambda} + w \cdot \bar{R} \right) \quad (2)$$

where \bar{R} is the mean walking distance after parking to the destination from within R -block search radius. Given that each block has an available space with probability λ , the number of blocks that the driver searches before finding a space has a geometric distribution with mean $1/\lambda$. The second term, $w \cdot \bar{R}$, corresponds to the average time to walk from a parking space that is within R block search radius of the destination. After parking the traveler walks a distance equal to the average radial parking distance from the destination. As the driver searches along the concentric circles outward from the destination, he encounters more blocks as he expands the search. This effect is evident in the formula for the circumference of a circle, $2\pi r$. However, this effect is counterbalanced by the fact that the driver may have found a space before venturing far from the destination. The geometric distribution is a decreasing function in the number of trials, and thus the probability of finding a parking space, at a distance, decreases with the number of spaces searched³ because a space is likely to have already been found.

We explicitly model these two factors when computing the average radial distance from the destination. In order to compute the mean walking distance, we calculate the average radius of a circle weighted by the probability of finding an available space

$$\bar{R} = \frac{\int_0^R r \cdot w(r) dr}{\int_0^R w(r) dr} = \frac{e^{-\lambda R} (-\lambda \cdot R \cdot (\lambda \cdot R + 2) - 2) + 2}{\lambda \cdot (1 - e^{-\lambda R} (\lambda \cdot R + 1))} \quad (3)$$

³The exponential distribution is the continuous space analogue of the geometric distribution. For the average radial distance calculation we use the exponential distribution.

where

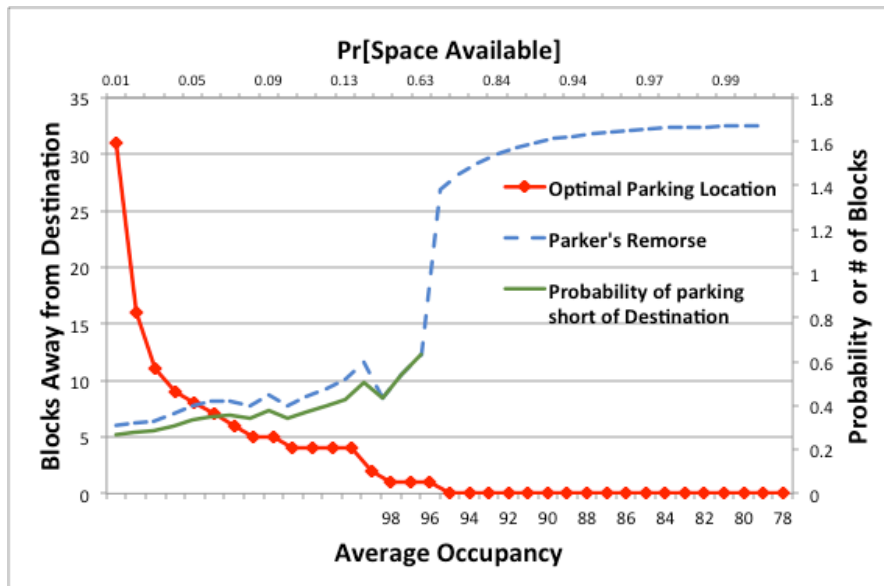
$$w(r) = 2\pi r \cdot \lambda e^{-\lambda r}.$$

Equation (3) implies that as the search radius, R, increases the average walking distance converges to $2/\lambda$.

While the model is formulated in terms of the probability that a block has a space available, the parking policy literature and field surveys of parking availability typically use a metric of percent occupied. For example, a common rule-of-thumb, popularized by Shoup (2005) aims for 85% occupancy (US Department of Commerce 1956). Therefore, we also express our results in terms of percent occupied, using the conversions that we empirically derived in previous work using a queuing theory model and data from San Francisco (Millard-Ball et al. 2014). For example, on a block with 15 spaces, 85% occupancy gives a probability of 0.95 that a space is available, and 99% occupancy gives a probability of 0.12. Since this relationship between average occupancy and the probability of finding a space is calibrated based on hourly occupancy data, and incorporates patterns of arrivals and departures over the course of the search, the calculation in Eq. (3) makes the simplifying assumption that the probability of an available space on a given block remains constant throughout the driver’s search.

Let’s assume that the walking time (w) is 4 times the driving time (2.5mph vs. 10 mph). Solving Equation (1), we find that when parking is perceived to be scarce, drivers will park further away and walk to their destination. Figure 2 shows that a driver who seeks to minimize their expected travel time desires to park short of the destination if the perceived availability falls below 70 percent. At higher availability levels, the driver ignores vacant spaces that they encounter en route, and attempts to park on the same block as the destination.

Figure 2 Parking location choice of the risk neutral driver



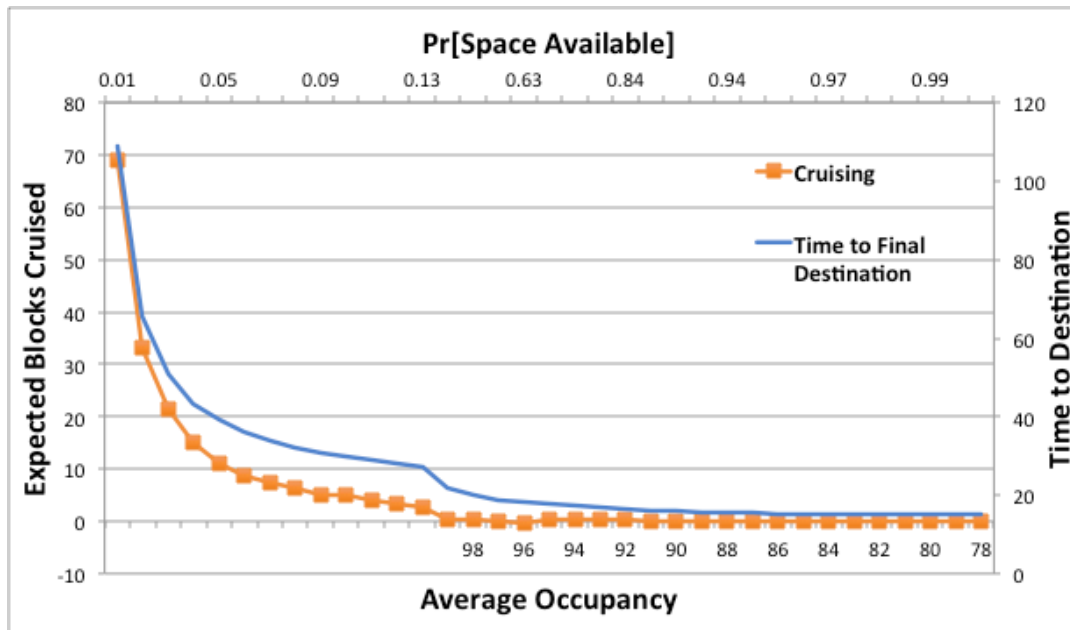
The parking locations chosen in Figure 2 minimize the expected travel time. However, due to the random availability of parking (λ), the driver may find no available parking at their desired location. The driver must then travel to the subsequent blocks until a space is found. Figure 2 also shows the probability of parking before reaching the destination. After the driver parks, during the walk to the destination, she might pass blocks with available parking. We call this *parker's remorse*. Formally, it is defined as the average number of blocks with an available parking space encountered while walking to the destination. Parker's remorse is found to be an increasing function of the average occupancy. An analogous quantity is *parker's greed*. It is defined to be the average number of available parking spaces that a driver passes before parking.

We calculate the expected cruising by accounting for both finding parking before reaching the destination, which we call negative cruising, and the average number of blocks searched, $1/\lambda$, after passing the destination. The model predicts that the expected number of blocks to find a parking space decreases with the probability of an available space. The time to the final destination, shown in Figure 3, is the sum of the driving time to optimal parking location, k , plus the optimal value function, V_{k^*} , which includes walking time. Time, shown on the vertical axes, is normalized to the time it would take to drive one block.

A key assumption is that the driver is risk neutral, and seeks to minimize her *expected* time to reach her destination. Such a driver would see no difference between a for-certain travel time of five minutes, and a situation with a 50% chance of one minute and 50% chance of nine minutes. In contrast, a risk-averse driver (or equivalently, one concerned with travel-time reliability) would be likely to take an earlier available parking space (which gives a for-certain travel time) at the expense of a longer walk, rather than taking a chance on finding a space closer to the destination. Hence, risk aversion would be likely to reduce cruising further.

Cruising might also be reduced to the extent that off-street parking is available, particularly if it is priced at a lower rate than curb parking. More generally, our model assumes the "worst case" for cruising in that it ignores potential policies such as off-street parking, parking information or guidance systems, or differential pricing that cities can use to reduce cruising and improve the driver experience.

In summary, this model demonstrates that if drivers perceive a parking scarcity, they will park before reaching the destination: sometimes, many blocks before the destination.

Figure 3 Relationship between cruising and perceived parking availability

EMPIRICAL EVIDENCE

The model elaborated in the previous section has two key testable predictions:

- As on-street parking availability declines, excess vehicle travel from cruising will not increase, i.e. there will be no correlation between the two
- As on-street parking availability declines, the average walking distance between a traveler’s parking location and final destination will increase

In contrast, under the Shoup (2006) model of “rational cruising,” parking scarcity would be expected to lead to an increase in cruising, as drivers take longer to find a space, and as more expensive off-street parking increases the returns to cruising.

We use evidence from the City of San Francisco and the State of California to test these predictions. San Francisco is a useful case study because on-street parking accounts for a large proportion (62%) of the publicly available supply (SFMTA 2014), and because there is substantial geographic variation in parking availability. San Francisco also offers rich datasets, discussed below, on parking and cruising.

Data and Methods

We use two complementary datasets. Our **cruising** dataset is derived from GPS traces purchased from a commercial provider. For the last portion of each trace (after the driver enters a 400m radius from the end of the trace), we compute the difference between the actual distance driven and the most direct route. A driver is considered to cruise if (i) the actual distance is more than 200m greater than the network distance or any block segments (edges) are repeated, and (ii) at least 50% of the “cruising” is within the 400m buffer. This last condition filters out most drop-offs and errand trips, such as taking a child to school. Our final sample consists of 96,765 traces

with trip ends in San Francisco.³ Our data sources and methods are described in detail in Weinberger et al. (2017).

Our **parking location** dataset is taken from the 2010-12 California Household Travel Survey (CHTS). Respondents are asked how long (in minutes) it took to walk from the parking location to the destination, as well as the type of parking (e.g. on-street or garage) and the cost, if any. Note that the walk time is only recorded for the 5,805 respondents who park on-street or in an off-site lot or garage, and so the dataset excludes those who report that they park at their destination or in a driveway or personal garage.

The walk times in CHTS are self-reported, and it is plausible that respondents' recollections may be inaccurate. However, we are interested in the relative walk times between locations with different parking availabilities, rather than absolute values. Even if the self-reported times are biased, this would not affect our analysis as long as the bias is consistent across different neighborhoods.

For each dataset, we use the natural log of the census tract residential and employment density as a proxy for parking scarcity. We also test a direct measure of parking availability provided by the San Francisco County Transportation Authority, although the geographic resolution of this measure is much coarser. Both log density and parking availability are highly correlated, with a Pearson coefficient of 0.59. Descriptive statistics are shown in Table 1. Unfortunately, we do not have a measure of perceived parking availability.

For each dataset, we regress the dependent variable (distance cruised or distance walked) on log density. For distance cruised, we test both log-log and negative binomial specifications, the latter taking account of the large number of zero values. We also test the robustness of our results to further controls, specifically dummy variables for hour of day, and to omitting census tracts in downtown San Francisco, where on-street parking is more limited. For the parking location dataset, we restrict the analysis to the 4,526 respondents who parked on street.

Results

Cruising vs density

Figure 4 shows the graphical relationship between density and cruising, while Table 2 (columns 1-5) shows the regression results. In neither case is there any evidence that cruising is worse in dense neighborhoods with more limited parking availability, and the regressions explain almost none of the variance in cruising for parking.

Walk distances vs density

Figure 5 shows the graphical relationship between density and walking, while Table 2 (column 6) shows the regression results. Both use the self-reported CHTS dataset. In dense neighborhoods, drivers who park on-street tend to walk further to their destination. There is no effect at low-to-moderate densities, where parking is unlikely to be scarce, but walking distances climb at the highest densities in the dataset (above about 3,000 residents and employees per km²).

³ The sample is slightly smaller than the 97,445 trips reported in Weinberger et al. (2017), due to a more restrictive process of dropping trips with a parking location just outside of the city limits.

The non-linear relationship can be captured in a regression through the addition of a squared term in the regression model (column 7 in Table 2).

Table 1 Descriptive Statistics

| Variable | N | Mean | Std dev | Min | Max |
|--|--------|--------|---------|-----|---------|
| Cruising dataset (trips) | | | | | |
| Distance cruised (m) | 96,765 | 32.1 | 177.5 | 0.0 | 5274.8 |
| Residential + employment density (persons km ⁻²) | 96,765 | 27,309 | 28,118 | 234 | 130,711 |
| Parking location dataset (census tracts) | | | | | |
| Minutes walked from parking location | 5805 | 2.22 | 2.58 | 0 | 30 |
| Residential + employment density (persons km ⁻²) | 5804 | 6596 | 12,654 | 1 | 145,798 |

Figure 4 Density vs cruising

San Francisco census tracts. Excludes 6 census tracts with < 50 trips

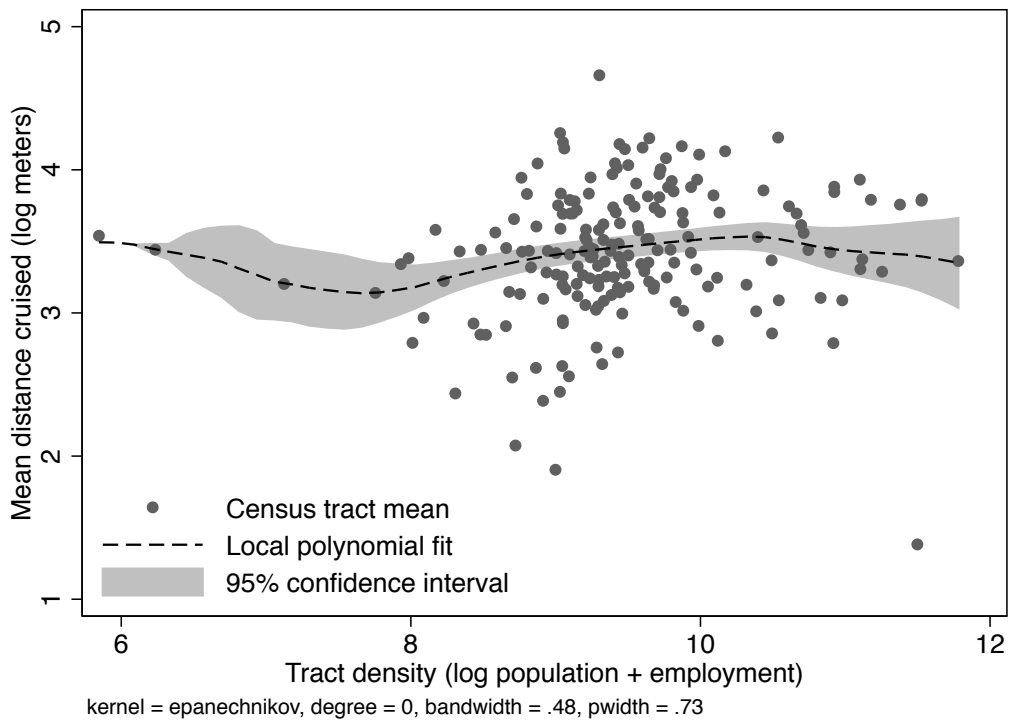
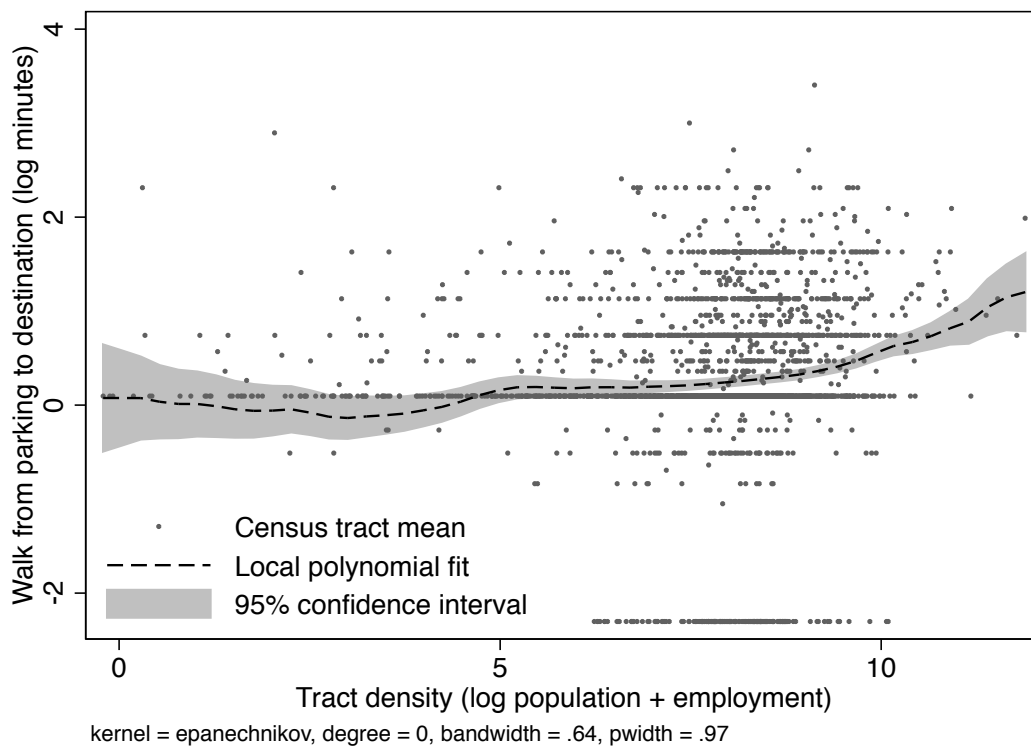


Table 2 Density vs cruising and walking regressions

| Model | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|----------------------------|--------------------------|--------------------------|--------------------------|--------------------------|-----------------------------------|--------------------------|--------------------------|
| Dependent variable | Log cruising distance | Log cruising distance | Log cruising distance | Cruising distance | Log cruising distance | Walk minutes | Walk minutes |
| Predictor variable | Census tract log density | Census tract log density | Census tract log density | Census tract log density | Neighborhood parking availability | Census tract log density | Census tract log density |
| Coefficient | -0.00153 | -0.00307 | 0.0004 | 0.00977 | 0.00256 | 0.0718 | -0.1665 |
| Standard error | 0.00516 | 0.00516 | 0.00589 | 0.01689 | 0.01018 | 0.0113 | 0.0432 |
| Coefficient (squared term) | | | | | | | 0.0187 |
| Standard error | | | | | | | 0.0034 |
| Specification | Log-log | Log-log | Log-log | Negative binomial | Log-linear | Linear-log | Linear-log |
| Time of day controls | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Geographic scope | San Francisco | San Francisco | SF excl. downtown | San Francisco | San Francisco | California | California |
| N* | 96,765 | 96,765 | 82,290 | 96,765 | 96,765 | 4,525 | 4,525 |
| R ² | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.03 |

Figure 5 Density vs walking

CHTS data, California census tracts, respondents parking on-street only. 0.1 added to zero values prior to log transformation.



CONCLUSIONS

In this paper, we provide a theoretical rationale for how the self-regulating nature of cruising can avoid negative impacts on vehicle travel and congestion. Drivers seeking to minimize their travel time while still parking on street will be more willing to take an acceptable, available space if parking is scarce, even if that space involves a longer walk to their final destination. While some unlucky drivers will still generate excess vehicle travel as they cruise in search of a space, in aggregate this excess travel will be offset by reduced vehicle travel from drivers stopping short of their destinations.

Crucially, this insight holds even at extreme parking occupancies. Shoup (2005) recommends a policy target of 85% occupancy, which he argues will ensure an available space on every block. However, even at 99% occupancy on a street with 20 parking spaces, an empirical model derived from queuing theory shows that a driver has a 19% chance of finding a space (Millard-Ball et al. 2014), and thus would expect to find a space within six blocks. A driver who starts her parking search four blocks away would, on average, experience negative cruising.

Our dynamic programming model suggests that parking search by a rational driver who correctly perceives parking occupancy should start in advance of the destination. Moreover, driver behavior is likely to reinforce our findings in that risk aversion will encourage a driver to start searching even further away from the destination. Since parking is often perceived to be more scarce than it is in reality, cognitive biases are likely to also promote an earlier start to the parking search and reduce cruising.

The model does make several other simplifying assumptions. Most importantly, it does not account for off-street parking, which if [priced appropriately](#) could reduce cruising further. Indeed, much of the cruising literature already emphasizes a price mismatch between cheaper on-street and more expensive off-street parking as an underlying cause of cruising. We also assume that drivers' perceptions of parking availability are correct, and that they act rationally on this information. To the extent that drivers believe parking to be scarcer than it is, cruising will be less than our model indicates. At the other extreme, a naïve belief or irrational exuberance that parking will be available right outside the destination will increase cruising, and also collapse the difference between parking search and cruising; in such a case, all parking search will lead to excess travel.

Empirically, we find suggestive evidence for the self-regulation of cruising in San Francisco. We find that—contrary to the implicit or explicit assumptions in the literature—cruising does not increase as on-street parking availability becomes more limited. Instead, drivers park further away from their destinations, consistent with the theoretical predictions that they stop short and walk. Our empirical results are suggestive rather than conclusive, and there could be other reasons for drivers to park in more distant locations, such as trading off a longer walk for lower-cost or free parking. Regardless, however, our theoretical and empirical results indicate that cruising does not increase with parking scarcity, except at the most extreme occupancies above 99%.

Inspired by the work of Donald Shoup, cities such as San Francisco and Seattle have made substantial and successful efforts in recent years to improve on-street parking availability in a bid to reduce cruising (Millard-Ball et al. 2014). These policies have also sought to achieve other goals, such as making payments easier and improving information. However, the results presented here suggest that from a transportation management perspective, cruising may not be a pressing policy concern. Our earlier work (Weinberger et al. 2017) finds that cruising is

relatively limited; in this paper, we provide an explanation that also draws attention to the vehicle travel reduction implications of scarce parking. Indeed, insofar as limited parking availability encourages drivers to park further away and walk the final portion of their journey, there may be a public health benefit from scarce parking. The interplay between walk times, parking fees and in-vehicle costs, and the impacts of policies such as time limits, are still poorly understood (Marsden 2006), and there is considerable scope for future research on drivers' willingness to walk.

There is also likely to be an indirect private vehicle trip reduction impact as the fear of being unable to find a parking space shifts trips to walking, cycling, transit, taxis/ridehailing services, and similar modes. Scarce curb parking in residential neighborhoods, meanwhile, is likely to dissuade households from owning a car.

Instead, the problems with cruising primarily relate to transportation reliability, and the economic effect on neighborhood businesses. Even though in aggregate, excess vehicle travel from cruising may be minimal, the aggregate picture obscures the long tail of the distribution. A driver who wishes to guarantee arrival at a particular time must leave an ample buffer in the event that the parking search takes longer than usual. On the economic side, a perceived scarcity of parking may deter travelers from making the trip at all, or shift destinations to places with off-street parking.

Drivers in urban centers often complain vociferously about the limited availability of on-street parking. Inadvertently, researchers may have given credence to such complaints by focusing on the length of the *search* for parking, which exaggerates the scale of the problem relative to the potentially more useful metric of *excess travel* from parking search. Limited availability certainly results in longer searches, but due to drivers' adaptive behavior, longer searches do not necessarily mean excess vehicular travel. But this adaptive behavior relies on drivers' fear of being unable to find a space. Paradoxically, the more that drivers believe that cruising is a serious problem, the more likely it is that cruising will solve itself, and cease to be an issue for traffic safety, congestion, and pollution.

The normative value commonly held that drivers should be able to park exactly at their destinations may conflict with realities of the physical world. Transportation planners see no harm in expecting travelers to walk a quarter-mile to a bus stop, rail station, or to a parking garage. It is perhaps reasonable, therefore, to expect the same level of walking from those parking on-street.

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