Parking Search Caused Congestion: Where's all the fuss?

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Rachel R. Weinberger
Weinberger & Associates, Brooklyn, NY 11217
rrw@pobox.com

Adam Millard-Ball
Environmental Studies Dept., University of California Santa Cruz, Santa Cruz, CA
adammb@ucsc.edu

Robert C. Hampshire
Gerald R. Ford School of Public Policy. University of Michigan, Ann Arbor, MI
hamp@umich.edu

ABSTRACT

This paper presents a method for determining parking search behavior using GPS traces. The research takes advantage of a GPS based household travel survey, an extensive dataset of GPS with video, and a commercially purchased set of trip segments. Strategies for data cleaning, matching traces to digitized networks, assessing the probability that a trace is of good quality, and strategies for determining whether or not a trip involves excess travel due to parking search are described. We define and operationalize two definitions of excess search – popularly known as *cruising*. Our results suggest that cruising in San Francisco, CA and Ann Arbor, Michigan is acute in some locations but overall experienced in less than 5-6% of vehicle trips, and that it accounts for less than 1% of vehicle travel in these cities–considerably less than in previous estimates.

HIGHLIGHTS

- We develop a method to use GPS traces to quantify cruising for parking
- The approach allows development and robust testing of targeted policy interventions
- We operationalize cruising in two ways: excess travel and blocks traversed repeatedly
- Cruising in San Francisco and Ann Arbor is experienced in < 5–6% of vehicle trips
- Cruising accounts for less than 1% of vehicle travel in these cities
- Cruising is but one of many reasons for excess travel in the final portion of a trip

KEY WORDS: Cruising, Parking, GPS, Big Data

INTRODUCTION

Searching for parking, colloquially known as cruising, has been a concern almost since the beginning of automobile mass production; two of the first known studies of cruising date to 1927 (Shoup 2006). Problems associated with cruising include an excess of vehicle miles traveled, i.e. after arriving at their destinations, drivers continue to drive in search of a parking space. This excess travel implies additional congestion, air pollution, time wasted, and driver frustration which could translate to increased risk of accidents and loss of economic competitiveness at destinations where parking is hard to find, especially if alternative access options are also scarce.

The extent of cruising remains unclear. Several attempts have been made to quantify cruising and how much it contributes to vehicle travel, congestion and air pollution. Such research, understandably, has been conducted in the locations where cruising is known to be an issue. Unfortunately, results are then extrapolated across wide regions. For example, it is often taken on faith that "…30% of urban traffic comes from cars hunting for parking spaces" (Zimmerman, 2011). This has been traced to an analysis by Donald Shoup (2006) that averages the results of a limited number of studies and concludes that 30% of vehicles in congested downtowns are searching for parking. The misinterpretation stems from taking the straight average of these disparate studies without regard to community size, date of the analysis, whether it was conducted in a downtown or neighborhood, or any other conditions that might affect the outcome. There have been attempts to debunk the number (Polzin, 2016; Barter, 2013), but the figure of 30% is still widely used in academic and policy settings.

Over time, concerns about cruising have heightened in spite of many efforts to "solve" the problem; and the extent of cruising remains unclear. Much policy discourse centers around the 30% rule-of-thumb, but more recent studies suggest that this is a large overestimate. For example, a recent simulation study of San Francisco found that the average motorist cruised just 50 feet in search of metered parking (Millard-Ball, Weinberger, and Hampshire, 2014). Other methods, such as intercept surveys, video detection and shadowing vehicles by bicycle, have been developed but as discussed in the following section, all have limitations. In the current state, cruising is neither well quantified nor is cruising behavior well understood. Without a clear understanding of the problem, solutions will likely remain elusive.

Moreover, many of the existing research methods, such as shadowing vehicles by bicycle, quantify the percentage of traffic that is searching for parking, rather than the excess traffic and pollution from cruising. The difference is subtle but important for policy. Almost all trips, with the main exceptions of drop-offs and those ending in reserved parking, end in a "search" for parking. A driver may accept an available parking space even if she has not yet begun to circle and incurred excess travel (Millard-Ball, Hampshire and Weinberger 2020). Furthermore, such circling may never occur during a parking search. When close to a destination, up to 100% of traffic is searching for parking, and so a study that finds that a high percentage of traffic is searching for parking may reflect the absence of through traffic as much as the scarcity of available parking.

In this paper, we provide a new method for quantifying cruising for parking, employing the emerging technologies that have been developed to capture and process Global Positioning System (GPS) traces from smartphones and in-car navigation devices. We work with GPS traces with the goal of using such traces to develop nuanced understandings of cruising for parking. Though we present quantified results in two locations (Ann Arbor, Michigan and San Francisco, California), the primary purpose of the research is to develop a method by which the new abundance of GPS data can be harnessed to provide policy-relevant insights on cruising, and avoid the biases in previous, manual methods such as surveys and shadowing of vehicles. We offer a precise definition of cruising based on the difference between the length of the driver's actual route and the shortest path, once he or she first reaches a 400m radius of the destination. The excess travel definition of cruising is a more restrictive definition than typically implied in the literature, but it more closely matches the negative externalities implied in the term "cruising for parking." In this paper, we use the terms "cruising" and "excess travel" interchangeably.

Our method measures the overall amount of cruising, and illustrates spatial and temporal patterns. It can be adapted to use different streams of GPS data, which are becoming increasingly available through new technologies such as GPS-enabled travel surveys (Bricka et al. 2012), smartphones and navigation devices. The work builds on an increasingly rich body of research and provides a promising path forward for the creation of robust tools that any city can employ at any level of geography to better understand parking search behavior and, in turn, create better policy responses than have been available to date.

PREVIOUS RESEARCH

Introduction

Parking search behavior has been a subject of interest to researchers since the private automobile became a popular mode of travel in the early 20th century (Weinstein, 2002; Shoup, 2006). Despite the decades of study, there is little agreement on either a precise definition or the extent to which parking search affects travel, traffic, and people's experience of urban places. A review of 16 studies between 1927 and 2001 showed a range of 3.5 to 14 minutes of added trip time due to searching for parking, increasing overall traffic levels in the areas studied by 8% to 74% (Shoup 2006). A range of other studies has estimated that cruising can represent as much as 30% to 50% of traffic on a given downtown street (Shoup, 2006; Arnott and Rowse, 1999; Schaller, 2006; Transportation Alternatives, 2008). A review of multiple surveys from Europe has estimated that parking search comprises 25 to 40% of overall auto travel time and vehicle miles traveled in central urban areas (Bonsall and Palmer, 2004). Though these findings are abstracted broadly, a caveat is that they were conducted in places where parking search was previously believed to be a problem, and such abstraction is, therefore, misleading (Barter, 2013).

Excess parking search has received a great deal of attention because of the range of costs associated with it. For drivers, costs include extra time and fuel spent searching for an open space (Shoup, 2006). In their review of cruising studies, Polak and Axhausen (1990) surmised that the time spent cruising is valued more than general travel time, but still, under certain circumstances, can account for a considerable share of total travel time. They also observed that the routes of those cruising for parking are generally longer and less efficient than those of other traffic, contributing significantly to traffic congestion in urban areas (Polak and Axhausen, 1990).

In addition to added traffic congestion and vehicle kilometers related to excess parking search, the behavior burdens communities and their residents with the harmful effects related to additional traffic, such as air and noise pollution and increased collision risk (Box, 2004; Humphreys, Box, Sullivan, and Wheeler, 1978). As a result, new technologies have emerged to reduce cruising through adaptive pricing based on data from in-street sensors (Millard-Ball, Weinberger, and Hampshire, 2014), parking guidance systems (Shin and Jun 2014) and parking reservation systems (Liu, Yang, and Yin, 2014). However, fewer emerging technologies have been devoted to understanding the cruising process itself.

Defining and Understanding Excess Parking Search (Cruising)

There is no concise operational definition of cruising. Where descriptions are given, cruising tends to be defined informally or simplistically. Shoup describes the activity as waiting in "a queue of unknown length, where the next person called to the window is determined by lottery" (Shoup 2006).

Perhaps, the difficulty of defining cruising is related to the ambiguous nature of the origination or initiation of the search itself. Almost any trip that does not end with a drop-off, valet, or in a known or reserved parking space—for example a home driveway—involves a parking search. This is true even when the trip ends in a parking garage or lot. Horni, et al. encapsulate the difficulty in establishing the starting point of a search by remarking that it cannot be "sharply specified, let alone easily operationalized" (Horni, Montini, Waraich and Axhausen, 2013). They further note that the start of cruising is likely "dependent on the linear distance to the destination" (Horni, et al. 2013), but also note that it could be initiated earlier than planned based on the individual drivers' on-route observations (Horni, et al. 2013). Similarly, Brooke, Ison, and Quddus (2014), indicate that cruising "occurs when a motorist reaches his or her destination, intends to park, and circulates in the vicinity of their destination'' (Brooke et al. 2014). Kaplan and Bekhor also use "arrival within a certain distance of the destination" as a defining characteristic of the start of a search, but acknowledge that identifying that point will be the primary challenge of future studies (Kaplan and Bekhor, 2011). Hampshire et al. (2016) use video evidence to identify the start of the parking search through driver eye, head and upper body movements, finding that the search begins at a median (radial) distance of 100m from the final parking location.

On the other hand, Thompson and Richardson contend that the process is actually initiated when the trip begins, when drivers decide on a general parking strategy based on prior knowledge of the area around the destination, and give no further consideration to search initiation based on the differences in the characteristics of the search process (Thompson and Richardson, 1998). Meanwhile, van der Waerden, et al. in an attempt to identify search initiation using GPS data, pin parking search to travel speeds, defining the start of the search process as when average speeds dip below 23 kilometers per hour and differences in speed between measured time periods is less than 5 kilometers per hour (van der Waerden, Timmermans and Hove, 2015). Overall, the decision-making process involved in each element of the search is highly dependent on a complex interaction between individual drivers' parking preferences, their feelings on the relative utility of different types of spaces weighed against the time and/or financial costs of those spaces, and a variety of other variables, including the characteristics of the individual, the characteristics of the trip, and the characteristics of any given parking location (Millard-Ball et al., 2014; Shoup, 2006; Polax and Axhausen 1990; Kaplan and Bekhor, 2011)

Data Collection

Numerous data collection methods have been developed to measure cruising behavior. Simulation modeling is one approach (Leurent and Boujnah 2014; Du et al. 2019). However, we focus here on empirical studies, which tend to rely upon surveys, video recording (or other visual techniques), manual data-collection methods like driving or using bicycles to emulate driving (Shoup, 2006; Schaller, 2006; Hampshire et al., 2016; van Ommeren, Wentink and Rietveld, 2012; Lee, Agdas and Baker 2017), or some combination thereof. Brooke, et al. (2015) relied on data from a revealed-preference on-street parking survey in their assessment of cruising influence factors in the East Midlands, UK. Data from the Dutch National Survey were likewise used to gauge the levels of search behaviors in the Netherlands (van Ommeren et al., 2012). Bicycles have been used to collect data in Westwood, California (Shoup, 2005) and San Francisco (Alemi, Rodier, and Drake, 2018; Joy and Schreffler 2015). Guo, et al. (2011) employed a visual technique, described as a license plate method, to record travel times at the entrance and the exit of a test section at select time intervals in their assessment of the travel time influence of on-street parking.

Tertiary parking data has also been used to measure and estimate cruising. Millard-Ball, et al., used occupancy data from in-street sensors to investigate the relationship between occupancy and the probability of finding a parking space. For this study, a three-stage empirical analysis approach was used to estimate parking availability and arrival rates, and simulate cruising (Millard-Ball et al., 2014).

Each of these methods of data collection described is subject to different biases. Surveys rely upon a driver's estimation of search time which can vary considerably and is often exaggerated (van Ommeren et al., 2012). It is unclear whether drivers are able to objectively or accurately recall their cruising experience and it is difficult to devise a sampling strategy that is at once cost effective and representative. Visual techniques provide potentially robust data but are extremely limited in geographic scope and subject to selection bias, given that resources are usually deployed only in areas that are known to be problematic. In fact, Guo et al., meticulously selected their test sections under specific criteria, which included very low bicycle volumes to prevent vehicles from being influenced by bicycles, thereby selectively influencing their own data (Guo et al., 2011).

To address shortcomings of these methods, researchers have begun, in limited ways, to use GPS to collect and track cruising data in real time. GPS data are already widely employed for travel demand analysis, often as a part of household travel surveys (Bricka et al. 2012; Gadziński 2018). In the context of cruising for parking, however, use of emerging GPS technologies is just beginning to gain traction. Horni, et al. (2013), developed an agent-based cellular automaton cruising simulation that combines microsimulation and parking choice models in one framework. This simulation process is anticipated by Horni et al. (2013) to provide a useful testing ground for estimation using GPS data. Meanwhile, Kaplan and Bekhor (2011) developed a multi-method data collection approach of self-reported surveys coupled with GPS field experiments as a part of a methodological framework to measure and reveal the determinants of cruising. According to them, the start of the search could potentially be identified using this method by syncing the user's recollection of the initiation of the search with notable speed and direction changes in the GPS data. van der Waerden, et al. (2015) later selected a city based on the Kaplan and Bekhor methodology and recruited volunteers to use GPS loggers to record their trips and combined this data with participant surveys or travel diaries. However, the sampling for this study was not representative, as only 15 participants recorded the 97 trips analyzed, and these participants were not evenly distributed.

DATA AND METHODOLOGY

Data Sources

For this study, we relied on three GPS datasets to develop, test, and refine a cruising identification strategy. To understand the human element of the parking search and how that might be relayed as a cruising signature we used a substantial set of GPS traces with accompanying video collected in Ann Arbor by the University of Michigan Transportation Research Institute (UMTRI). These traces are discussed in more detail in Hampshire et al. (2016). In addition, much of the analysis is based on a large set of anonymized segments of journeys taken in San Francisco. These data were purchased from a data broker, and to maintain anonymity we refer to the data here as "commercial." The third, a small set of trips ending in San Francisco, are part of the California Household Travel Survey (CHTS), which included a travel diary with supplemental GPS traces. These data were accessed through the Transportation Secure Data Center.[1] Additional data included a host of geographic information system (GIS) layers including street networks, curblines, parking lots and garages.

[1] The Transportation Secure Data Center is hosted by the National Renewable Energy Laboratory, and provides access to the raw GPS traces. See *www.nrel.gov/tsdc*

Data Caveats

Each dataset was used in a unique way during the course of the study and each comes with certain cautions and caveats. One concern that is common to the UMTRI, Commercial, and CHTS datasets is that the GPS trace tells only where the trace ends but not the actual destination. Hence, we have no way to understand how far the driver parks from their destination. Some drivers will park short of their destination (reducing excess travel) and some will continue beyond it (Millard-Ball, Hampshire, and Weinberger, 2020); we assume that these effects cancel each other out.

An advantage of the UMTRI and CHTS data is that there are repeat trips by a limited set of individuals. This allows us to see patterns wherein a trip out of context would seem to be cruising but ultimately represents a preferred path or an error in the GIS layer. While we cannot identify a participant, we can group trips as being made by the same vehicle. Additionally, the CHTS data is a representative sample of Californians.

The Commercial dataset can be considered the workhorse of the effort; it provides by far the largest sample, but has some important limitations. The most critical is a possible bias toward unfamiliar trips. The data are collected from on-board and hand-held navigation systems and it is impossible to discern which records derive from each source. On-board systems transmit continually providing a data feed for all trips. Historically, hand-held devices transmit only when the user has asked for navigational assistance. Thus, the data are potentially biased toward unfamiliar trips, those wherein the user would request directions. We expect that by viewing these trips we would learn something about the ease or difficulty of parking on a particular block but inferences about cruising generally could overstate the problem. We base the assumption on the idea that someone familiar with an area would have a strategic sense of where to look for parking while someone unfamiliar would take a more haphazard approach. More broadly, because the data are anonymous, we do not know how representative they are of trip-making in general. Thus, the Commercial data are most useful for identifying broad geographic and temporal patterns of cruising, and for testing our algorithms on a large dataset.

The geographic coordinates from a GPS trace are subject to some inaccuracies. Errant pings, likely caused by the signal bouncing off a building and defined where the speed from the previous point was more than 130 km/h, were removed from each trace. Also, as noted below, low ping density --a long time elapsed between pings-- can create uncertainty with respect to the actual path. The map-matching process discussed in the following section helps to mitigate these problems, but we still discard many traces due to low ping density and/or inaccuracies.

Matching Trips to the Network

To calculate the actual path length, we map-matched the traces to the street network, ignoring the final part of the trip if it took place within a parking lot or garage, appeared to involve a walk segment, or consisted of noise after entering a building. Map-matching is important because the length of the GPS trace does not equal the length of the actual route, and thus will not be directly comparable to our network-based calculation of the shortest paths. For low-resolution traces, the raw trace will "cut corners," taking a straight line between each GPS ping. For high-resolution traces, there will also be jitter caused by imprecision in the GPS coordinates.

We found that off-the shelf map-matching software does not handle circling or poor-quality traces well – these software packages are sometimes programmed to assume that the driver takes the shortest path, and thus any observed circling is treated as an error in the data. We therefore developed a custom algorithm, pgMapMatch, to map-match the trace to the street network. This algorithm is flexible enough to deal with circling, U-turns and other behavior characteristic of cruising. It allows low-resolution GPS data (e.g. those with pings only every 30 seconds) to be used in the analysis, through interpolating the streets that were most likely to be followed by the driver. We restrict our sample to traces that have a match score of > 0.9 (i.e., the probability that the map-matching was successful is greater than 90%.) The map-matching algorithm itself is documented in a separate paper (Millard-Ball, Weinberger and Hampshire, 2019), and open-source code is available at https://github.com/amillb/pgMapMatch.

SEARCHING FOR PARKING

Typically, a driver will begin searching at or near their destination and find a parking spot on the same block. We are interested in trips that involve "excess" search that would include circling or a measurable deviation from a shortest path. We began with two definitions of excess search or cruising:

- Actual path is greater than the shortest route of the final segment of a trip
- At least one block is traversed more than once (a subset of the trips identified by the first definition)

The comparison between actual path and shortest path is measured from the last GPS ping identified before a vehicle enters the area circumscribed by a 400 meter radius of the trip's final coordinate location. This is illustrated in Figure 1 where the red star represents the last location transmission from this trip. The pink line shows the vehicle's trajectory – derived by matching the GPS trace to the network. The dashed circle circumscribes the 400 meter "search" radius around the trip end. We measure the distance the vehicle has traveled from when it first enters the "search" radius until it stops (we assume in a parking place). In addition, we calculate the shortest legal network path from that first point of entry to the final location (shown in blue) using the Turn Restricted Shortest Path algorithm in the pgRouting software[2]. In this example, it is obvious that the driver traveled some distance beyond the shortest path, even exiting the search radius before reentering and settling on a parking space.

[2] See pgrouting.org. We use version 2.4.1. The algorithm approximates the shortest travel time based on the road classification.

Figure 1 **Definition of Cruising**

To test against a real-world example, we applied the process to the CHTS, and also manually inspected a sample of 100 trips from the "commercial" data. While we do not know the driver's intent, we can infer whether a trip was cruising from the path taken and, in the case of CHTS and UMTRI, from repeat trips taken over the course of the week.

This validation step was critical in that it revealed that the operational definition did not perfectly match to driver behavior. Most importantly, cruising is just one reason why the actual route may not correspond to the shortest path, meaning that we generated a number of false positives. That is, we identified a trip as "cruising" in several non-cruising situations: (i) when the underlying road veers from a grid –perhaps to traverse a geographic feature like a hill or a park; (ii) when the driver is running an out-and-back errand, such as dropping off a child at school, which could appear as a circuitous trip and therefore is misidentified as cruising; (iii) when the driver makes a mistake, such as missing a turn or a freeway exit; (iv) when a driver takes a preferred path seeking to avoid a long light cycle, a difficult intersection or wishes to end the trip on a particular side of the street; and (v) there is an error in the underlying road-network or GPS data, or temporary street closures or construction work. Figure 2 shows several of these situations.

Figure 2 Non-Cruising Examples of Trips Exceeding the Shortest Path

Figure 2a Following the Street in Lieu of "Shortest" Path

Figure 2b Probable Errand Appearing as Parking Search

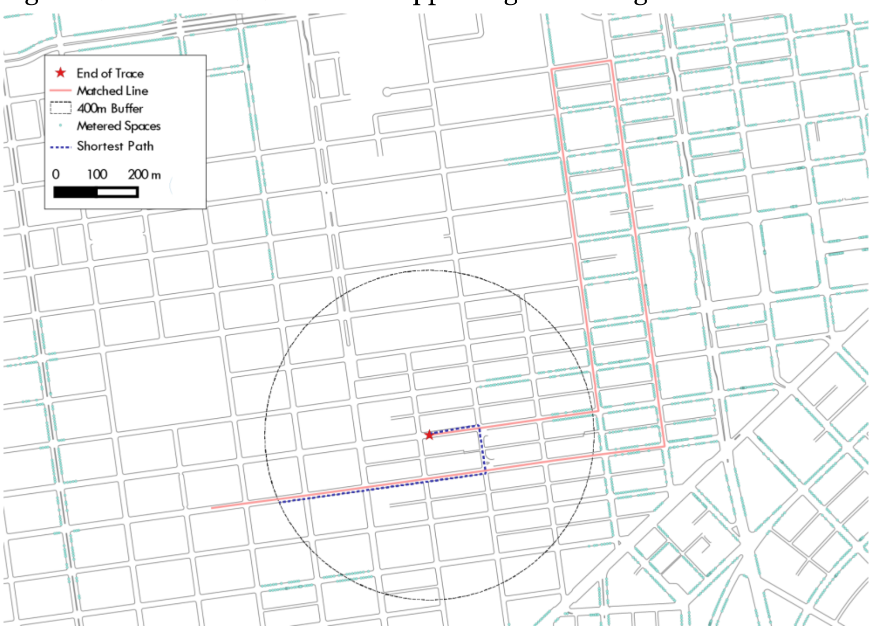


Figure 2c Preferred Path; Reason Unknown

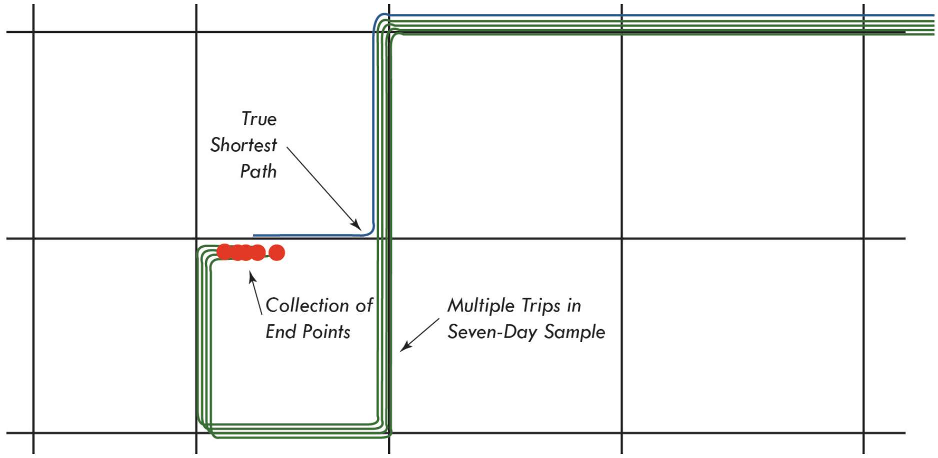
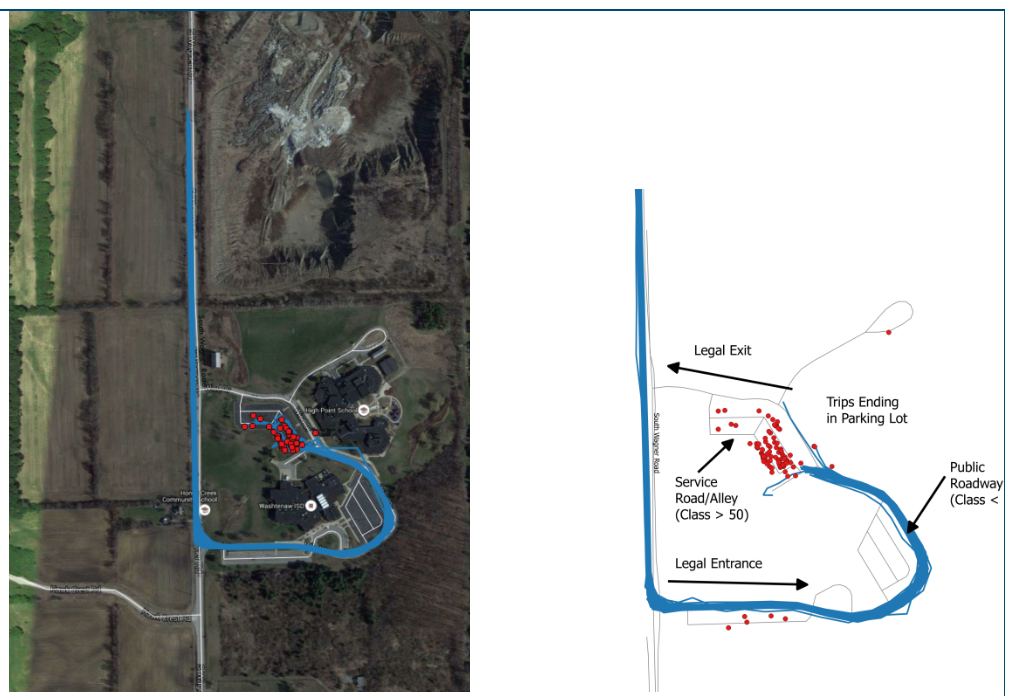


Figure 2d Restricted Turn into a High School parking lot not Coded and Driveway Mis-Coded as Public Road



We reduce the number of these false positives by adding two additional restrictions to our operational definition. First, the difference between actual path and shortest path must exceed 200 meters. This helps to avoid classifying trips such as the ones in Figure 2a as cruising, by allowing for drivers to take a slightly longer but perhaps simpler route to their destination.

Second, to eliminate some errand trips with an intermediate destination, such as that suggested in Figure 2b, we require a minimum threshold of excess travel to occur within the 400 meter area that we have defined as the search radius or parking catchment. In many cases, the driver exits the 400m area while searching for a parking space (indeed, this is the case in Figure 1). However, if more than 50% of the travel takes place outside the 400m area, we assume that the driver has passed the ultimate destination on the way to an intermediate errand. Given the driving pattern, time of day, and the location of the trip illustrated in Figure 2b, it is likely the driver was dropping a passenger at a separate location and then returned to park in a place that s/he had only passed by coincidence in the earlier part of the trip.

The 50% threshold improves the accuracy with which we classify trips as cruising or not. It is worth noting that the threshold level influences the tradeoff between false positives and false negatives. Based on empirical testing of 200 traces, we chose the threshold of 50%, which yields the least error in terms of both identifying a cruising trip as not cruising and identifying a trip that is not cruising as cruising. While in many cases it was not possible to discern the driver's intent, there were many instances where a trip appeared to be a clear-cut case of cruising, as in the example in Figure 1, or "not cruising," as in the illustration in Figure 2b.

The 50% threshold is somewhat arbitrary, as it is based on qualitative inspection of a relatively small sample. However, using a lower threshold does not significantly change the results. Eliminating the threshold entirely increases the percentage of trips classified as cruising in the Commercial dataset to 5.3%, from 4.9% under the 50% threshold. Increasing the threshold to 60% reduces the percentage of cruising trips to 4.5%.

The additional restrictions to the algorithm do not control for cases where restricted turns are not coded or where driveways are miscoded as in Figure 2d. Additionally, cases of taking a longer preferred path, as in Figure 2c, remain as possible false positives. In the Ann Arbor sample some residential areas have alternate side parking restrictions that provide an incentive to drive around the block, rather than execute a U-turn, to obtain a parking space. These types of false positives bias our cruising estimates upwards.

We visually inspected a random sample of 100 traces identified as cruising from the Commercial dataset, and all but three unambiguously met our definition of cruising. (One trace was misclassified as cruising due to noise in the GPS signal, and a further two were ambiguous.) Of the remaining 97, the vast majority appear consistent with a driver searching for parking, but underscores the estimate as an upper-bound on cruising. It appears that at least 5-10% of trips identified as "cruising" represent drivers taking a wrong turn, getting lost, taking a longer but reasonable path as shown in Figure 2a, or taking a preferred path as in Figure 2c. For example, in one trip in San Francisco, a driver passes a motel, circles round the block and then pulls into the motel parking lot; presumably, this driver is a visitor who missed the turn on the first pass. These are the most obvious examples; in most cases, we cannot infer driver intent from the GPS traces alone, and so in practice more than 5-10% of our "cruising" trips are likely to represent similar behavior.

EXTENT OF CRUISING

Though the purpose of this project is to test whether the proposed approach is adequate to provide insights to municipalities regarding the extent of cruising within their borders, it seems appropriate to reveal something of the "cruising findings." In Figure 3 we list the number of records we began with in each dataset, the remaining set after we determined whether the trace was useable, and our estimates of cruising.

In both Ann Arbor and San Francisco, cruising appears to affect 5-6% of the automobile trips that end in each city, and a smaller fraction of ~2% as judged by the more restrictive criterion of a block traversed more than once. Among cruising drivers, the mean excess distance cruised per vehicle trip is 547m (Ann Arbor) and 660m (San Francisco). Their mean time spent cruising is two to three minutes, based on each vehicle's speed after entering the 400m analysis area (an average of 11mph in San Francisco and 14mph in Ann Arbor).

From a policy perspective, it is more helpful to express cruising as a percentage of total vehicle traffic, which can be calculated from the percentage of household vehicle trips that involve cruising, mean cruising distances, the number of household vehicle trip ends, and daily vehicle travel within the city limits. In both cities, cruising accounts for less than 1% of vehicle travel by private car[3].

Analysis of the CHTS dataset shows a higher percentage of trips identified as cruising by our definition (9%), although the sample is small and thus the confidence intervals are wide. Moreover, a closer inspection of individual trips suggests that six of the 22 "cruising" trips are unlikely to represent actual cruising. In four of these cases, the driver takes the long way around to end up on the preferred side of the block, while in two cases the chosen route is longer but makes intuitive sense, for example to stay on major streets. In a further five trips, the intent is difficult to discern; one appears to involve a wrong turn, and another a valet parking operation. These inspections suggest that the actual share of trips that involve cruising is closer to 6%; our method provides an upper bound given the multitude of reasons why drivers take circuitous paths.

[3] In San Francisco, the estimate is based on regional travel model data, which show an average daily 1.040 million household vehicle trips ending in the city, and an average daily household VKT of 9.3 million within city limits (excluding freeways). Note that we are unable to reliably estimate total VMT from the Commercial GPS sample, hence our use of the travel model outputs. First, because our sample of GPS traces is restricted to those that end in San Francisco, we cannot account for through traffic. Second, there are biases from GPS inaccuracies; we would need to discard trips where the cruising portion is usable, but where there is too much noise in an earlier portion of the trace. Note that there is little methodological consistency in earlier studies about the definition of "traffic," i.e. the denominator. For example, Shoup (2006) aggregates various studies that use different definitions, to come up with the oft-cited baseline that an average of 30% of traffic in the downtowns studied was cruising.

Figure 3 Extent of Cruising

		UMTRI (Ann Arbor)	CHTS (San Francisco)	Commercial (San Francisco)
1	Relevant GPS traces	13,503	293	556,908
2	Usable GPS traces*	9,830	251	97,445
3a	Cruising (definition 1: actual trip is at least 200 meters longer than shortest legal path and 50% of excess occurs within the search area)	570	22	4,747
3b	Cruising (definition 2: block traversed more than once in the search area)	181	13	2,110
4a	Percent Cruising Definition 1 (row 3a/row 4) (95% confidence interval)**	5.8% ±1.7%	8.8% ±3.8%	4.9% ±0.1%
4b	Percent Cruising Definition 2 (row 3b/row 4 (95% confidence interval)**	1.8% ±0.4%	5.2% ±3.4%	2.2% ±0.1%
5	Excess distance for cruising trips: Mean (95% confidence interval) Median	 547m ±47m 499m	 599m ±192m 486m	 660m ±14m 506m
6	Excess time for cruising trips	126 secs	117 secs	168 secs
7	Percentage of private car traffic that is cruising (row 4a * row 5 mean * number of trip ends/total vehicle travel) (95% confidence interval)**	0.3% ±0.1%	0.6% ±0.5%	0.4% ±0.0%

* We exclude trips where the mean temporal resolution is > 30 seconds, or the maximum gap with pings > 60 seconds, or where there are < 3 pings within the 400m search radius. We also exclude traces that end on a freeway segment, and where the map-matching does not give reliable results (where the probability of a successful match is <= 0.9).

** Percentages and number of trips are based on trip ends, i.e. the number of private cars that cruise and park divided by the number that park. In Row 7, the number of trip ends is equal to the number of average daily household vehicle trips that end in each city, divided by average daily household vehicle travel within the city limits (excluding freeways). In Ann Arbor, we do not have the trip-end level data and so we use an approximation based on row 4a * row 5 mean / average trip length.

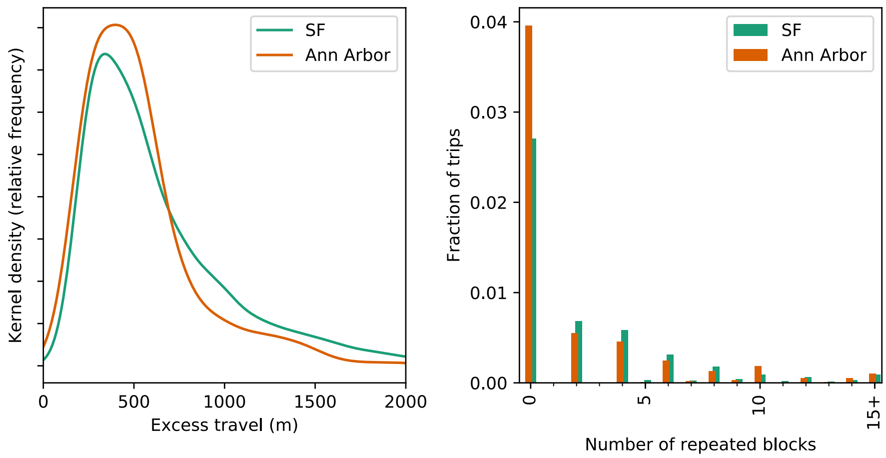
Confidence intervals for the UMTRI and CHTS take into account the clustering in the sample design, where GPS-equipped households make multiple trips, and are thus wider than those produced when assuming a simple random sample. The clustering formula used is from Dransfield and Brightwell (2018), using one stage clustering with unequal weights. The confidence intervals do not account for non-sampling error, which is likely to be particularly high in the Commercial dataset.

The amount of cruising for the mean driver may be almost trivial. Even among trips that involve cruising for parking, the median distance cruised is around half a kilometer in all three datasets – less than the distance to drive to the top floor of many parking structures. However, the average results disguise much larger amount of excess travel and repeated blocks for a small number of drivers. Figure 4 shows the distributions of excess travel and repeated blocks for the Commercial dataset (San Francisco) and UMTRI dataset (Ann Arbor). The long right tail, which is truncated in the plots, indicates that a small minority of drivers travel more than 1500m in search of parking, and revisit the same block more than 15 times. The experiences of this small minority of trips may partially explain why perceptions of cruising are much worse than our results for the average driver suggest.

Figure 5 shows the temporal patterns of cruising for weekdays in San Francisco and Ann Arbor, and also for a subset of trips that end in San Francisco's Mission District (a special case, defined as zipcode 94110). The Mission District is a high-density, mixed-use neighborhood close to the downtown core, where parking for both residents and visitors is often perceived to be challenging. While there is considerable noise in the time trends, the experience of the two cities is markedly different. In Ann Arbor, cruising is most prevalent in the afternoon. In San Francisco – and particularly in the Mission District – there are several peaks throughout the day, including one after 6PM when meters are switched off. In Ann Arbor there is an apparent double peak of cruising occurring between 4:00pm and 6:00pm. This may reflect the dominance of private automobile commuting (relative to San Francisco) and is, therefore, likely due first to the switch over from daytime employees parking on-street to evening employees parking on-street and the related search for parking by evening employees. The second spike is likely due to evening dining and entertainment customers searching for on-street parking.

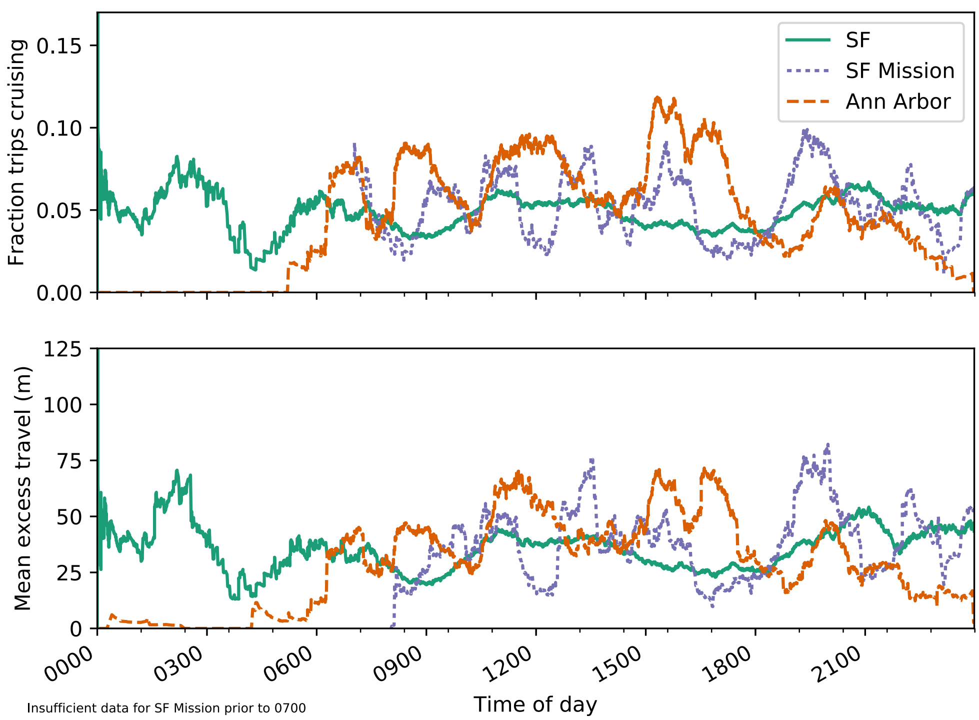
For a subset of the Commercial sample, we can evaluate the relationship between cruising and metered parking occupancy directly using data from in-street sensors that were installed on select blocks as part of the SF*park* program (SFMTA 2014; Millard-Ball, Weinberger & Hampshire 2014). In 2,202 trips, the last segment traverses a block for which contemporaneous parking occupancy data is available. Occupancy at meters averages 55% for non-cruising trips (N=2127) and 59% for the cruising trips (N=75). While the subsample size is small, the implication is that cruising drivers are often bypassing available spaces on metered blocks in search of permit-only or other unpriced spaces. Alternatively, it could mean that drivers are passing by open parking spaces well short of their destination (just within the 400m radius) in the hopes of finding a space closer by.

Figure 4 Distributions of Excess Travel and Repeated Blocks (cruising trips only)



Note: Left plot is truncated at 2,000m

Figure 5 Temporal Patterns of Cruising
(*60-minute rolling mean, weekdays only*)



Note: fractions refer to trip that end at a given time and/or in a given city or neighborhood.

SENSITIVITY ANALYSIS

Our quantification of the extent of cruising depends on several parameters:

- The radius (400m) within which the shortest path is compared to the actual distance
- The threshold (200m) above which any excess distance is considered cruising
- The proportion of travel (50%) which must occur within the 400m radius
- The cutoff (0.9) to exclude trips where the map-matching gives uncertain results

These parameters are chosen based on previous travel behavior research, expert judgment, and qualitative inspection of traces. For example, the 400m radius corresponds to about a five-minute walk—a distance frequently used in the transit ridership literature as a reasonable walk. Moreover, our previous results based on parking video analysis find that almost all (95%) of drivers begin looking for parking only after entering the 400m radius; the median distance between the start of the parking search and the parking location was 100m (Hampshire et. al, 2016). The 200m threshold (just over a typical city block), meanwhile, was chosen to exclude trips where a slightly longer route might be taken due to irregularities in the street grid, double parking, or the timing of traffic signals. In this section, we explore the extent to which our results are sensitive to these parameter choices.

The search radius is computationally intensive to vary, and so we conduct a reanalysis of the Commercial traces with two different values: 300m and 800m (Figure 6). The smaller the radius, the fewer trips are considered cruising, because there is less opportunity for the shortest-path distance to diverge from the actual distance. However, the difference between our 400m central case and a radius twice as large (800m) is just 0.3% of trips, suggesting that few drivers begin to cruise or to park more than 400m from their destination. The mean cruising distance is very similar across all three cases.

For the other parameters, we explore a larger range of potential values (

Figure 7). The round markers indicate the central case (50% of travel within the radius, 200m threshold, and 0.9 match score). Relaxing the requirement for 50% of the travel to be within the analysis radius (left panel) means that very few additional trips are classified as cruising, but that the excess distance from those trips tend to be very long – consistent with the running of errands and chauffeur trips. Conversely, a more stringent requirement would classify very few trips as cruising, suggesting that most cruising trips do encompass a wider area, and exit and reenter the 400m radius.

Adjusting the threshold distance (center panel) has a more substantial impact on the fraction of cruising trips, and a more limited impact on the total amount of cruising. Intuitively, many drivers do not take the shortest path to their destination, but it is unlikely that a detour of (say) 50m is indicative of parking search.

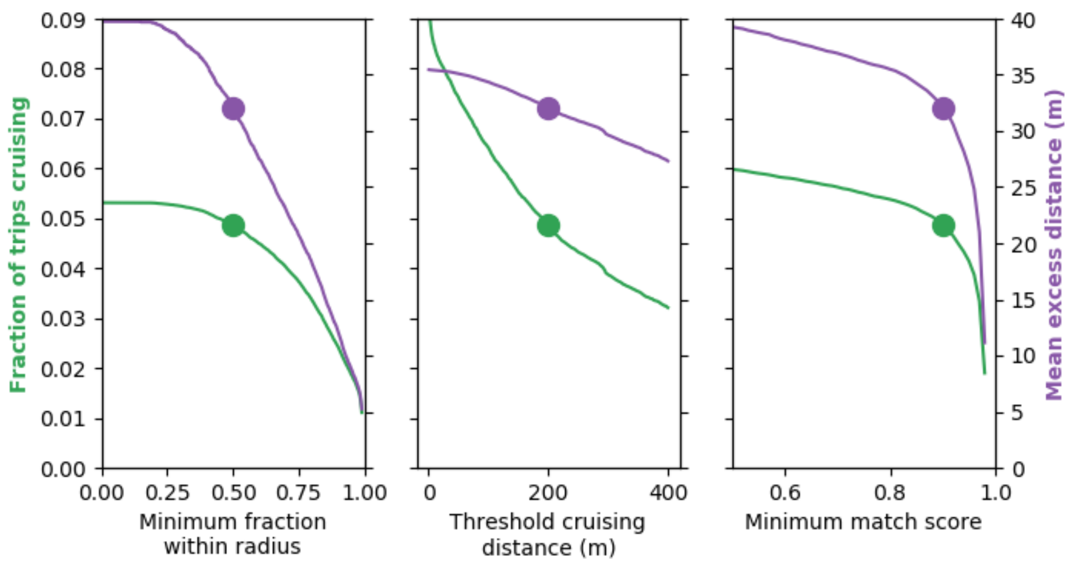
Allowing for poorer-quality map matching (right panel) also increases the fraction of cruising trips. However, visual inspection suggests that most of these trips are not cruising; rather, the difference between actual distance and shortest-path distance is an artifact of inaccuracies in the GPS data (for example, with signals deflected by tall buildings). Conversely, requiring near-certainty in the map matching restricts the sample to very simple traces, such as driving in a straight line, which rarely involve cruising.

Overall, the sensitivity analysis suggests that our qualitative conclusions are robust to a wide range of reasonable parameter choices. In practice, the other constraints of our data (such as the non-representative sample in our Commercial dataset) are likely to have a more substantial impact.

Figure 6 **Sensitivity to search radius**

	300m	400m	800m
Percentage of trips cruising	4.2%	4.9%	5.2%
Mean excess distance (all trips)	27m	32m	34m
Mean excess distance (cruising trips)	651m	660m	649m

Figure 7 **Sensitivity to other parameters**



THE GEOGRAPHY OF CRUISING

To analyze the geographic distribution of cruising trips we used an Inverse Distance Weighted interpolation to create a smoothed surface of estimated cruising in Ann Arbor and San Francisco. This approach allowed us to map GPS trace attribute values and to exclude areas of the city that have concentrations of trips too low to yield meaningful results. Here we present two views of cruising. Figure 8a shows the probability that trips are considered cruising using a definition of cruising as being 200 meters or more longer than the shortest path. The following image, Figure 8b, depicts a more classical definition of cruising in which drivers actually "circle" something we measure as blocks that are traversed multiple times. This is the second, more restrictive, definition of cruising that we presented above.

In analyzing the geography of cruising, we present results aggregated to trip ends, rather than the streets on which the cruising occurs. The previous literature uses a mix of the two approaches. For example, those that rely on intercept surveys (e.g. Lee, Agdas & Baker 2017) and "park-and-visit tests" normally aggregate to trip ends, while studies that observe how many drivers pass a vacant parking space (e.g. Shoup 2005) focus on the streets where cruising occurs.

Our choice of trip ends is partly for computational reasons, but also because such a measure is most closely related to the policy implications. For example, suppose that parking is scarce on a busy street. Suppose that 99% of the trips on this street are through traffic and do not want to park, and that all of the 1% of trips with a trip end on this street must cruise. It is most useful to think of cruising as "100% of trips" (which indicates the scarcity of parking), rather than 1% (which implies there is no problem). A measure that focuses on the portions of the trips or trajectories says more about the share of through traffic than about parking. At the city level, of course, there is almost no difference between the two approaches; the distinction is only relevant for small geographic areas.

Several conclusions are apparent from the maps. In San Francisco, there is little cruising in downtown and high-density adjacent neighborhoods. This may be because parking at meters is readily available in these neighborhoods (as found in Millard-Ball et al. 2014), and/or because most drivers to these areas park off street in lots, garages, or private residential spaces. While some lengthy cruising trips may occur, they are not experienced by most drivers. Second, the cruising "hot spots" vary considerably in character. Some hot spots are found in the west of the city center around public parking lots, which are unpriced and may be frequently fully occupied. In others, the hotspot appears to be an artifact of the street network, where the intersection of different grids at awkward angles means that drivers often take indirect routes. Others still represent medium-density residential neighborhoods with little off-street parking.

Like San Francisco, cruising in Ann Arbor (shown in Figures 8c and 8d) occurs in disparate settings. The prime cruising hotspots occur near the University of Michigan, which is located close to downtown, and in residential areas. In the south university area, over 30% of trips include some element of cruising. This is a relatively dense area providing access to university buildings, as well as other amenities like coffee shops, restaurants, and bars.

In general, we found much more "cruising" in residential areas than we anticipated, but while these trips involve excess travel and thus match our cruising definition, they may not represent a search for parking. Drivers frequently circle the block to obtain a parking space in front of their home and/or drive extra to comply with alternate-side parking restrictions. Also, we were surprised to find a greater proportion of vehicle trips in Ann Arbor tend to include some element of cruising but there are fewer instances of very long parking searches. For example, in Figure 8c there is a neighborhood in the southernmost portion of the image that shows a high concentration of trips that meet the definition of cruising. However, on close inspection there is no shortage of parking space in this neighborhood and all of the trips that are identified as cruising were made over multiple days in just one vehicle – presumably by the same driver. A further investigation suggests that this driver was simply driving around for no reason that we could discern. Again, this underscores our emphasis that the estimates provide upper bounds for the extent of cruising.

Figure 8a **Probability a Trip Contains Cruising > 200 Meters San Francisco (Inverse Distance Weighted Interpolation)**

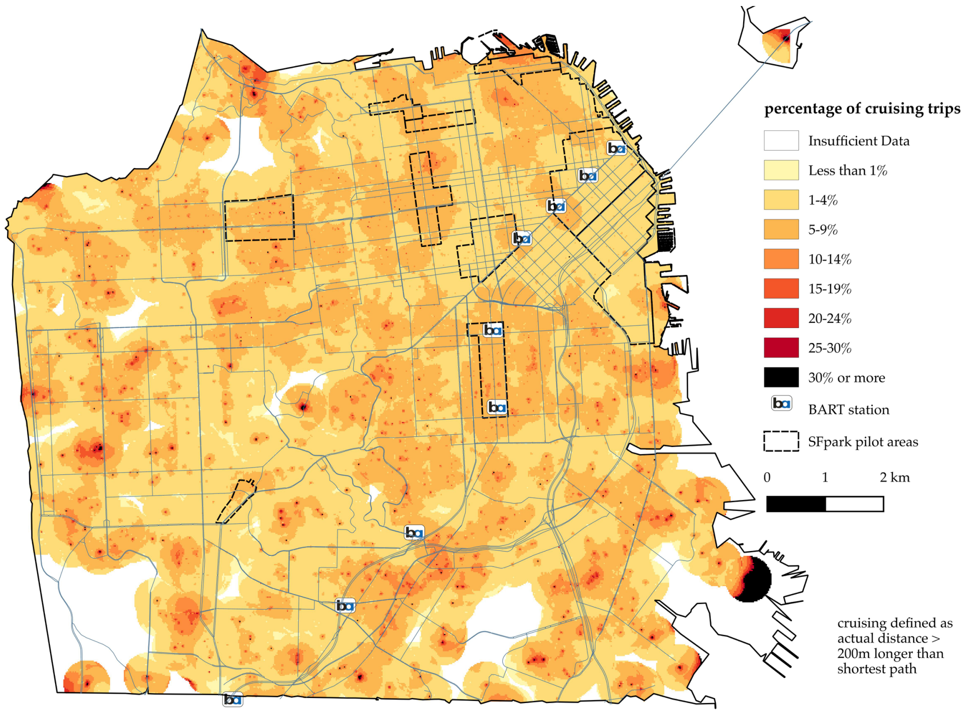


Figure 8b **Mean Number of Repeated Blocks San Francisco (Inverse Distance Weighted Interpolation)**

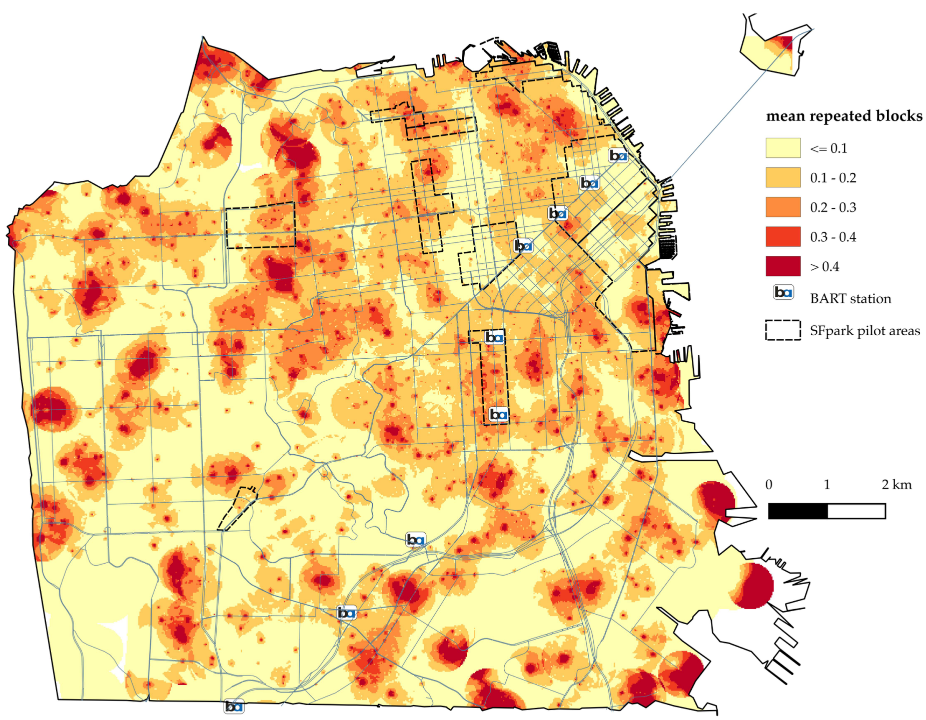


Figure 8c Probability a Trip Contains Cruising > 200 Meters Ann Arbor (Inverse Distance Weighted Interpolation)

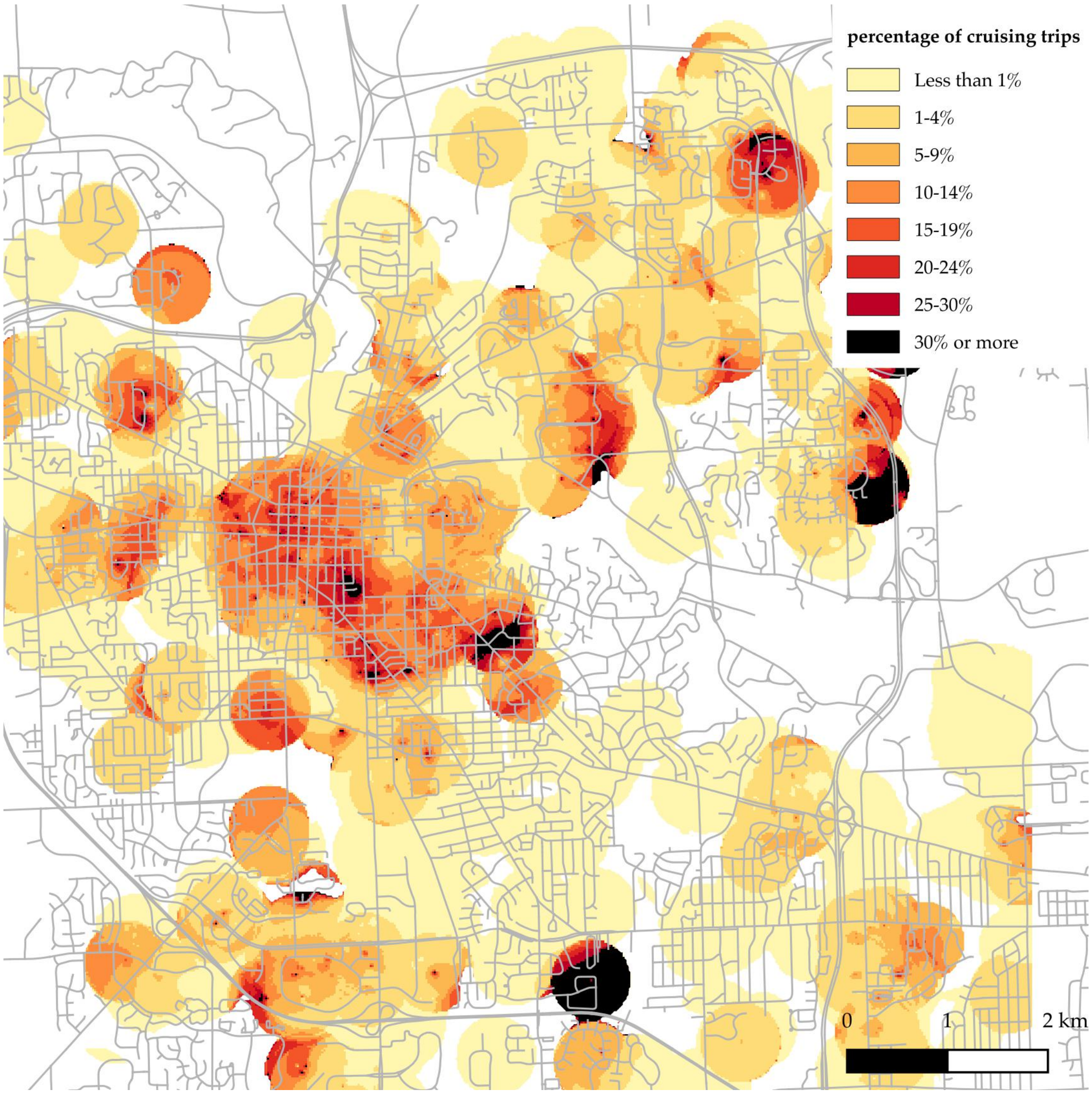
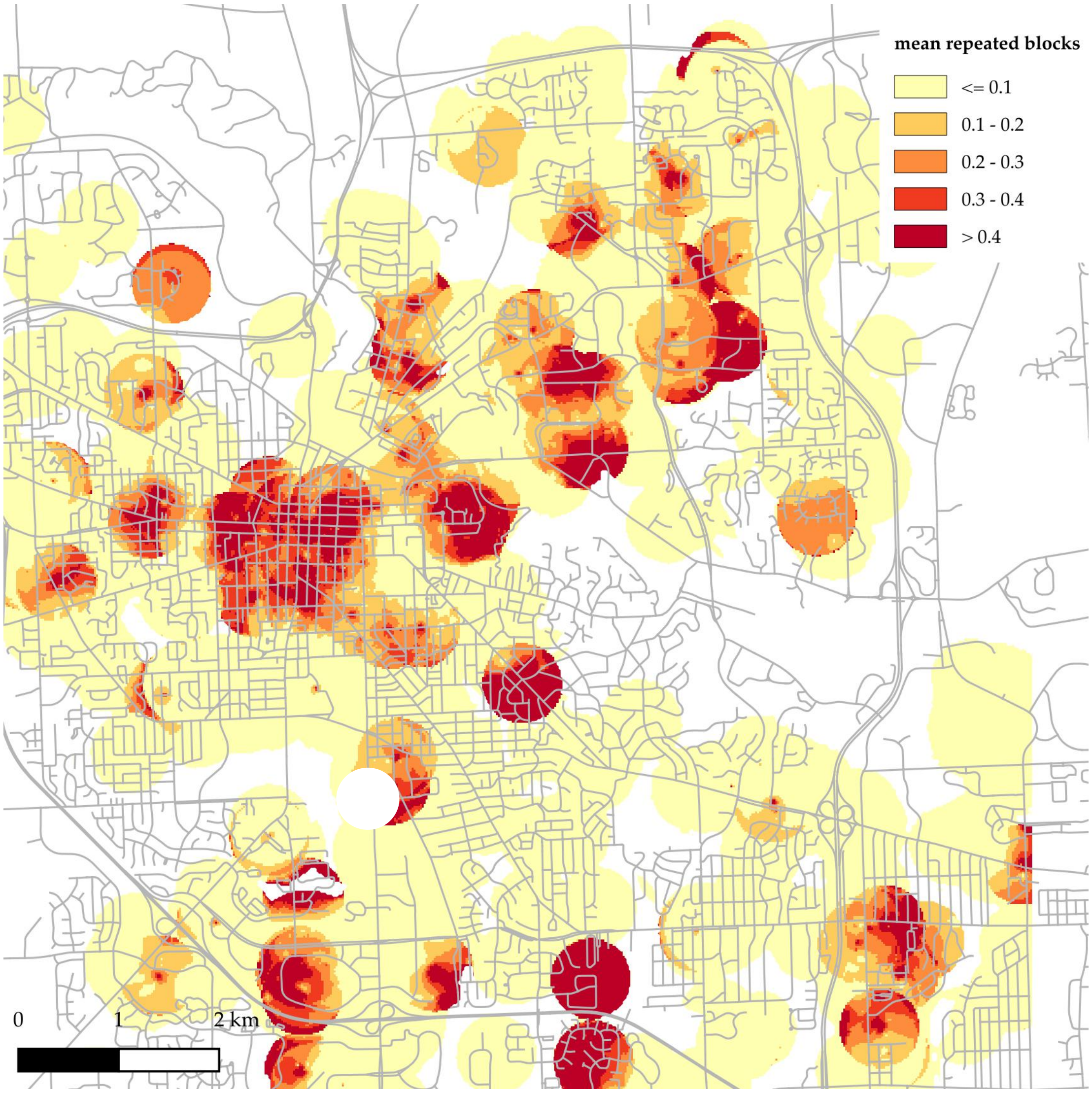


Figure 8d Mean Number of Repeated Blocks Ann Arbor (Inverse Distance Weighted Interpolation)



CONCLUSIONS

Most research on cruising to date has defined cruising as the percentage of cars that are searching for parking. Moreover, previous research has looked for cruising where it is already known to occur or where it is most likely to occur. Both these characteristics are likely to overestimate the excess travel resulting from parking search. A driver may be willing to take the first parking space available within an acceptable distance of his or her destination, or even the second or third, even if the destination has yet to be reached. In such a case, the driver searched for parking but there is no excess travel associated with the search. Had the driver been asked in a survey whether s/he was looking for parking the answer would have been "yes"; the trip would be identified as cruising but has no marginal negative or excess impact on traffic or emissions. In the case where a driver takes a space ahead of the ultimate destination, parking scarcity might technically reduce VMT, as we discuss in Millard-Ball, Hampshire & Weinberger (2020). And the dense downtowns and commercial neighborhoods where cruising researchers have focused are unlikely to be representative of all travel, or even of urban travel.

The research presented here focuses on the excess travel that results from parking search, and provides a method by which any jurisdiction can obtain a broad and nuanced view, identifying locations where parking search leads to negative externalities. Such a view would allow a richer policy response providing the jurisdiction with tools to better identify at what times of day and the extent—both in terms of intensity and geography—of the problem.

We offer two alternative definitions of cruising based on the driver's route once he or she first reaches a 400m radius of their parking spot (i.e. the final GPS location transmission): (i) that the actual path is at least 200m greater than the shortest path, or (ii) that at least one block is traversed more than once (a subset of the trips identified by the first definition). In both cases, a second condition is that at least 50% of the subsequent travel takes place within the 400m radius, in order to avoid classifying errands and drop-offs as cruising. The excess travel definition of cruising is a more restrictive definition than typically implied in the literature, but it more closely matches the negative externalities implied in the term "cruising for parking." It is also more precise than a definition based on parking search, because the start of the search process (i.e., the point at which a driver would take the first available space) is ill defined. The repeated blocks definition of cruising, in contrast, is less satisfactory. As our results indicate, it fails to capture the extent of cruising; many drivers do not circle around or drive back and forth, but instead adopt more varied search patterns.

Our method raises further issues, in that parking search does not appear to be the dominant reason for excess travel. Instead, pick-ups and drop-offs, an irregular street pattern, traffic congestion, driver inattention or the ease and simplicity of a longer route may be just as important contributors to longer vehicle travel distances in the final portion of a trip. In some cases, drivers may simply drive around to lull a baby to sleep, or they may circle while waiting for a passenger or to argue with the family over where to eat. These examples, which we observed in cases where on-board video footage was available, would appear as "cruising" in a machine-read set of GPS traces; thus, our estimates are best interpreted as an "upper bound" for cruising.

Our results leave areas for further work. Most notably, we do not explain the reasons for spatial and temporal differences in cruising. Previous research highlights price differentials between on- and off-street parking (e.g. van Ommeren et al. 2012; Inci 2014), but limited availability of all parking types may also be a cause of cruising. However, we have developed a strategy that allows researchers and policy-makers to look across any given geography to gain insight into cruising and excess travel. Ultimately, pinpointing the exact amount of cruising may remain an elusive goal. Circling around on urban streets has many causes, of which cruising for parking is just one.

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