Parking Cruising Analysis Methodology

Final Project Report

Report No. FHWA-HOP-23-004

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U.S. Department of Transportation

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FOREWORD

The Federal Highway Administration sponsored the research project, Parking Cruising Analysis Methodology, to develop a methodology to detect parking cruising. Cruising vehicles–motorists circling or cruising for on-street parking that is free or priced below market equilibrium–can contribute to additional congestion, air pollution, time wasted, driver frustration, and a potential loss of economic competitiveness at destinations where parking is hard to find and where alternative access modes do not exist. With increased sensitivity to the need for curb management, there is a need to better understand the prevalence of cruising for parking.

This report documents a methodology and tool that can be used by municipalities and other interested parties to understand cruising for parking and the effects of policy interventions on parking search behaviors. It also includes case analyses from four U.S. cities. The cases illustrate a range of applications, such as identifying cruising hot spots—by both time of day and location—and assessing policy impacts.

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Cruising vehicles—motorists circling or cruising for on-street parking that is free or priced below market equilibrium—can contribute to additional congestion, air pollution, time wasted, driver frustration, and a potential loss of economic competitiveness at destinations where parking is hard to find and where alternative access modes are limited. With increased sensitivity to the need for curb management, there is a need to better understand the prevalence of cruising for parking. This report documents a methodology and tool that can be used by municipalities and other interested parties to understand cruising for parking and the effects of policy interventions on parking search behaviors. It includes case analyses from four U.S. cities: Washington, DC; Atlanta, Georgia; Chicago, Illinois; and Seattle, Washington. The cases illustrate a range of applications, such as identifying cruising hot spots by time of day and location and assessing policy impacts. The highest rates of cruising were found in Seattle and Chicago where 7.3 and 6.8 percent of trips, respectively, showed some portion as cruising. Overall, the research team found that the level of cruising is consistent across the cities in this analysis, even when using different data sources. The report also documents lessons learned relating to data quality, tool implementation, and the analyses results.</td></tr>
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SI* (MODERN METRIC) CONVERSION FACTORS				
APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1,000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2,000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa
APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2,000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	2.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003)

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LIST OF ABBREVIATIONS

AADT	average annual daily traffic
CBD	commercial business district
ESS	explained sum of squares
FHWA	Federal Highway Administration
GA	Georgia
GB	gigabyte
G-ICE	GPS-independent cruise estimator
GIS	geographic information system
GPS	global positioning system
GRNN	generalized regression neural network
MLP	multilayer perceptron
SDOT	Seattle Department of Transportation
WA	Washington

EXECUTIVE SUMMARY

Motorists circling or cruising for on-street parking that is free or priced below market equilibrium can contribute to additional congestion, air pollution, time wasted, driver frustration, and a potential loss of economic competitiveness at destinations where parking is hard to find and where alternative access modes are limited. With increased sensitivity to the need for curb management, there is a need to better understand the prevalence of cruising for parking.

Strategies to quantify cruising have evolved from intercept surveys to deployment of wireless technology sensors. Intercept surveys are effective at understanding the proportion of traffic that is looking for parking (which may not imply excess travel),[1] while the wireless technology sensor deployment has been successful in distinguishing vehicles within the traffic stream that are circling for parking; both can be applied in very limited geographies.

The methodology and tool presented in this report extends previous work that relied on global positioning system (GPS) breadcrumb data to overcome the physical limitations of other research methods. Big data allows for a more comprehensive assessment of the extent and location of excess parking search.[2,3] The method also quantifies the measure of most direct policy interest—excess travel from cruising, rather than the proportion of drivers searching for parking. The tool developed to generate reliable estimates of cruising (called Cruise Detector within this report) is a computer program that takes location data harvested from smartphones and sorts out which series of data points represent trips and which do not. Identified trips are then matched to a street network and compared against a shortest path that might have been taken. A trip that exceeds an available shortest path by a given threshold is assumed to include excess travel, most likely, due to parking search.

The methodology and tool provide a data-driven way to identify the locations and times of day where cruising is most prevalent. They can be used by municipalities and other interested parties to understand cruising for parking and the effects of policy interventions on parking search behaviors in order to develop appropriate responses. The methodology and tool can be applied by a skilled geographic information system (GIS) analyst with some familiarity with programming languages. Potential computing resources are also described within the report.

The research team applied the tool and completed case analyses for four U.S. cities: Washington, DC; Atlanta, Georgia; Chicago, Illinois; and Seattle, Washington.

[1] Millard-Ball, Adam; Hampshire, Robert; and Weinberger, Rachel (2019), "The curious lack of cruising for parking." *Land Use Policy*, in press.

[2] Weinberger, Rachel; Millard-Ball, Adam; and Hampshire, R (2020) "Parking Search Caused Congestion: Where's all the fuss?" *Transportation Research Part C: Emerging Technologies* vol 120.

[3] Hampshire, R., Jordon, D., Akinbola, O., Richardson, K., Weinberger, R., Millard-Ball, A. & Karlin-Resnick, J., 2016. Analysis of Parking Search Behavior with Video from Naturalistic Driving. *Transportation Research Record: Journal of the Transportation Research Board,* 2543, pp.152–158.

The cases illustrate a range of applications, such as identifying cruising hot spots by both time of day and location and assessing policy impacts:

- **Washington, DC.** The focus in this case study is cruising for parking across Washington, DC. Special attention is focused on three sports stadiums, and when the stadiums have and do not have events planned. The analysis also emphasizes cruising in the areas around Metrorail stations. In lieu of a specific policy change that would lead to a before/after analysis, the findings here are cross-sectional, illustrating different cruising patterns for different urban forms: specifically proximate to Metrorail versus beyond the Metrorail catchment areas.

- **Atlanta, Georgia.** The research team explored the geography of cruising across two different time periods. To the extent possible, the research team looked at the differences in single use versus mixed use areas and contrasted metered areas with those that allow free parking. The data covered the areas of Atlanta located in Fulton County.

- **Chicago, Illinois**. This case study allowed the research team to showcase analyses that could be done with the raw location data. Raw location data were acquired for June 2019, 2020, and 2021. Unfortunately, the data for June 2021 were of insufficient quality to include in the final analysis. The analysis proceeds with a focus on the 2 years for which data are of sufficient quality.

- **Seattle, Washington**. Seattle has a performance pricing policy for its metered parking streets. Using annual surveys to estimate vehicle occupancy, the Seattle Department of Transportation (SDOT) raises, lowers, or leaves the same the parking meter prices in order to hit an occupancy/vacancy target. The research team examined cruising before and after price changes to the city's metered parking. The research team also examined cruising in the 2 weeks before and after SDOT temporarily suspended all parking meters to ease the burden on essential travel during the worst of the COVID-19 pandemic.

The report provides analyses results for each city, as well as overall observations considering all cities' analyses. The highest rates of cruising were found in Seattle and Chicago where 7.3 and 6.8 percent of trips, respectively, showed some portion as cruising.

Through the analyses of the cities, the research team concluded the following:

- Across all the cities in this analysis, the level of cruising is consistent, even when using different data sources. The estimates in this report are also comparable to earlier work using a similar methodology.
- The consistency, even at times of day or in places where parking is readily available, suggests that many trips identified as cruising may not be people searching for parking, but rather people taking a longer route for other reasons. Thus, estimates of cruising may overstate the parking problem.
- Consistency in the cruising estimates also point to an equilibrium level of cruising. Other work indicates that where parking is perceived to be scarce, drivers will often park short

of their destination, taking the first space they find.[4] Where parking is readily available, drivers may be more selective about their choice of a parking space. An analogy is how roadway congestion reaches an equilibrium as some users switch modes or departure times based on their tolerance for traffic delay.
- In general, cruising is a localized problem. The tool can identify hot spots, but even in these hot spots, the average time spent cruising is brief, and cruising only impacts a relatively small percentage of trips.

The report documents lessons learned relating to data quality, tool implementation, and the analyses results. For example, both third-party processed data and raw location data have their own advantages and disadvantages. Therefore, users should carefully assess options for data acquisition, considering factors such as budget and the degree of flexibility desired to conduct additional analysis to find new results beyond what was initially sought. Data quality can vary greatly, and it is recommended to obtain samples of data to assess the resolution and quality. Information on how the data are collected may help the analyst assess potential biases.

[4] Millard-Ball, Adam, Robert C. Hampshire, and Rachel R. Weinberger. 2020. "Parking Behaviour: The Curious https://doi.org/10.1016/j.landusepol.2019.03.031.

CHAPTER 1. INTRODUCTION

Cruising vehicles cause a host of problems, such as adding congestion and air pollution to already congested and polluted neighborhoods, driver frustration, and a potential loss of economic competitiveness at destinations where parking is hard to find and where alternative access modes are limited. With increased sensitivity to the need for curb management, many approaches to understanding curb use and the prevalence of cruising for parking have emerged.

Strategies to quantify cruising have evolved from intercept surveys to sophisticated wireless technology sensors. Intercept surveys are effective at understanding the proportion of traffic that is looking for parking (which may not imply excess travel).[5] Wireless technology deployment has been successful in distinguishing vehicles within the traffic stream that are circling for parking in very limited geographies.[6]

The extent of cruising remains unclear. Research has been conducted in the locations where cruising is known to be an issue. However, results have been inappropriately extrapolated across wide regions. For example, it is often taken on faith that "…30% of urban traffic comes from cars hunting for parking spaces."[7] This has been traced to an analysis[8] that averaged the results of a limited number of studies and concluded that 30 percent of vehicles in congested downtowns are searching for parking. The misinterpretation stems not only from the fact that the studies were performed just where cruising was perceived to be a problem, but also from taking the straight average of these limited number of studies without regard to community size, date of the analysis, whether the analysis was conducted in a downtown or neighborhood, or other conditions that might affect the outcome. There have been attempts to debunk the 30-percent figure,[9,10] but it is still widely used in academic and policy settings.

Many existing research methods, such as counting vehicles passing an empty space and tracking parking availability by bicycle, quantify the percentage of traffic searching for parking, rather than quantify the excess traffic and pollution from cruising. The difference is subtle but important for policy; the strategy is also applicable only in limited geographies. Almost all trips end in a search for parking, with the exception of drop-offs and those ending in reserved parking. When close to a destination, up to 100 percent of traffic is searching for parking. A study that finds a high percentage of traffic is searching for parking may reflect the absence of through traffic as much as scarcity of parking. As shown in Figure 1, in some circumstances scarce

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[5] Adam Millard-Ball, Robert Hampshire, and Rachel Weinberger, "Parking Behaviour: The Curious Lack of Cruising for Parking in San Francisco," *Land Use Policy* 91 (2020): 103918.

[6] Gregory Barlow, Isaac Isukapati, Stephen Smith, Soumya Dey, Stephanie Dock, Benito Perez, Alex Pochowski "Measuring Cruising for Parking in Washington, DC Using Dense, Ubiquitous AVI Sensor Networks" 2018 TRB paper (https://trid.trb.org/view/1495676)

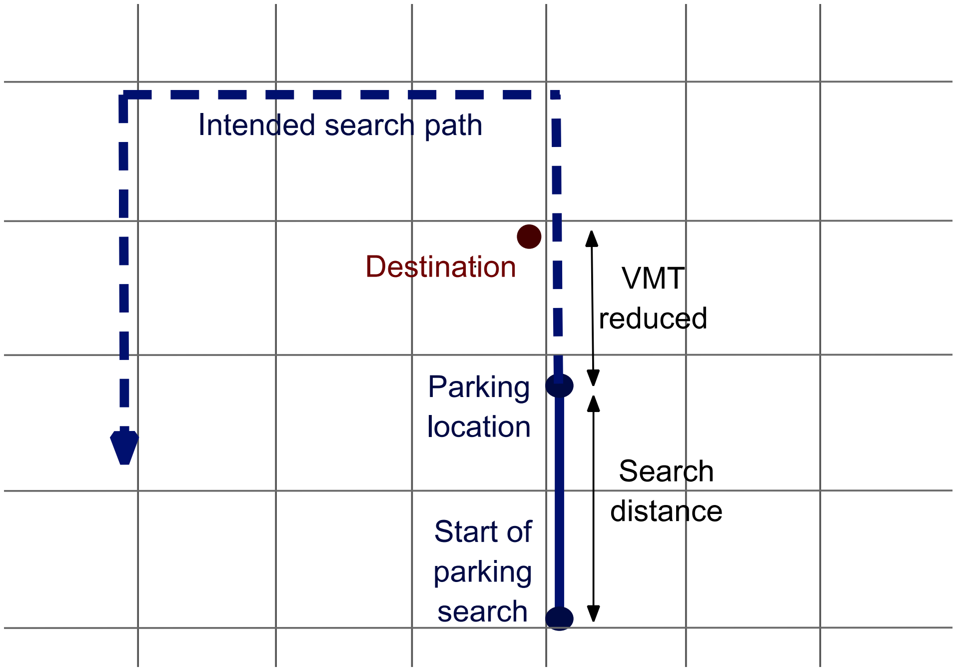
[7] Eilene Zimmerman, "A Silver Bullet for Urban Traffic Problems," CNN Money, April 29, 2011, http://money.cnn.com/2011/04/29/technology/streetline/.

[8] Donald Shoup, "Cruising for Parking," *Transport Policy* 13, no. 6 (2006), 479–486.

[9] Steven Polzin, "Playing 'Telephone' with Transportation Data," Planetizen, July 11, 2016. http://www.planetizen.com/node/87288/playing-telephone-transportation-data.

[10] Paul Barter, "Is 30% of Traffic Actually Searching for Parking?," *Reinventing Parking*, October 7, 2013, http://www.reinventingparking.org/2013/10/is-30-of-traffic-actually-searching-for.html.

parking could even reduce vehicle miles traveled. This occurs when drivers park short of a destination because they perceive parking to be scarce at the destination (not to mention when, for the same reason, they choose to forgo driving and instead access the destination using transit or non-motorized modes).[11]



Source: FHWA.

Figure 1. Illustration. Scarce parking can reduce vehicle miles traveled.

This report extends previous work that had relied on global positioning system (GPS) breadcrumb data to overcome the physical limitations of other research methods. Big data allows for a more comprehensive assessment of the extent and location of excess parking search.[12,13] The method also quantifies the measure of most direct policy interest—excess travel from cruising, rather than the proportion of drivers searching for parking.

Along with documentation of the research strategy and Cruise Detector (i.e., the tool the study team developed to generate reliable estimates of cruising), this report includes case analyses from four U.S. cities. The cases illustrate a range of applications, such as identifying cruising hot spots by both time of day and location and assessing policy impacts. To assist cities in making parking policy and investment decisions, Cruise Detector is freely available and can be openly accessed.

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[11] Millard-Ball, Adam; Hampshire, Robert; and Weinberger, Rachel (2020), "Parking Behavior: The curious lack of cruising for parking in San Francisco." *Land Use Policy*, 91: 103918.

[12] Weinberger, Rachel; Millard-Ball, Adam; and Hampshire, R (2020) "Parking Search Caused Congestion: Where's all the fuss?" *Transportation Research Part C: Emerging Technologies* vol 120.

[13] Hampshire, R., Jordon, D., Akinbola, O., Richardson, K., Weinberger, R., Millard-Ball, A. & Karlin-Resnick, J., 2016. Analysis of Parking Search Behavior with Video from Naturalistic Driving. *Transportation Research Record: Journal of the Transportation Research Board,* 2543, pp.152–158.

PURPOSE AND SCOPE

There are uncertainties and a lack of understanding of the full impact that parking cruising has on cities. There is also a paucity of understanding about the effectiveness of interventions. Recently funded studies include the direct precursor to this one,[14] which provided a proof-of-concept to use GPS traces to identify a signature of cruising for parking. A related project[15] deployed a set of wireless sensors throughout a study area that connects to devices in passing vehicles and identifies how often a vehicle passes the same point. Using information on how frequently and in what time frame a vehicle passes a certain point, an assessment is made regarding the extent of cruising in that area.

The National Cooperative Highway Research Program has undertaken a recent review of dynamic curb management.[16] Any number of departments of transportation have looked into the question as well, with many adopting performance pricing (designed to align parking demand with parking availability) and other strategies to combat problems that stem from parking shortages. The scope and purpose of this work is to develop a robust, freely available tool (i.e., Cruise Detector) that allows cities to understand the impact and extent of traffic generated by parking search and to test policy interventions. This report provides documentation on Cruise Detector and discusses its application.

Cruise Detector can address the following questions (for the first four questions, specific examples of the analysis are provided in Chapter 3 of this report):

- **How big a problem is cruising?** The question is addressed using Atlanta, Georgia, as a use case.
  - How much cruising is there in specific urban locations?
  - How does cruising vary across space and time of day?
- **Does cruising change from year to year?**
  - An analysis of Chicago cruising in 2019 and 2020 is used as a month-over-month use case for the longitudinal analysis. The Atlanta case is also used to examine longitudinal differences examining travel and parking behavior in the months leading to March 2020 when pandemic lockdowns began and then for several months after.
- **Where do people cruise?** Washington, DC, serves as a use case to illustrate how a city might address these questions.
  - Is cruising more prevalent at tourism destinations?
  - In denser neighborhoods?
  - Around particular land uses?
- **Are policies such as performance pricing effective in deterring cruising?** Seattle, Washington, serves as a use case to determine this by answering these questions:
  - How effective are different management strategies in reducing cruising?

[14] Rachel Weinberger, Adam Millard-Ball, Robert Hampshire. 2016. Parking-Cruising Caused Congestion Final Report SBIR, USDOT Available at SSRN: https://ssrn.com/abstract=2906528.

[15] Rapid Flow Technologies "Parking-Cruising Caused Congestion & Targeting Public Mitigation Investments" SBIR contract DTRT5715C10025.

[16] NCHRP "Dynamic Curbside Management: Keeping pace with the new and emerging mobility and technology in the public right-of-way." Web only https://www.trb.org/Publications/Blurbs/182823.aspx

    - What happens when meter prices are adjusted to better match parking demand with supply?
    - What about meter suspension?
- **Why do people cruise?** No specific use case is presented for this question (although this study provides some insights related to the second question below), but it is an obvious question for Cruise Detector to address.
    - Do people cruise: 1) because no space is available, 2) because no space is available that is free of cost, 3) because no unrestricted (e.g., overnight allowed) space is available, or 4) because of other reasons?
- **How do people cruise?**
    - What are the patterns of a cruising driver?
    - Do these cruising behaviors cluster into types?[17]
    - Given types of cruising behaviors, what policy interventions will reduce cruising?
- **What are the long- and short-term impacts of cruising on congestion**?
    - How do they affect mode choice or car ownership decisions? For example, does reducing cruising promote mode shift to the private car, as finding parking becomes less onerous?

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[17] Adam Millard-Ball, Rachel R. Weinberger, and Robert C. Hampshire, "The Shape of Cruising," Findings (September 15, 2021), https://doi.org/10.32866/001c.28061.

CHAPTER 2. PROJECT DESCRIPTION

METHODOLOGY AND APPROACH

The approach in this project is to create and demonstrate a free, publicly available tool that municipalities and other interested parties can use to understand cruising for parking and the effects of policy interventions on parking search behaviors.

There are two segments to the project: developing a GPS-dependent system, Cruise Detector, to analyze parking search, and a GPS-independent cruise estimator (G-ICE). The methodology for developing each is described in turn.

CRUISE DETECTOR

Cruise Detector uses large data sets comprised of GPS locations (or breadcrumbs) harvested from smartphones or navigation devices. By studying the circuity of paths and concentrations of circuitous paths, an analyst can visualize and quantify the extent of cruising for parking. A circuitous path, defined as 200 meters in excess of a counterfactual shortest path, is designated as excess travel due to parking search, or simply as cruising. Geographic information system (GIS) analysis shows where cruising trips are located within the geography the data are analyzed.

The project developed a methodology and related code to analyze the breadcrumb data. Instructions for how to use the code are given in appendix B. Components of the code are described in detail in a number of journal articles that are incorporated in this document by reference. The process is divided into these steps:

1. Determine streams of GPS location pings that represent travel.
2. Match the GPS data streams to a street network.[18] Each trace match is given a probability score.
    a. If the probability score exceeds a certain user-defined threshold, the match is considered acceptable for analysis.
    b. If the probability score is below the user-defined threshold, the trace is rejected and dropped from further analysis.
3. Build a potential parking search radius around the final location.
4. Determine a shortest path from the search radius boundary to the final location.
5. Compare the path taken with the shortest path.
    a. If the path taken is equal to the shortest path or longer, up to 200 meters, the trip is designated as not cruising.
    b. If the path taken is greater than 200 meters longer than the shortest path, the trip is designated as cruising.
6. Analyze the processed data to gain insight into cruising conditions in the area of interest.

[18] Adam Millard-Ball, Robert C. Hampshire & Rachel R. Weinberger, "Map-Matching Poor-Quality GPS Data in Urban Environments: The pgMapMatch Package," *Transportation Planning and Technology* 42, no 6 (2019): 539-553, 10.1080/03081060.2019.1622249.

Two data approaches to using Cruise Detector are tested. The first approach uses raw location data purchased directly from a data consolidator. This preserves the geometry of the trip, enabling the analyst to aggregate to spatial units and time periods for which there are sufficient data and allowing for insight regarding the actual search paths. The Chicago analysis and some of the Seattle analysis rely on these disaggregate data. The second approach relies on processed output of the system described here. A third-party owns the relevant data and processes the data behind a privacy firewall using the software developed in this project. The output is provided as point data at the street or block group level (or a requested aggregation). The shortcoming of this approach is the inability to understand the parking search path.

Using raw location data purchased from a vendor is likely to be the more common implementation of Cruise Detector. Many such data consolidators are available, and the data will vary from one vendor to the next. In some cases, data may already be segmented into trips, while in other cases the vendor may provide unprocessed GPS points and require the user to clean the data and identify which points represent trips rather than a static location, such as home or work.

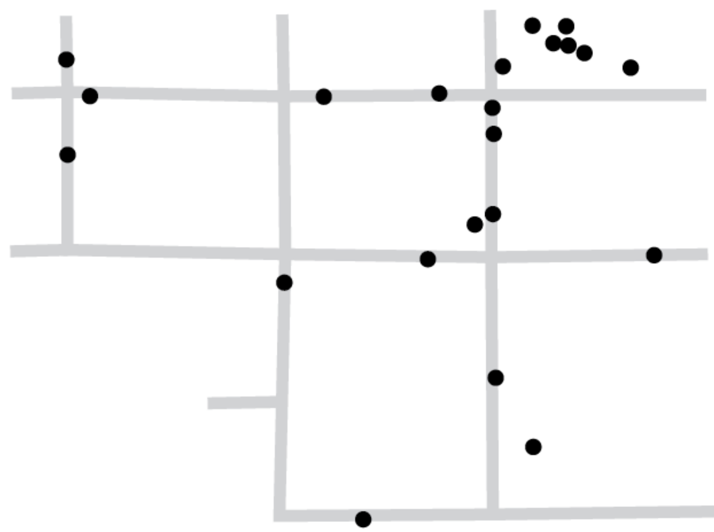
This project does not attempt to assess consolidators, as the relative strengths are highly dynamic. Instead, users of Cruise Detector will have to assess data quality when using the tool. Privacy protections are dynamic and can affect data quality. Even within the time line of this project, applications that had previously broadcast steady streams of location data were modified to allow users to set preferences as to whether data would be transmitted only when that application was in use or at all times. This privacy protection limits the quantity and quality of data that had previously been available. Appendix A provides a data comparison between the processed output and the raw location data.

Determine Streams of Global Positioning System Location Pings That Represent Travel

The data will come in the form of anonymized location data from navigation devices or an unknown set of cellular phone applications. The data are messy and of variable quality but there is generally a large quantity, and sufficient trips can be identified to make inferences about relative frequency of trips and cruising trips. The data are unweighted and not useful for making inferences about the total number of trips or trip lengths.

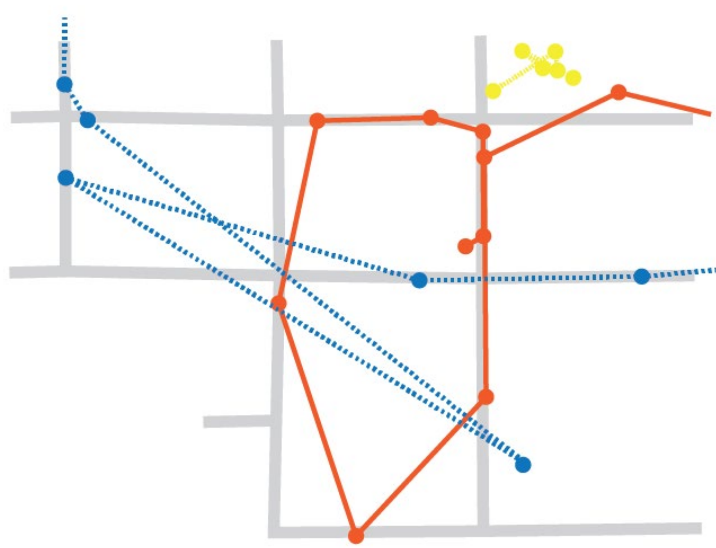
Location pings from each specific device are organized chronologically and linked together to form traces. If there is a 10-minute or greater gap between two location pings, a new trace designating a new trip is formed. To create a trip that can be fitted to a street network, a trace must comprise relatively consistent and frequent pings. A threshold of 90-second intervals is a minimum requirement; otherwise, some cruising trips are likely to be missed and results will be biased downward. Greater frequency is preferred. Pings with low horizontal accuracy, i.e. incorrectly recorded latitude and longitude, are removed. Pings that would require unrealistic travel speeds to get from one location to the next are also removed.

Many of the traces represent only that the transmitting device is being moved around a single location, such as the owner's home or office. To be considered a trip, a minimum distance of 400 meters must exist between the start and the end of the trace. The final trip filter required the trip to be at least 5 minutes in duration. Figure 2 illustrates a series of pings overlaid on a hypothetical street grid. Figure 3 includes lines that link the dots in chronological order. The various groupings show 10-minute or greater gaps between the end of one trace and the beginning of the next. Once the trips are established they are matched to a map so useful comparisons to network paths can be made.



Source: FHWA.

Figure 2. Illustration. Locations overlaid on a hypothetical street grid.

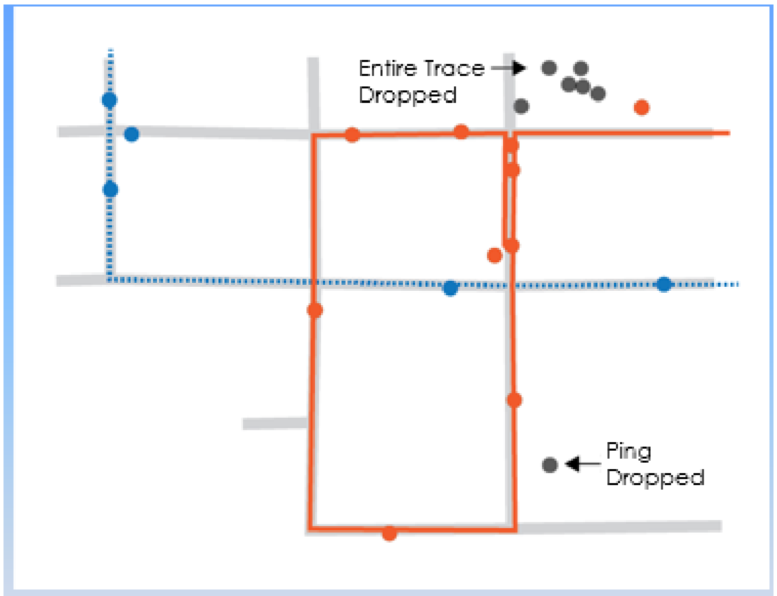


Source: FHWA.

Figure 3. Illustration. Locations linked chronologically.

Match the Global Positioning System Data Streams to a Street Network

Figure 4 shows how the trace is aligned to the street grid. The cluster in the top-right of the figure fails the criterion of 400 meters from beginning to end; it is therefore rejected as a trip (it may well represent someone walking around a home or an office). The ping in the bottom-right of the figure that attaches to points in the top-left of the figure fails the credible speed test and is also eliminated. After these trip parsing and data cleaning steps, the mapmatch algorithm determines the most likely path a trip will have taken.



Source: FHWA.

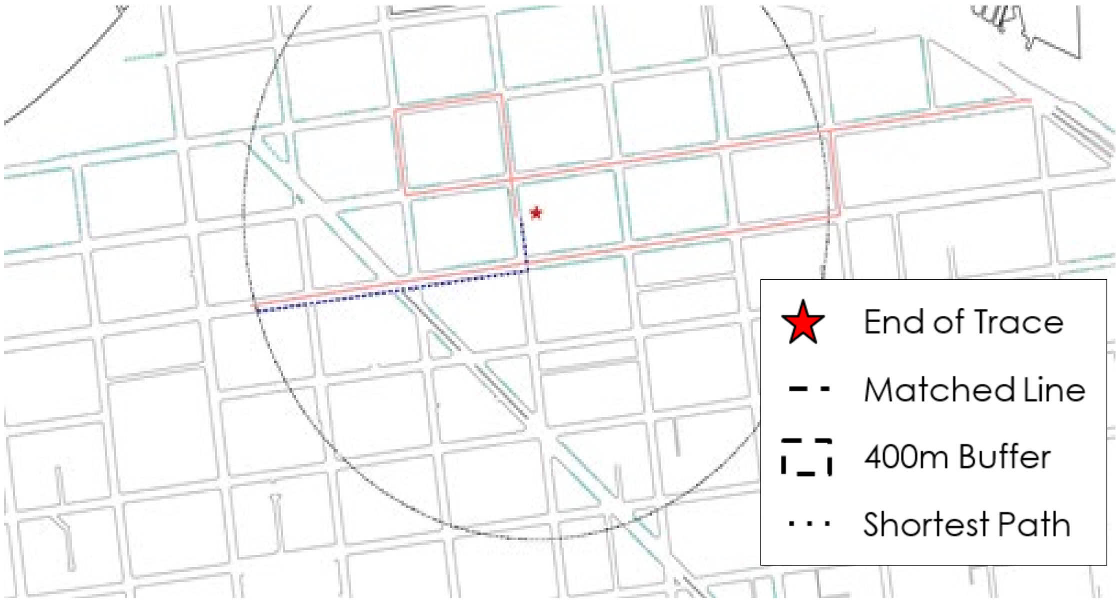
Figure 4. Illustration. Probable trips.

The matching relies on a probabilistic model that considers candidate streets on which a ping might actually belong; from there, the actual path is estimated with probability.[19] Each trace is given a score reflecting the likelihood it is correctly matched to the underlying street grid. The analyst would select and only use the ones that meet a threshold for likelihood of being a good match.

Build a Potential Parking Search Radius around the Final Location

The next three steps are to: 1) build a parking search radius around the end point of each trip, 2) determine the shortest path between the trip end point and the point of entry to the search radius, and 3) map the actual path taken from the point of entry to the trip end point. Figure 5 shows all three steps. The star in Figure 5 indicates the final ping of the trip, the dashed line shows the path taken, and the dotted line shows the shortest path. In this example, the path taken exceeds the shortest path by over 200 meters and the trip is identified as cruising.

[19] Adam Millard-Ball, Robert C. Hampshire & Rachel R. Weinberger, Map-Matching Poor-Quality GPS Data in Urban Environments: The pgMapMatch Package" (2019).



Source: FHWA. Map data ©2022 OpenStreetMap® contributors.

Figure 5. Illustration. Cruising: identified when paths traveled exceed shortest paths.

It is assumed that drivers do not begin searching for parking until they are 400 meters from their final location. The trace is truncated so that it includes all points after it enters the 400-meter radius, plus the preceding point. The trace can enter and leave the 400-meter radius several times—for example, if drivers cruise for parking over an extended area. Figure 5 illustrates the boundary and a hypothetical trip that has left and reentered the search area.

Determine a Shortest Path from the Search Radius Boundary to the Final Location

The pgRouting package is used to calculate the shortest path to their final location from when the driver first enters the 400-meter radius. The path takes account of one-way streets and turn restrictions, provided they are correctly mapped in the underlying street network data. This analysis uses OpenStreetMap® data, which is high quality and freely available. Again, refer to Figure 5.

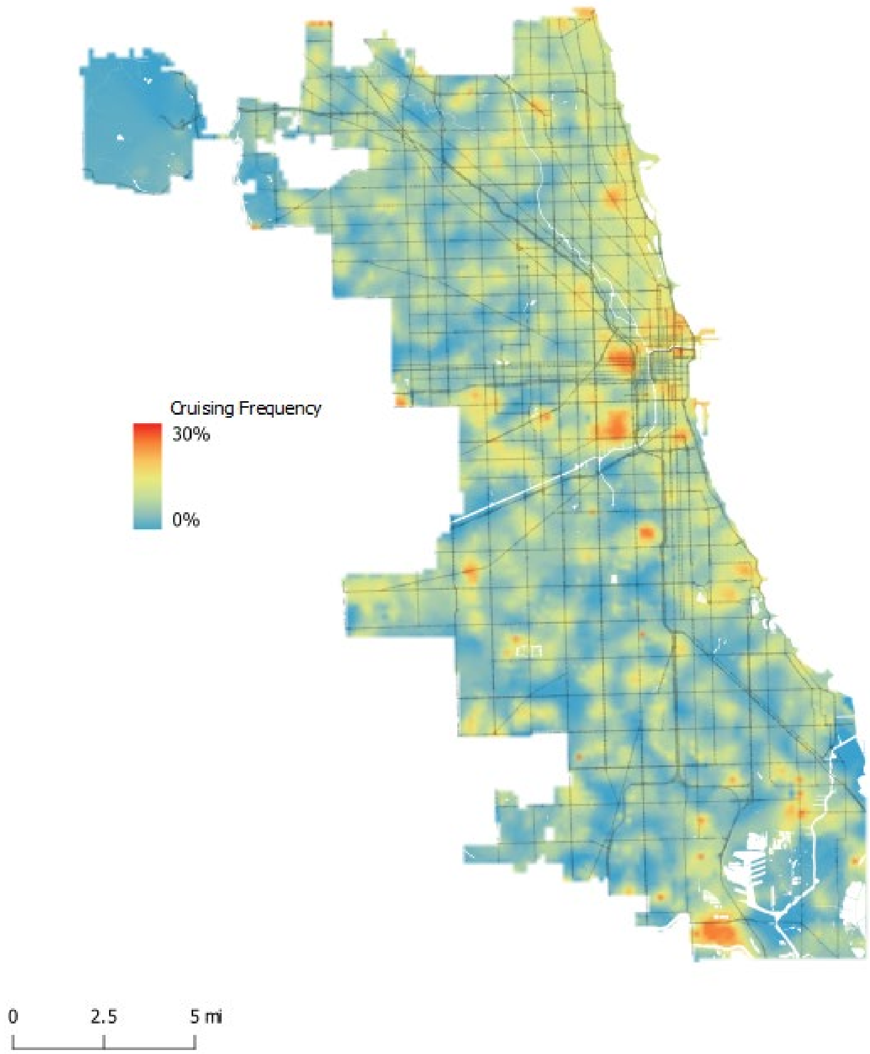
Compare the Path Taken with the Shortest Path

The difference between the actual (map-matched) path and the shortest path indicates whether cruising occurs. If the difference is greater than 200 meters, the trip is classified as cruising. If the difference is zero, the driver takes the most direct route and no cruising occurs. The 200-meter threshold[20] is used because small deviations from the shorter path are generally due to irregularities in the street grid or other imperceptible differences to the driver.

[20] Rachel Weinberger, Adam Millard-Ball, & Robert Hampshire, Parking search caused congestion: Where's all the fuss?. Transportation Research Part C: Emerging Technologies (2020). 120. 102781. 10.1016/j.trc.2020.102781.

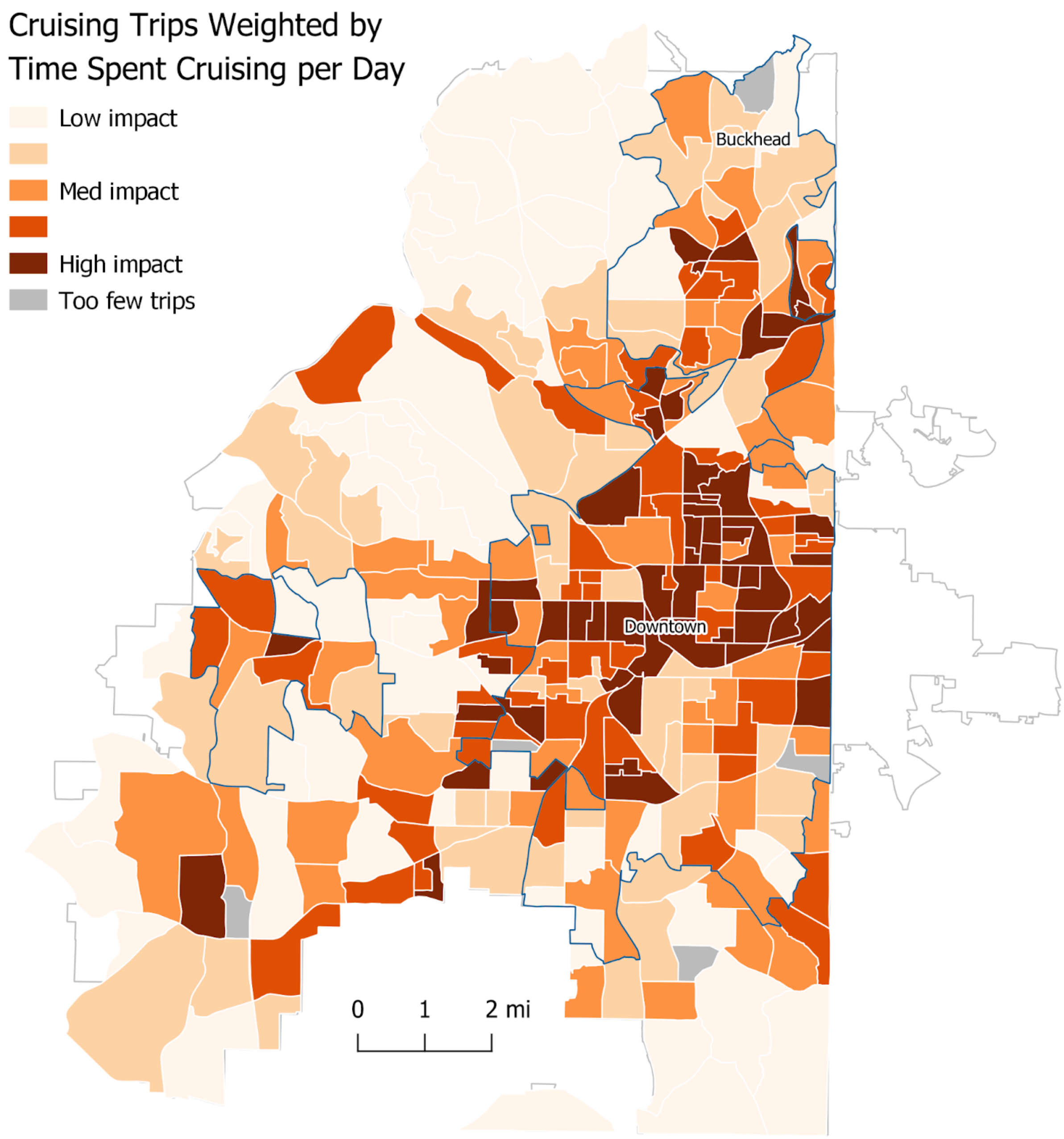
Analyze the Processed Data to Gain Insight into Cruising Conditions

The final step is to analyze the processed trips. Chapter 3 provides four use cases that demonstrate how the data can be analyzed. Statistics of interest could include average time spent cruising in different parts of a city or at different times of day, before-after-analyses bracketing a policy change, or location of cruising hot spots. Analysis can be presented as maps. Figure 6 shows cruising in Chicago based on disaggregate data and Figure 7 shows cruising in Atlanta based on data aggregated to the census block group level. Analysis can also be presented as a tabulation, as shown in Table 1, or a graph, as shown in Figure 8.



Source: FHWA.

Figure 6. Map. Example showing Chicago cruising hot spots disaggregate data.

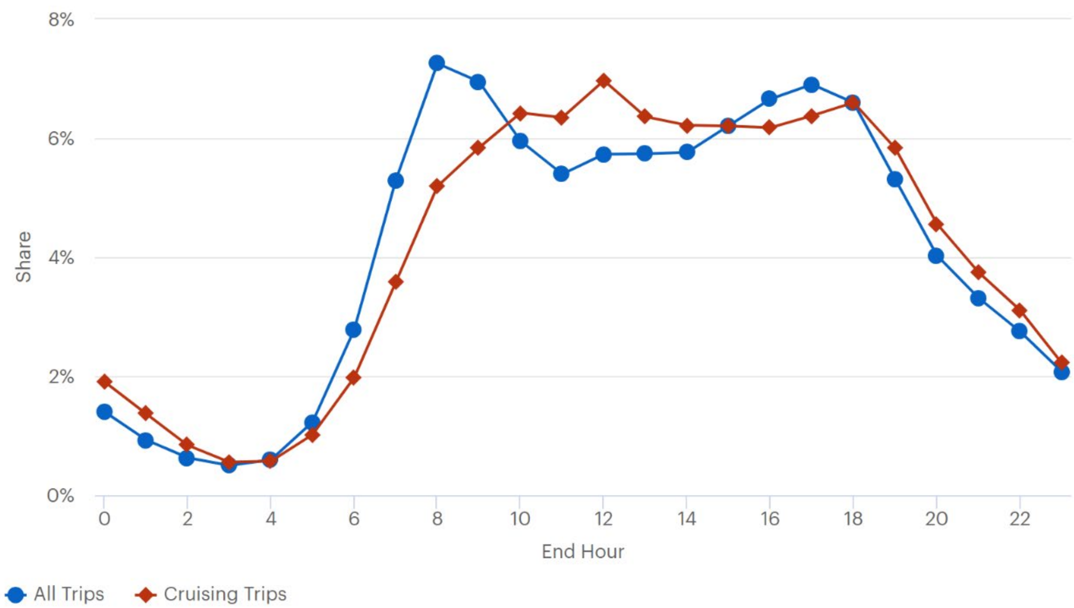


Source: FHWA.

Figure 7. Map. Example showing Atlanta cruising hot spots aggregate data.

Table 1. Seattle mean cruising time by street type and time of day, in seconds.

Street Type	2–4 p.m.	6–8 p.m.	Other Times
Metered streets	148	140	113
Near metered	110	117	111
Non-metered	57	49	56



Source: FHWA.

Figure 8. Graph. Example showing diurnal distribution of trips and cruising trips Washington, DC.

The project used and tested two primary data sources in the project execution. The first data source and accompanying basic analysis accrue to a GPS data aggregator that provides other transportation planning data analysis. The code developed in this project was given to the data aggregator and run on its secure server. The aggregator's data represent trips inferred from large samples of location data collected from smartphone applications. The second data source is also a GPS data aggregator that sells data, but it does not provide other data analysis services. Using these location data, the project team inferred directly from raw location data and conducted further analysis to determine the extent of cruising.

CODE DEVELOPMENT

Cruise Detector uses three bespoke software processes. The first process converts location data into trips. The second process is a map-matching algorithm that snaps the trips to a transportation network so the trips can be analyzed and compared against an underlying transportation network; this is done to make a fair comparison to shortest path. This process determines the likelihood that a series of location points is correctly aligned with a known underlying geographic path. The third process compares trips to a potential shortest path and determines, with probability, whether a trip implied excess driving in pursuit of a parking place. Appendix B provides instructions for using the code.

GLOBAL POSITIONING SYSTEM-INDEPENDENT CRUISING ESTIMATES MODEL

Not every jurisdiction will be able to obtain GPS data, or GPS data of sufficient quantity and quality to be of use. A project goal had been to develop G-ICE, a GPS-independent cruise estimator. After several development attempts, the project team determined that, based on the data available, an effective tool could not be developed. Appendix C provides details of this effort.

CHAPTER 3. SPECIFIC CITY FINDINGS

The use cases provide baseline information for each location, followed by a comparison to the baseline. The Washington, DC, and Atlanta cases rely on processed output from the third-party GPS aggregator. The aggregator analyzed its data for trips and cruising trips using the system developed by the Federal Highway Administration (FHWA) and this project team. The research team specified 15,000 geographies (i.e., streets or aggregations of streets—in this case, sometimes census block groups). The limit was a contract condition of the aggregator/processor. Thus, individual results for each street face were unobtainable. Instead, street faces of particular interest were specified with other results aggregated to the census block group level. For the Washington, DC, and Atlanta cases, the data are therefore presented at the block group level with more detailed analysis into the areas where street faces have been specified.

The Chicago analysis uses raw location data that were processed by the project team. In the Chicago case, data are available at the street-face level for wherever trips have been made. The Seattle case includes processed output by the third-party GPS aggregator and analysis based on individual location data provided by a data broker. The approach in Seattle was designed to facilitate comparisons between the two different data sources.

Each case answers certain questions, but also raises questions related to data sources and interpretation that can be mediated in future analyses. For example, the Seattle case shows an increase in cruising on metered blocks after a price change. Given that the analysis is based on locations of trip ends and not cruising paths, the meaning of that finding is unclear. From the trip end locations alone, the analyst knows with certainty where the trip ends, but not the process of parking search. The following possible interpretations are listed in order of likelihood, based on professional judgment:

- Drivers cruised for parking and more quickly found a spot on a metered street because the price change affected availability as intended.
- Drivers reacted to the price increase and searched for a better bargain. Quickly realizing a bargain was not to be had, the driver accepted a vacant space on the metered block.
  - This problem might resolve itself and can be studied again after the market has had time to absorb the price shock.
  - This may be an unintended consequence of the policy change.
- The policy change had no effect on availability; other research[21,22] has shown that multiple price changes may be needed before a change in driver behavior can be measured.

Similarly, in the Chicago case, data were analyzed for the month of June across 3 years. Data for the third year were poor quality and were not useful for the analysis. The analysis shows

[21] A. Millard-Ball, R. Weinberger, and R. Hampshire. 2014 “Is the Curb 80% Full or 20% Empty? Assessing the Impacts of San Francisco’s Parking Pricing Experiment” Transportation Research Part A Vol.63, 2014, pp. 76-92.

[22] A. Millard-Ball, R. Weinberger and R.C Hampshire. 2013. “Comment on Pierce and Shoup, Evaluating the impacts of performance-based parking” *Journal of the American Planning Association*, 79(4) 330-336.

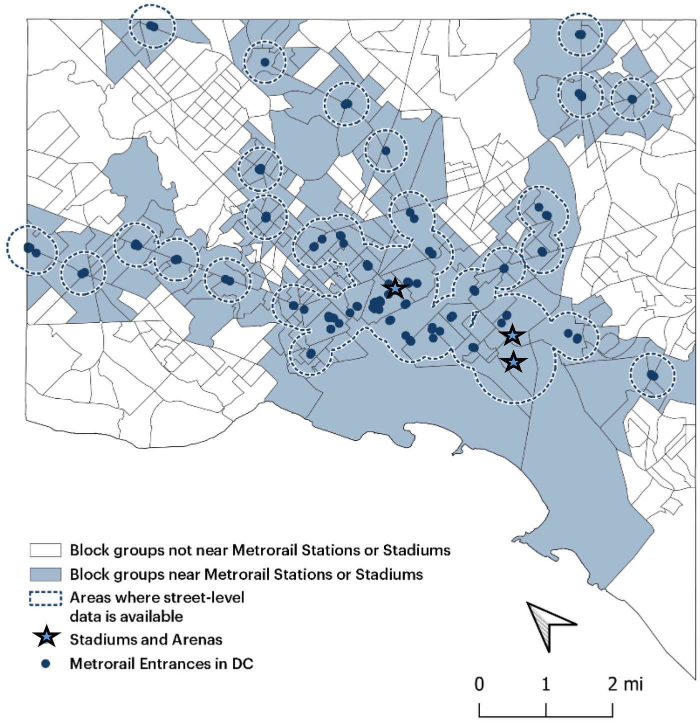
potentially important differences between the 2 years for which there are good data. However, given the experiment, whether the observed differences are true differences or sampling differences is unclear. Had the analysis been strictly an analysis of Chicago, rather than a study of use cases for broad application, the recommended approach would be to acquire additional data to corroborate the findings. Instead, the analysis is presented with these caveats. While the results are potentially interesting, caution should be exercised when drawing conclusions as abstraction may not be justified on the basis of this analysis.

The following sections show baseline and comparative case conditions for Washington, DC; Atlanta; Chicago; and Seattle in that order. The Seattle case comprises multiple analyses showing a business-as-usual meter price adjustment—a special case wherein all metered pricing is revoked, and a data comparison showing the benefits and shortcomings of two different data sources.

WASHINGTON, DC: CROSS-SECTIONAL ANALYSIS FOCUS ON METRORAIL STATIONS

Washington, DC, has a varied landscape with respect to density, activity type, and transportation infrastructure. The focus in this case study is cruising for parking across Washington, DC. Special attention is focused on three sports stadiums, and when the stadiums have and do not have events planned. The analysis also emphasizes cruising in the areas around Metrorail stations. Washington, DC, data span January 1–December 3, 2018. In lieu of a specific policy change that would lead to a before/after analysis, the findings here are cross-sectional, illustrating different cruising patterns for different urban forms: specifically proximate to Metrorail versus beyond the Metrorail catchment areas.

The data have been processed by a third-party data consolidator. This analysis is based on a data set of trip ends by time of day. Figure 9 illustrates the study area indicating the streets for which street-level data are available.



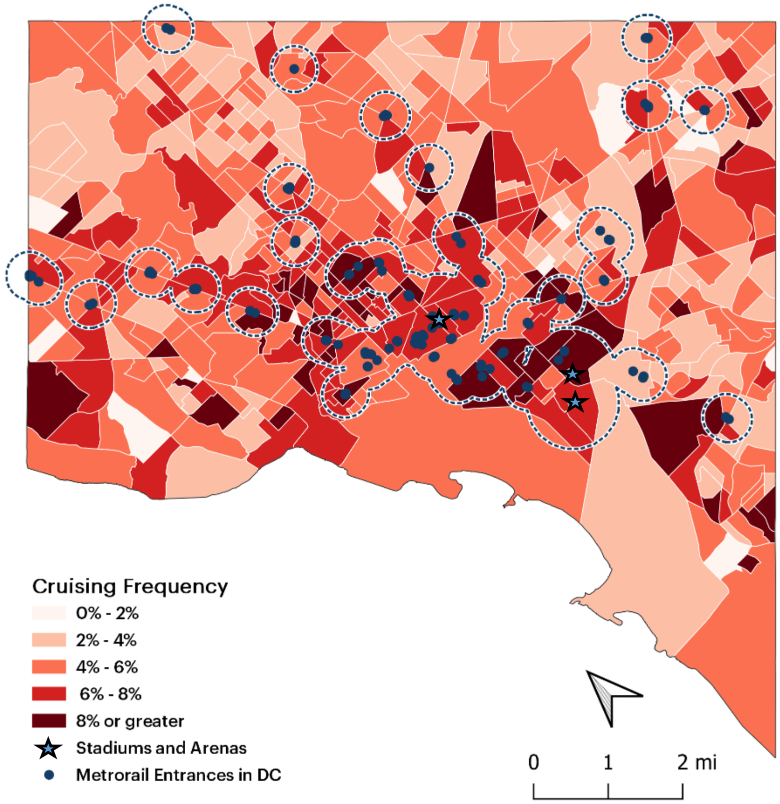
Source: FHWA.

Figure 9. Map. Washington, DC, study area.

Where Cruising Occurs

Cruising is higher in the areas around Metrorail stations where there is an overall higher concentration of trips relative to street length. The streets in the Metrorail catchments comprise 23 percent of Washington, DC, street length and account for 45 percent of trip ends. Thus, the trip intensity in the Metrorail catchment area is almost twice what it would be if trips were evenly distributed throughout the street network. Cruising is almost evenly split between the Metrorail catchment areas and the rest of the city (51/49), meaning that half of the cruising is concentrated on about one-quarter of the streets. In comparing trips, cruising trips are slightly disproportionately represented near the Metrorail stations (45 percent of trips and 51 percent of cruising trips) and heavily concentrated there on a street-length basis (51 percent of cruising trips and 23 percent of street miles).

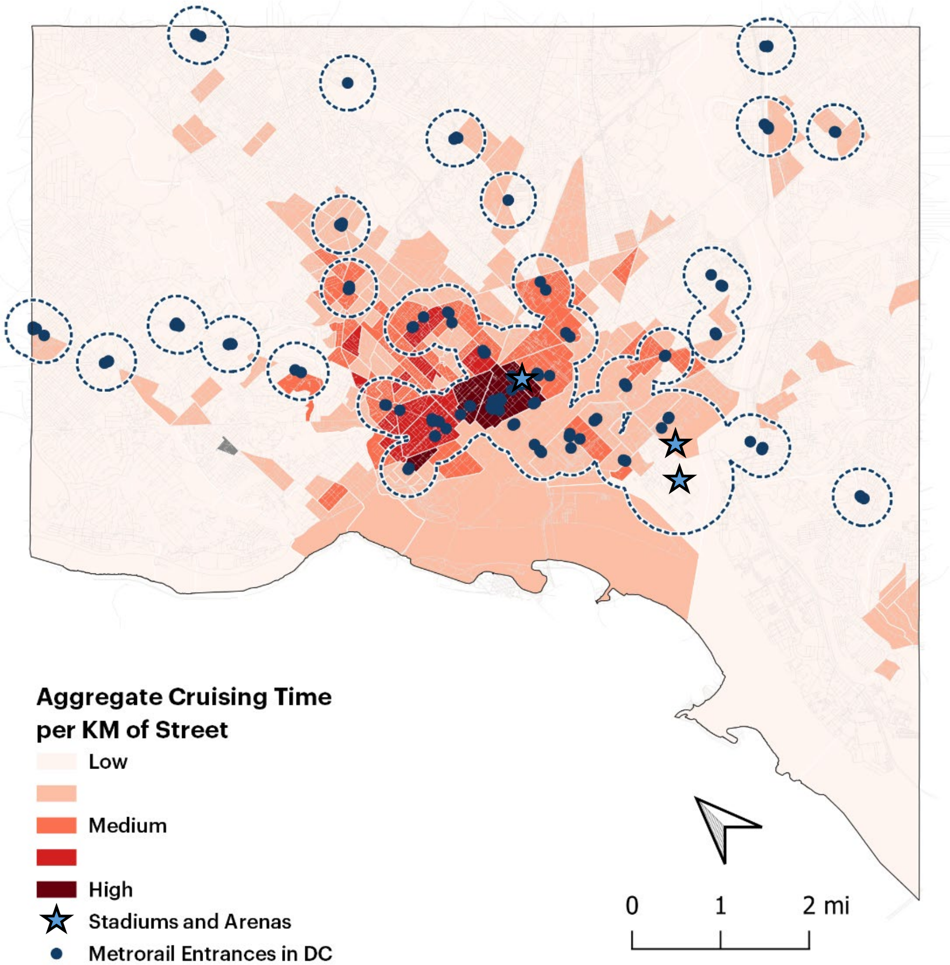
Washington, DC, has an aggregate cruising rate of 5.8 percent and 6.6 percent around Metrorail stations where the concentration of all trips (cruising or not) is very high. Figure 10 shows cruising frequency by block group. To avoid the potential problem of statistical outliers, areas with fewer than 30 observations are not shown.



Source: FHWA.

Figure 10. Map. Washington, DC, cruising frequency.

The amount of time spent cruising and the distance cruised are also important urban concerns. The average length of a cruising trip is just over 2 minutes, but the time can vary substantially. Figure 11 captures and ranks cruising in Washington, DC, by showing the aggregate time spent cruising in each block group. The block group average cruise time is weighted by the number of trips for which cruising is a component; this aggregate is divided by the street length of each block group to account for differences in size (i.e., if one block group has twice as much land area and corresponding street length than another, more trips relative to the smaller block group are expected). The modified measure is average time spent cruising per block within each block group.



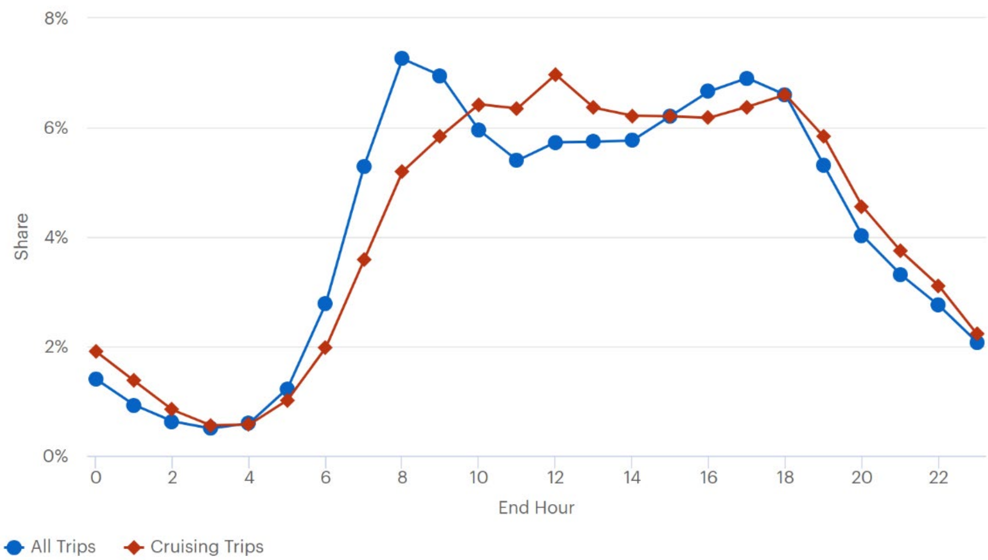
Source: FHWA.

Figure 11. Map. Washington, DC, cruising impact.

When Cruising Occurs

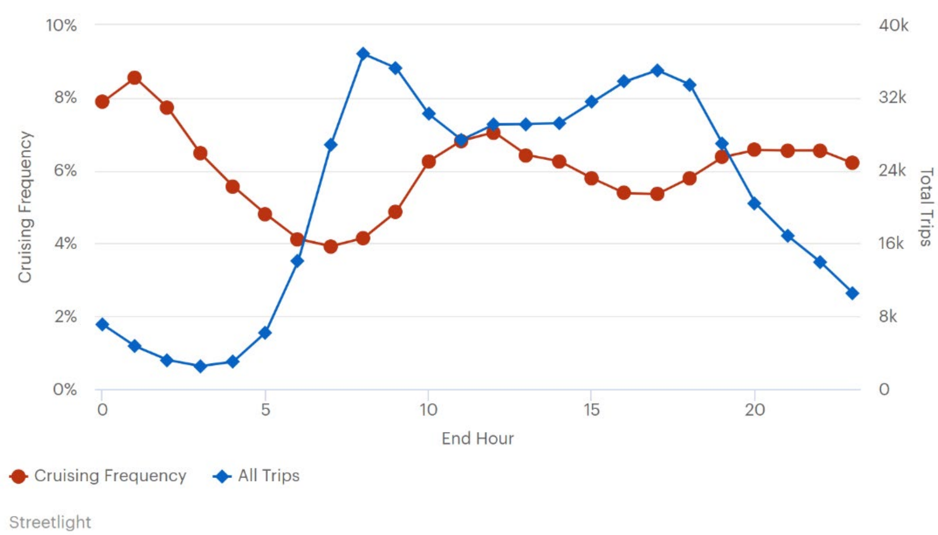
Figure 12 shows the diurnal distribution of all trips and trips that include cruising. Cruising trip intensity lags trip making. This can be interpreted as resulting from earlier trips using available parking leaving fewer spaces open for later trips, which can show up as cruising. Other ways of looking at the data follow; the primary hypothesis holds.

Figure 13 shows the diurnal pattern of trip making with traditional morning and afternoon peaks, superimposed on the rate of cruising (number of cruising trips/number of trips). The rate of cruising is highest in the hours just past midnight, although that coincides with the time of lowest trip making and fewest absolute cruising trips (see Figure 14 for cruising trips by time of day). Cruising is lowest during the morning peak travel period and increases as the day wears on. A probable explanation for higher levels of cruising during midday and early dawn is that most people will have reached their destinations and parked at those times, leaving a relative scarcity of available spaces. This is the same phenomenon shown in Figure 12 as a lag. Early arrivers get the spaces, which leaves none for those who come after. At the same time, there is likely both more turnover and more availability during the traditional travel peaks, as some travelers are departing, others arriving, and many others en route somewhere.



Source: FHWA.

Figure 12. Graph. Diurnal distirbution of all trips and cruising trips.

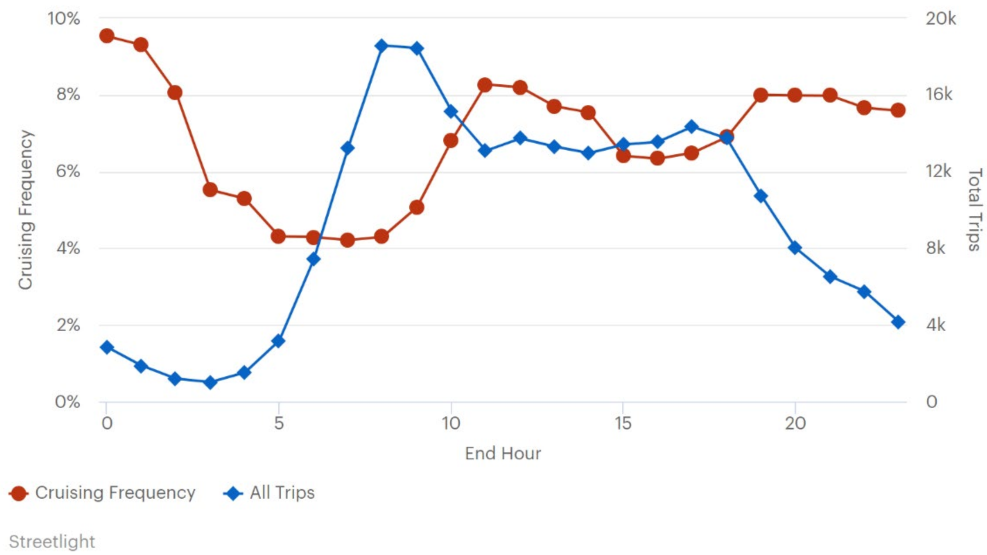


Source: FHWA.

Figure 13. Graph. Cruising frequency and overall trip making.

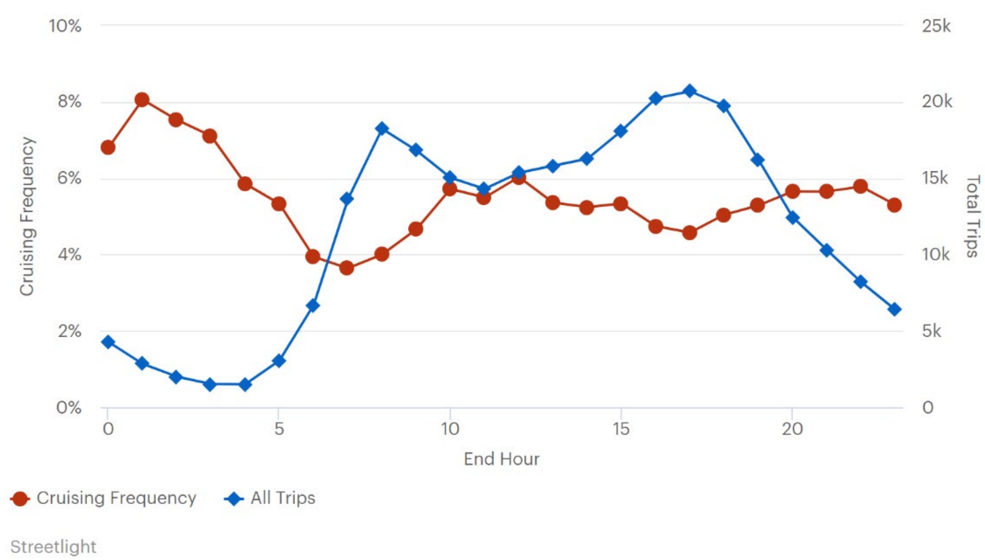
A close look at the Metrorail catchment areas shows a similar pattern. Trip making is highest in the morning peak period, when the proportion of cruising trips is low. As more trips have been completed and more parking spaces used, the relative difficulty of parking increases and cruising trips as a proportion of all trips begins to rise. As more trips are made in the traditional afternoon peak, parking eases—demand may drop at the same time that supply increases—and cruising as a proportion of all trips declines. Cruising as a percent of all trips is relatively stable in the

Metrorail catchment area, climbing between 8 and 11 a.m. and remaining between 6 and 8 percent through the afternoon and evening.



Source: FHWA.

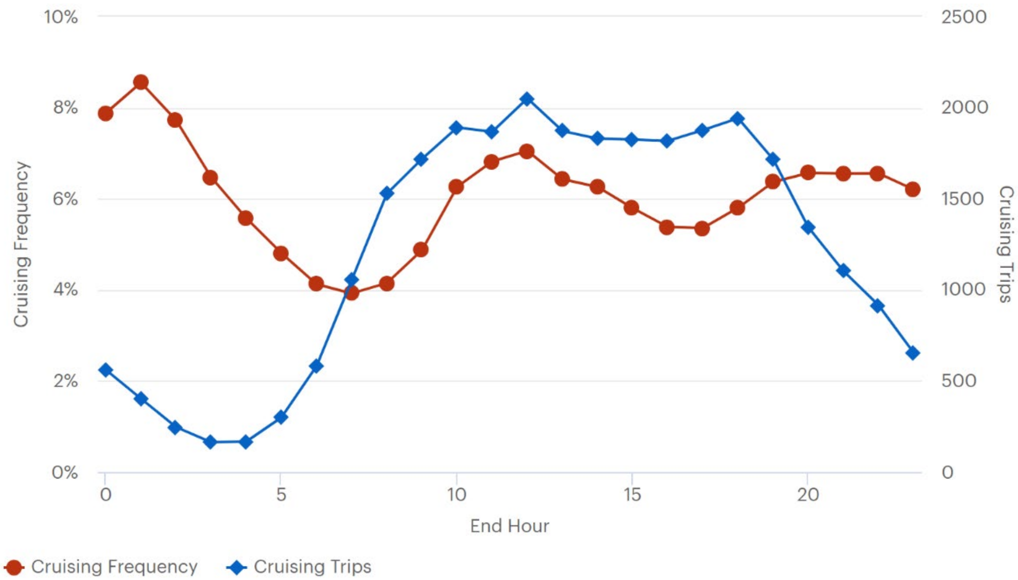
Figure 14. Graph. Cruising frequency and total trips, Metrorail catchment area.



Source: FHWA.

Figure 15. Graph. Cruising frequency and total trips, outside Metrorail catchment.

Figure 16 shows what time of day cruising trips occur, superimposed with the frequency relative to all trip making. From the perspective of when cruising occurs in Washington, DC, the highest occurrence is during traditional business hours. Cruising trips are increasing as a proportion of total trips and in absolute numbers from 8 a.m. to about noon; thereafter, the hourly rate of cruising remains relatively steady until about 6 p.m., when it begins to drop off sharply. However, as a percent of all trip making, cruising trips decline from noon to about 5 p.m., at which time they increase again relative to all trip making. Most noteworthy is the late afternoon/early evening period when absolute cruising is near its highest but as a percentage of trips it is relatively low.



Source: FHWA.

Figure 16. Graph. Diurnal distribution of cruising and cruising as percent of all trips.

The team hypothesized that cruising on stadium event days might be more intense than on other days, but the analysis does not support that finding. All Washington, DC, stadiums are relatively easily accessed by Metrorail, and additional impacts were not detected.

Summary

Overall cruising rates in Washington, DC, tend to the national average at around 5.8 percent of trips. Both trip making and cruising are highly concentrated on the streets surrounding Metrorail stations. These streets comprise about 23 percent of street miles. However, 45 percent of trips end on streets in the Metrorail catchment and 51 percent of cruising trips end on streets in the Metrorail catchment areas. This disproportion puts the cruise rate for trips ending near Metrorail at 6.6 percent. Cruising impact is further concentrated in the area considered downtown Washington, DC.

The diurnal distribution of cruising trips is similar to findings in other cities in that there is a trip-making lag. Cruising for parking as a proportion of trips is at its lowest during the morning commute hours and steadily builds from there, peaking at midday. Cruising as a percent of all trips hits a local minimum during the afternoon commuting peak, increasing into the evening. Finally, it appears from these data that cruising is not exacerbated by events held at the Washington, DC, stadiums, which are relatively well served by transit.

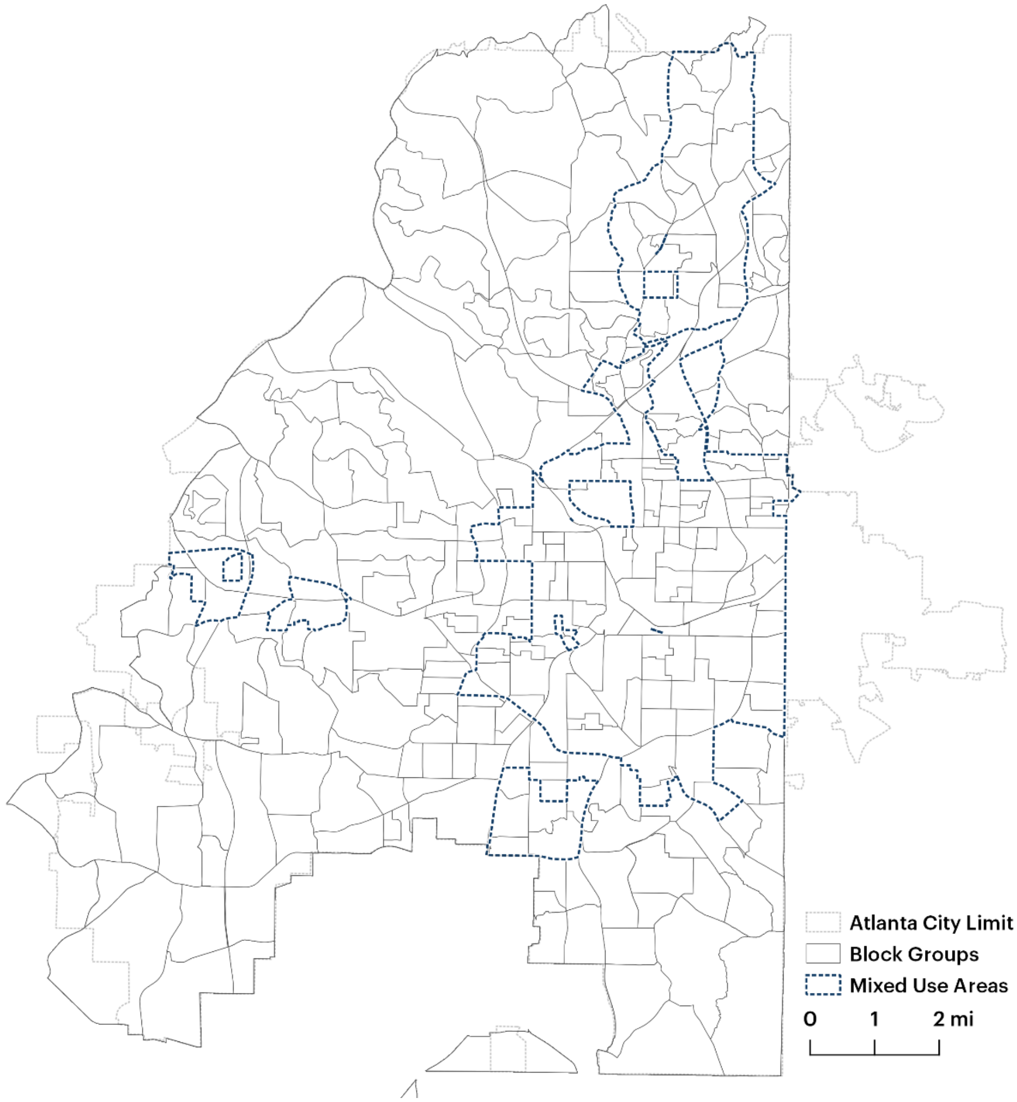
ATLANTA, GEORGIA: LONGITUDINAL ANALYSIS AND MIXED-USE FOCUS

In this case study, the research team explored the geography of cruising across two different time periods. To the extent possible, the research team looked at the differences in single use versus mixed use areas. The data span from October 2019 to September 2020 and covered the areas of Atlanta located in Fulton County.

There are two defined periods within this time frame:

- Baseline: October 1, 2019–March 31, 2020, with a carve-out for the holiday period from November 25, 2019, to January 5, 2020
- Early COVID: April 1, 2020–September 30, 2020

The data are processed by a third-party data broker and results are reported at census block group level for much of the city in Figure 17). Street level outputs are available for the areas outlined and shown in green; these streets are characterized as mixed use. The data reported refer to the end locations of cruising trips. The area of detail (i.e., mixed use areas) includes downtown Atlanta and Buckhead.



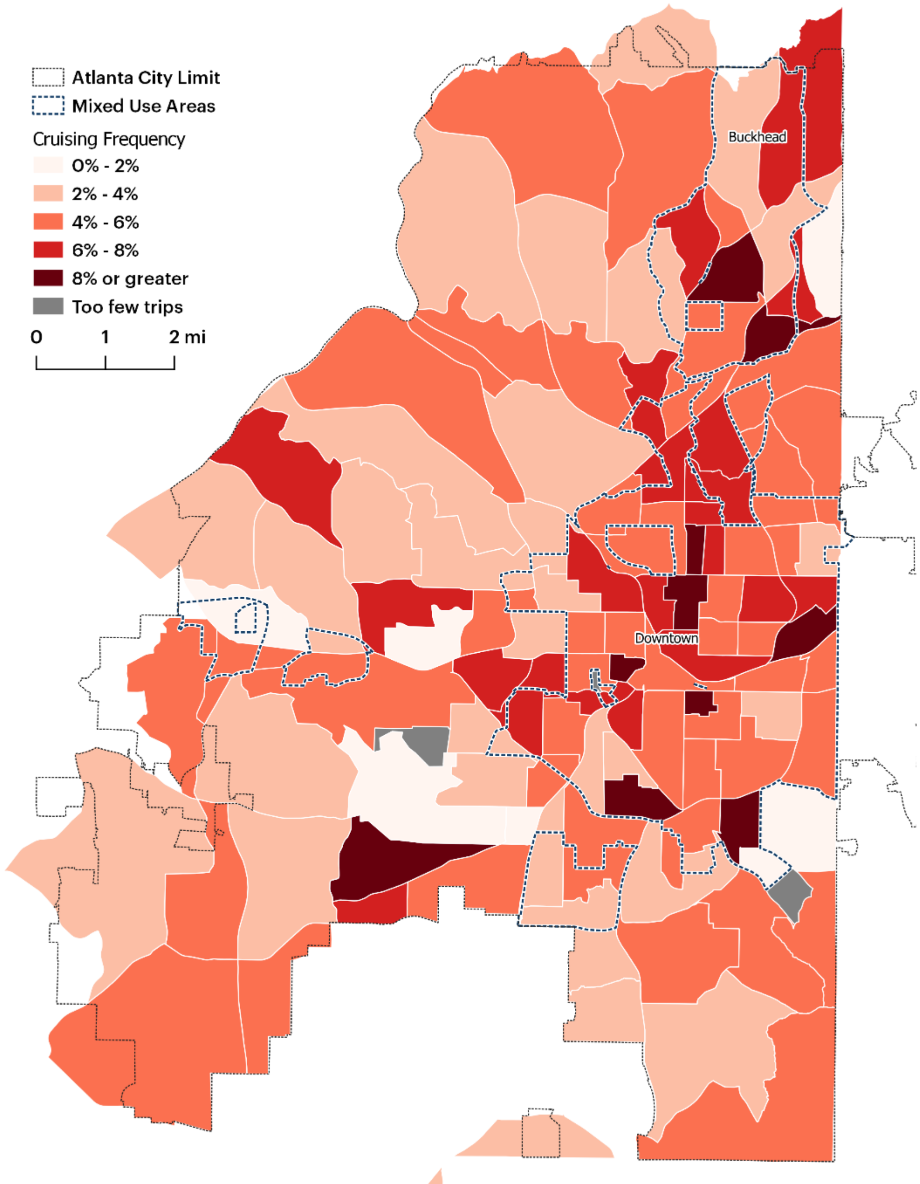
Source: FHWA

Figure 17. Map. Atlanta study area.

Where Cruising Occurs

Figure 18 shows cruising frequency by census tract. Tracts that had fewer than 30 trips were excluded from the analysis The outline delineates the areas for which street-level output is available. These subareas are examined in greater detail later in this chapter.

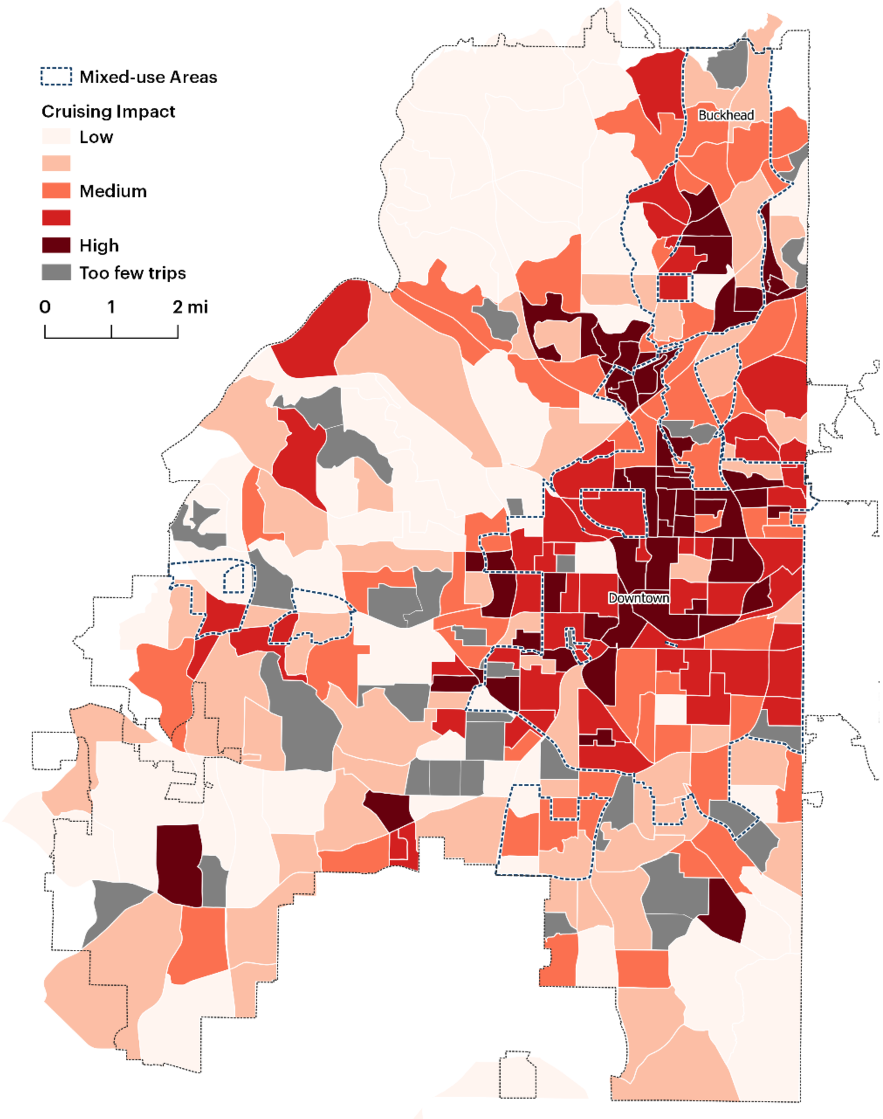
The baseline average weekday cruising rate in Atlanta is 4.9 percent of trips; the 75th percentile rate for block groups is 6.5 percent, suggesting very little variation. In mixed use neighborhoods, those for which the project team was able to analyze street-level data, baseline cruising averages 7.4 percent.



Source: FHWA.

Figure 18. Map. Baseline cruising Atlanta.

Not all cruising is equal, and although the mean time spent looking for parking among cruising trips is under 2 minutes, it can vary. Figure 19 shows total cruising time for each block group by weighting the average cruising time by the number of cruising trips that occur. To account for the different sizes of block groups, the result is normalized by the street length within each block group. The darkest areas in figure 3 indicate the areas of Atlanta with the most severe cruising concern.



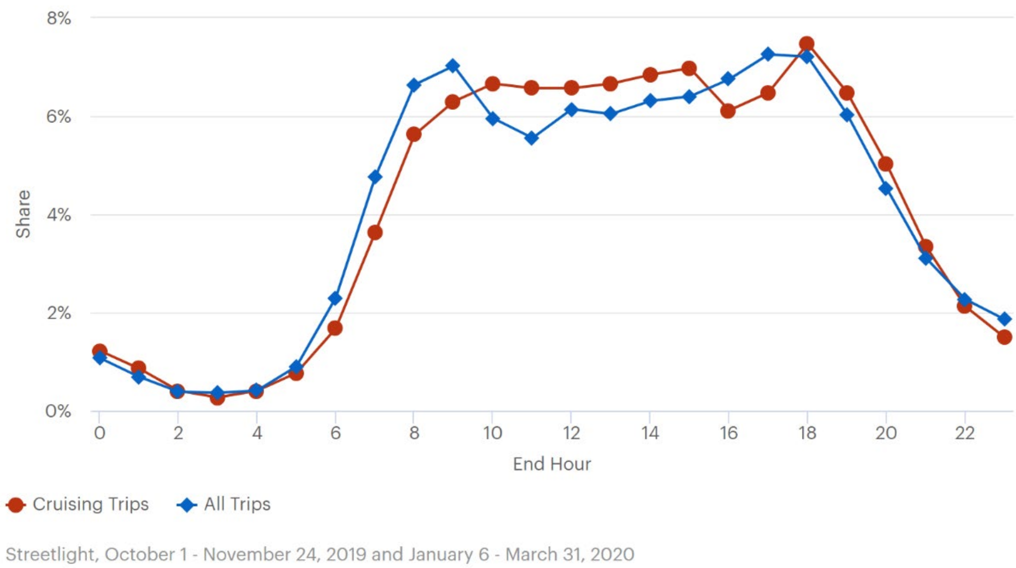
Source: FHWA.

Figure 19. Map. Cruising impact.

When Cruising Occurs

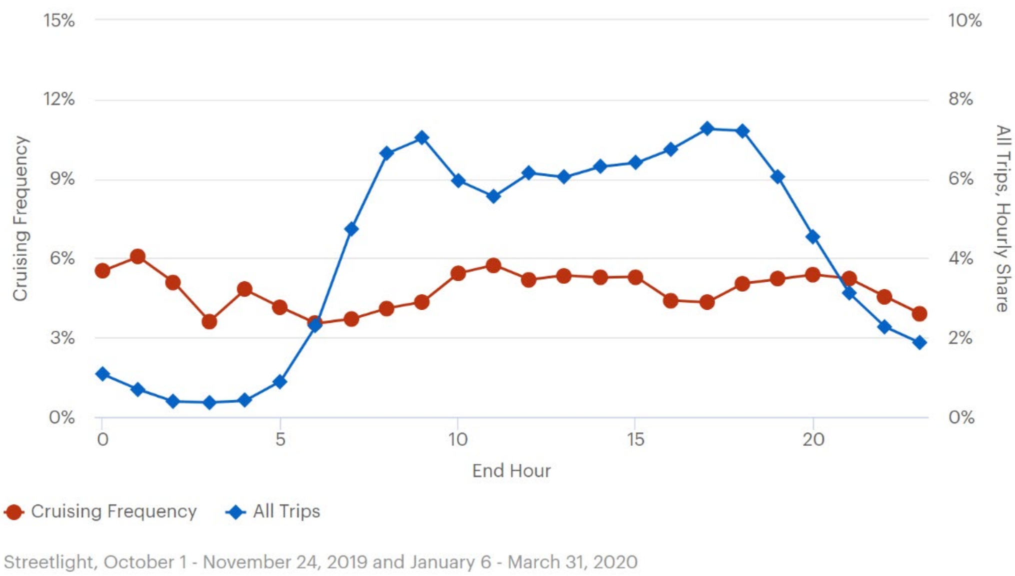
Figure 20 illustrates cruising over the course of an average weekday in Atlanta. As occurs in other cities, cruising tends to lag trip making—the first arrivers would easily find parking. Cruising disproportionately occurs starting around 6 a.m., earlier than is seen in other cities, but possibly due to the relative paucity of on-street parking. The proportion of cruising trips drops sharply along with all trips after 7 p.m.

Cruising, as a proportion of all trips, is relatively stable, remaining between 4 and 6 percent of trips throughout the day. There is a small spike at around 1 a.m., as is documented in other cities, when trip making is at its lowest. This is illustrated in Figure 21.



Source: FHWA.

Figure 20. Graph. Diurnal distirbution of all trips and cruising trips.

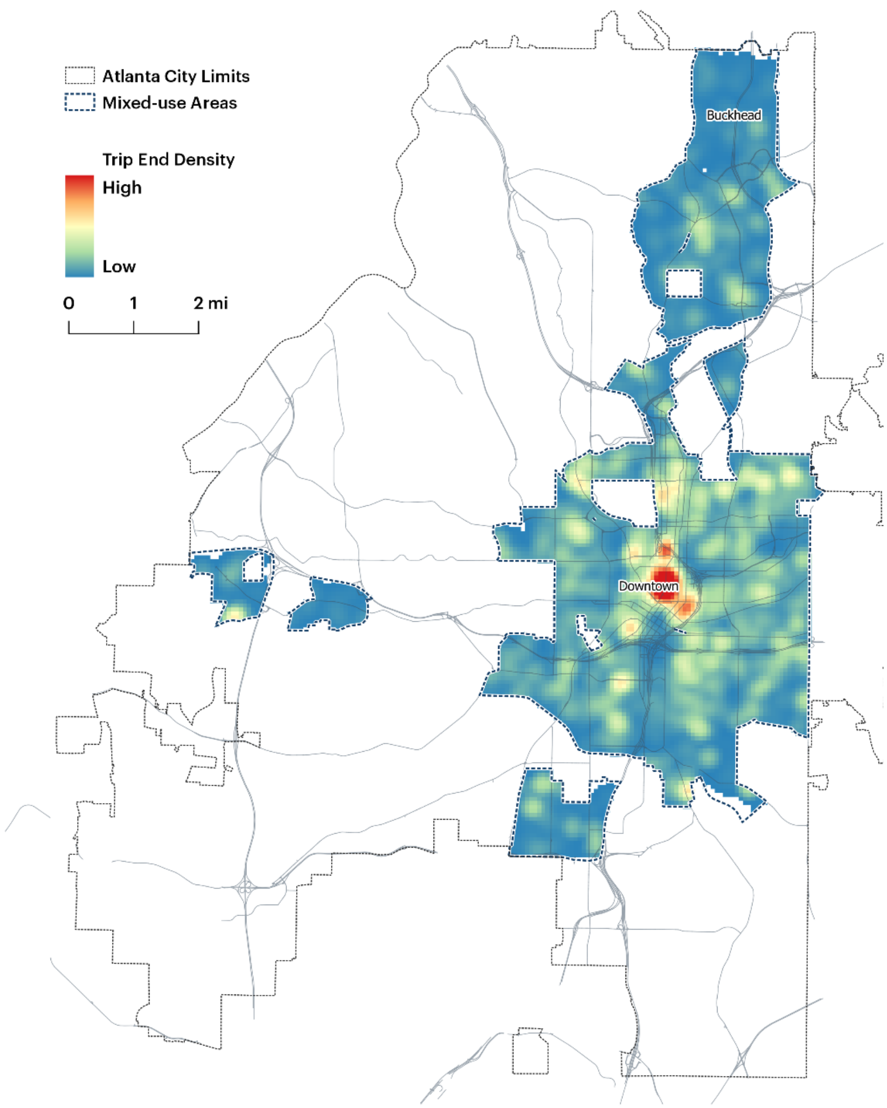


Source: FHWA.

Figure 21. Graph. Cruising frequency and overall trip making.

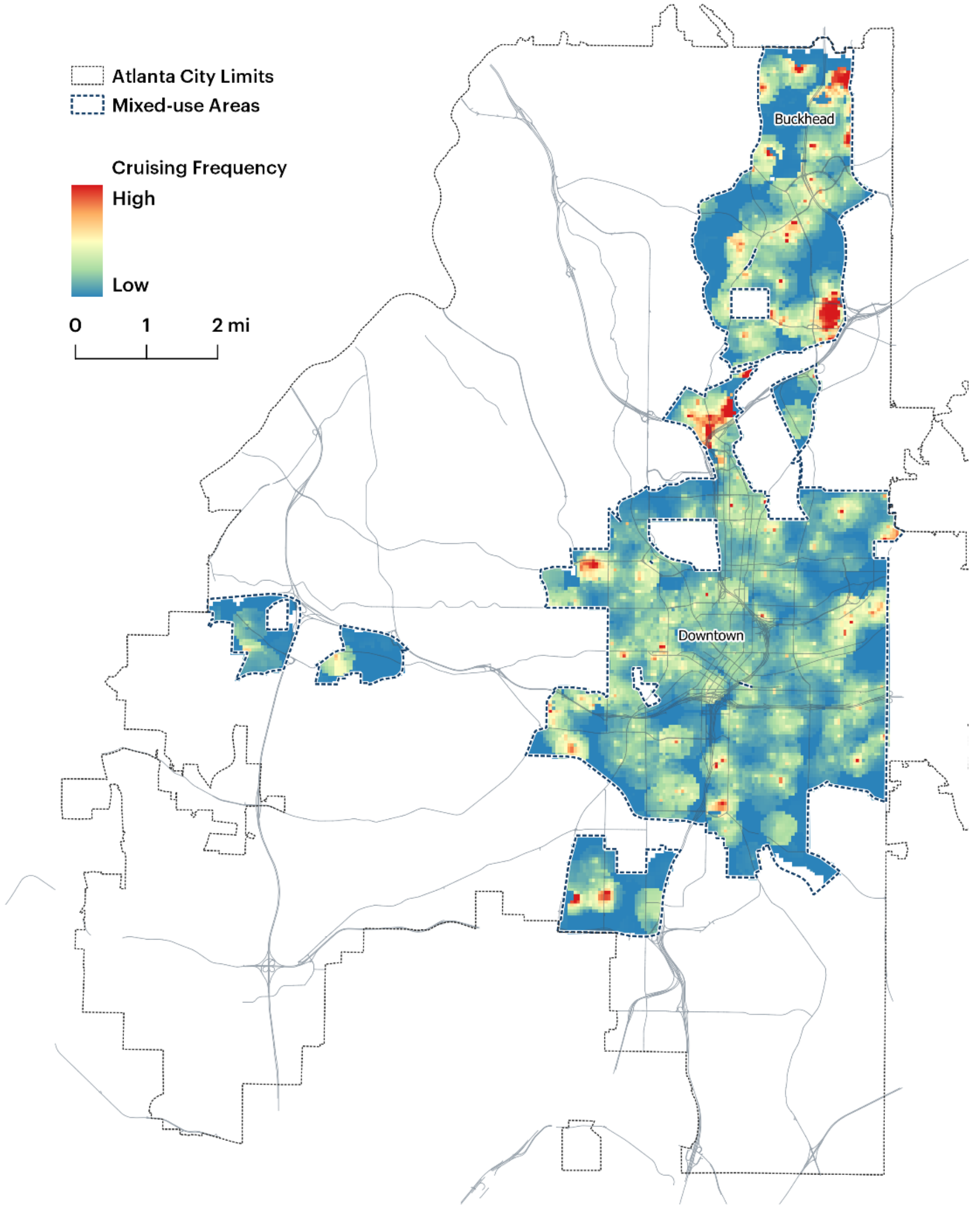
Downtown and Buckhead

The analysis in this section is of street-level data; it provides a close up of what is happening in downtown Atlanta and Buckhead. The streets were selected for the characteristic of having mixed land use. Figure 22 exploits the block-specific trip end data to show, for the smaller area, where trips end. The highest trip density is heavily concentrated in the center of downtown. Figure 23 shows the frequency of cruising. Almost no cruising occurs where the most trips end; instead, there are small pockets of high-intensity cruising scattered throughout downtown with some of the most intense cruising hot spots located in Buckhead. The baseline average weekday rate of cruising in the sub area is 7.4 percent. The average time spent looking for parking is about 2 minutes.



Source: FHWA.

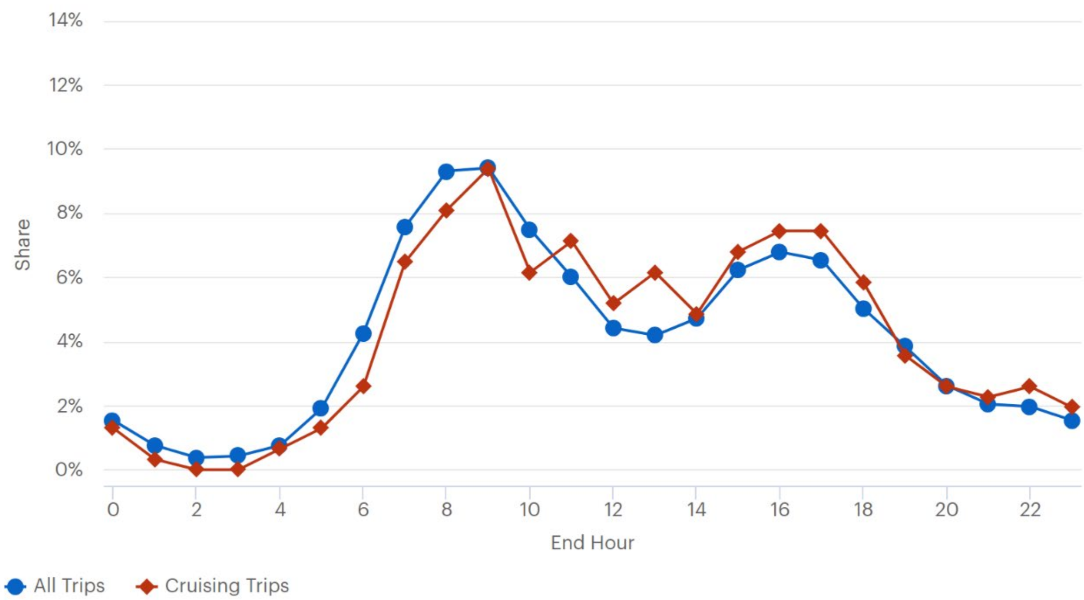
Figure 22. Map. Atlanta area of detail trip ends.



Source: FHWA.

Figure 23. Map. Atlanta area of detail cruising trip ends.

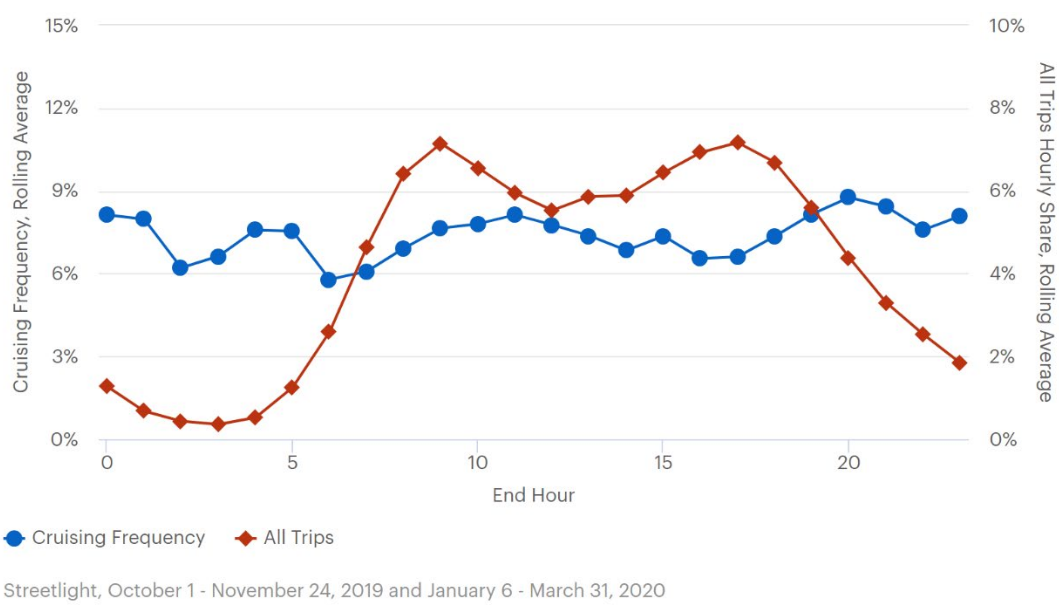
Downtown Atlanta cruising follows a similar pattern to citywide cruising, showing a slight lag in the morning. Both trips and cruising trips peak in the morning, slowly decline at midday, and reach a muted peak in the afternoon (Figure 24). The data are presented using a rolling average to allow an easier visualization in an otherwise more erratic presentation that would have been due to the smaller data set.



Source: FHWA.

Figure 24. Graph. Diurnal distribution of trips.

Figure 25 shows the diurnal distribution of trips, with a line showing the proportion of trips that are cruising throughout the day. The cruising rate in downtown Atlanta and Buckhead is relatively flat, ranging from around 6 to almost 9 percent of trips. This is shown in Figure 25.



Source: FHWA.

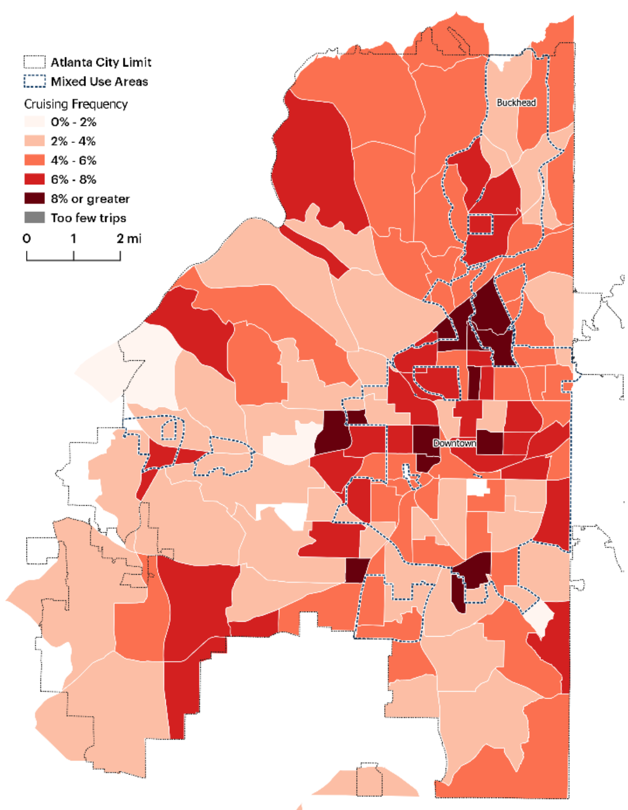
Figure 25. Graph. Proportion of trips cruising.

Comparison Case: April 1–September 30, 2020

After mid-March 2020, many U.S. cities instructed their residents that only trips defined as essential travel should be taken. Trip making was highly curtailed. The next section compares travel during this period with the baseline described above.

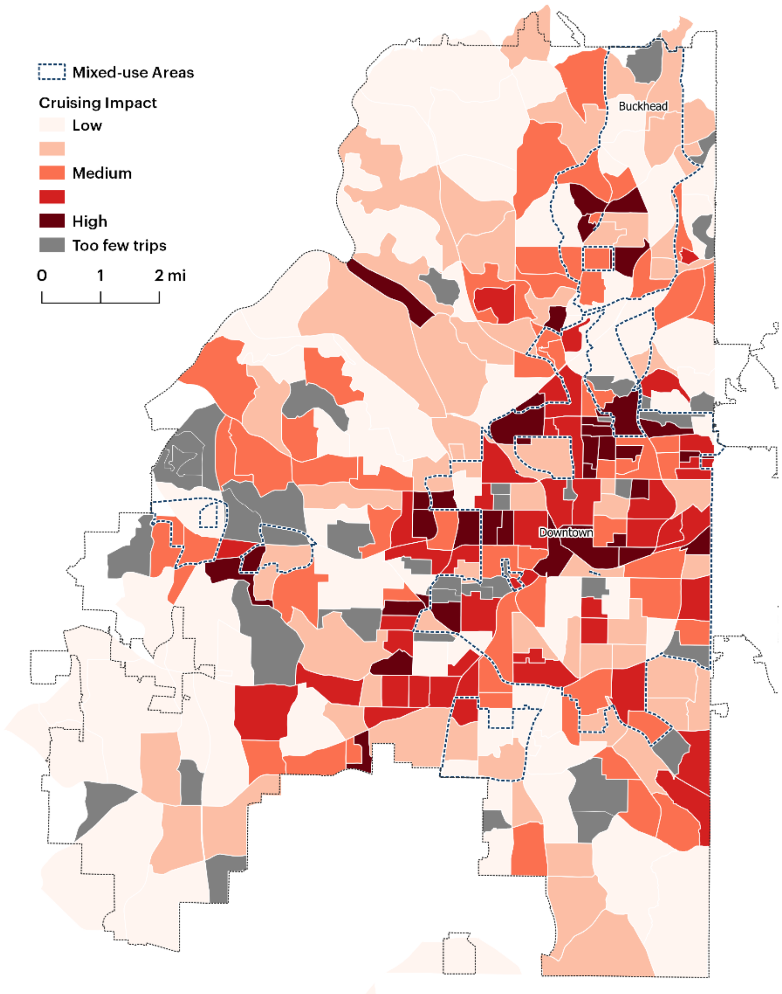
As illustrated in figures 26, 27, 28, and 29 during the comparison period, different patterns for trip destinations and cruising emerged. Even with patterns shifting, cruising remained relatively stable, at 4.7 percent, citywide (compared to 4.9 percent) and 7.9 percent in the area of detail (an apparent, but statistically insignificant, increase from the baseline 7.4 percent) in the mixed use areas of downtown and Buckhead.

Figure 26 corresponds to the baseline representation of Figure 18 to show cruising by census tract in the April–September period. Figure 27 corresponds to Figure 19 illustrating cruising impact (i.e., cruising trips weighted by the amount of time spent cruising and normalized by street length for block groups). Compared to the baseline maps, there are some visible shifts. The primary differences appear in the downtown area and in Buckhead. After a presentation of citywide trip-making and cruising summaries, a closer look is taken in these areas using the street-level data.



Source: FHWA.

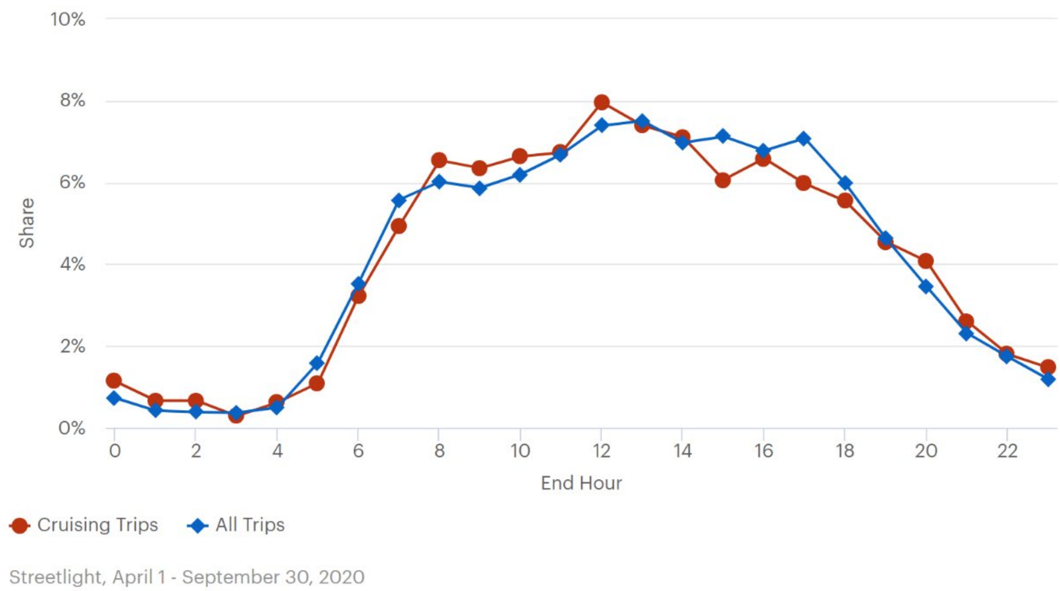
Figure 26. Map. Cruising trip ends, April–September, 2020.



Source: FHWA.

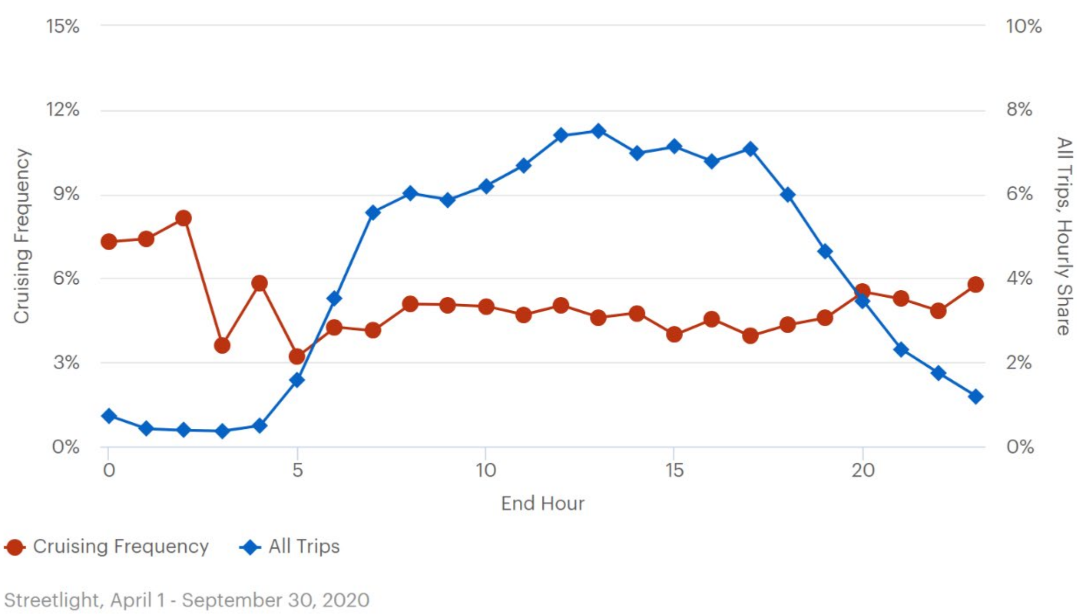
Figure 27. Map. Cruising impact, April–September, 2020.

In the period of initial restricted travel, the diurnal distributions of trips and cruising trips line up quite closely. This is shown in Figure 28. Unlike the historical pattern of a morning and an afternoon travel peak, the Atlanta data show trip making increases sharply in the morning from 5 or 6 to around 8 a.m. Thereafter, trip making remains relatively steady, displaying a somewhat flat distribution until around 6 p.m., when the share of trips made declines quite steadily. Figure 33 superimposes cruising trip rates with time of trip making. Except from midnight to approximately 4 a.m., where the proportion of trips cruising is relatively high, the proportion remains relatively stable throughout the day, staying consistently between 3 and 6 percent of trips.



Source: FHWA.

Figure 28. Graph. Diurnal distribution of trips and cruising trips, April–September, 2020.

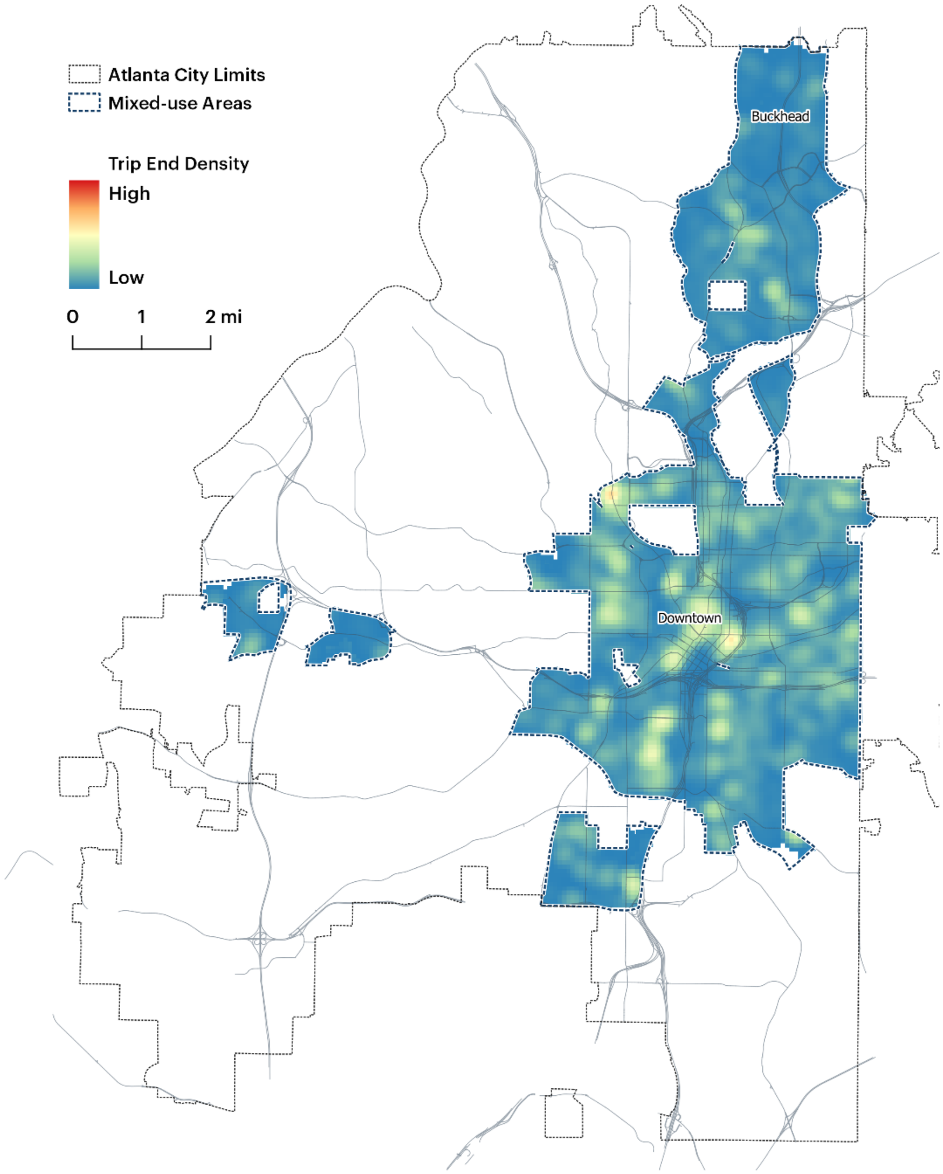


Source: FHWA.

Figure 29. Graph. Diurnal distribution of trips and rate of cruising, April–September, 2020.

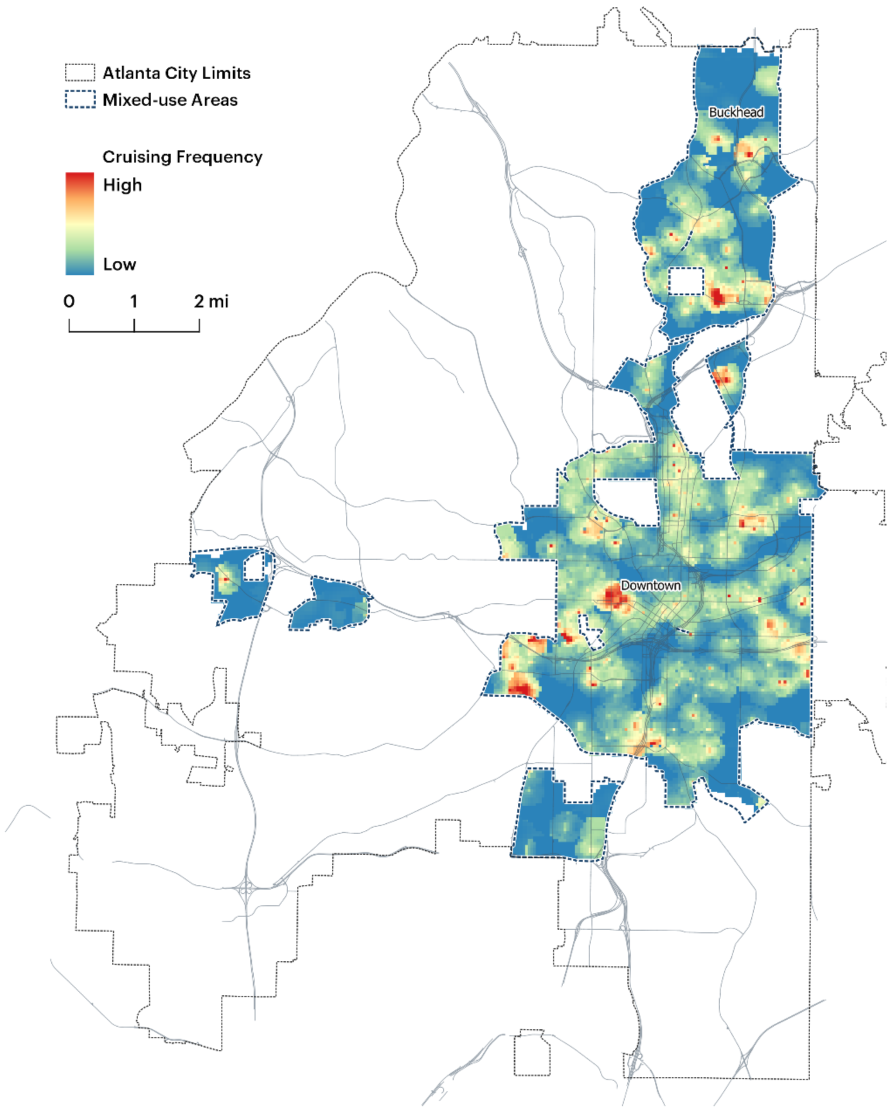
Relative to the baseline, the trips in the comparison period are far more evenly dispersed across the area of detail (Figure 30). The intense destination indicated in the center of downtown in the baseline map (Figure 22) no longer exists.

Looking at Figure 31, which illustrates cruising hot spots, it appears that problematic locations for cruising in the baseline have also redistributed to the periphery of the downtown area.



Source: FHWA.

Figure 30. Map. Trip ends area of detail, April–September, 2020.



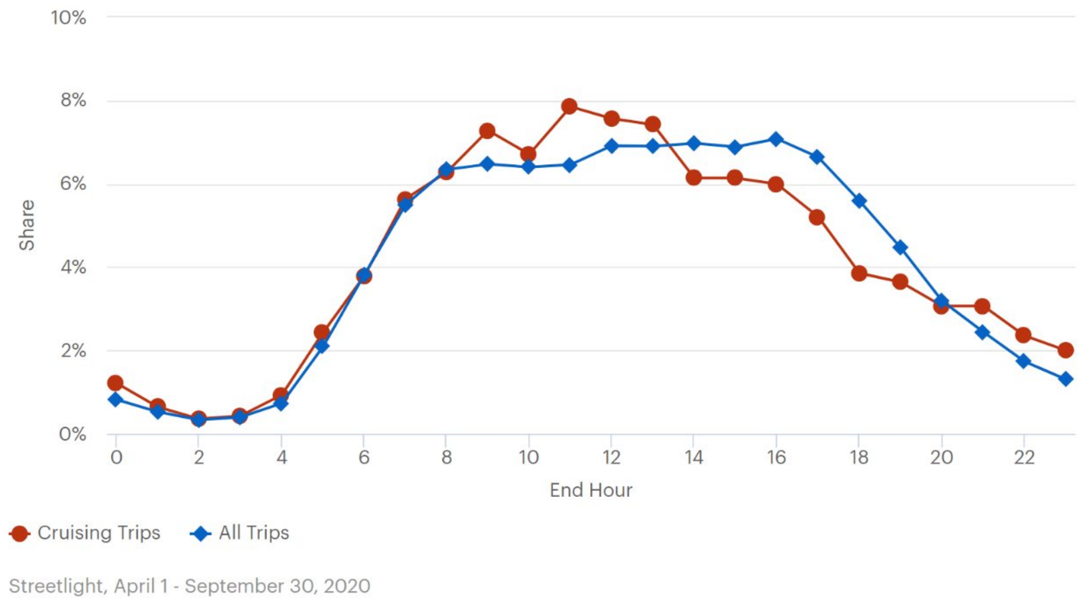
Source: FHWA.

Figure 31. Map. Cruising area of detail.

The final section in this use case looks at the diurnal distribution of trips and cruising trips, and the rate of cruising on the mixed use streets in Atlanta.

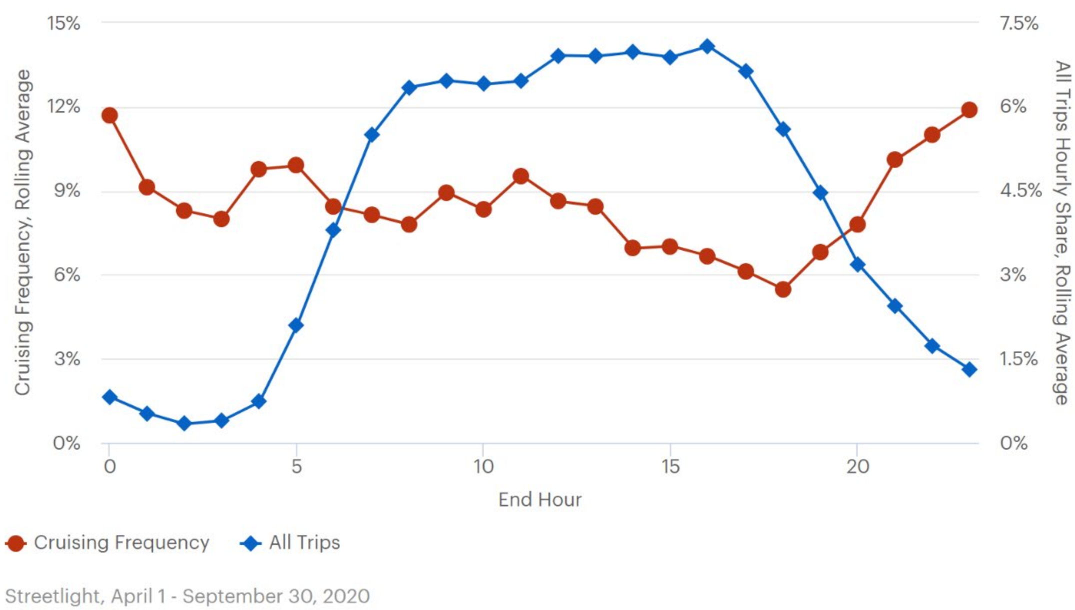
When focusing on the mixed use streets, it appears that trip making follows the citywide pattern, in that traditional peaks are blunted with one peak period lasting from around 6 a.m. to around 6 p.m. The existence of this peak does not imply congested streets for the period—as peak often implies—rather, that trips are concentrated in this time block with no apparent other peaking feature. Cruising trips are tracking exactly with all trips until about 8 a.m., after which they are more highly concentrated. At about 1 p.m. the daily share of cruising trips begins to fall below the rate of all trips, though both are declining.

Figure 32 shows a pattern of greater variation in the cruising rate, compared to the same geography in the baseline and compared to the citywide averages. Figure 33 shows the diurnal distribution of trips with cruise rate superimposed.



Source: FHWA.

Figure 32. Graph. Diurnal distribution of trips and cruising trips, April–September, 2020.



Source: FHWA.

Figure 33. Graph. Diurnal distribution of trips with cruise rate superimposed, April–September, 2020.

Summary

This section described trip making and cruising in Atlanta, focusing on mixed use areas and a comparison between the October 2019–March 2020 and April–September 2020 time periods. There is no particular policy intervention that had been implemented in the time frame. The study team looked instead at areas characterized as mixed use, relative to the rest of the city, and two distinct time periods marked by a change in direction with respect to essential travel.

Top line findings indicate:

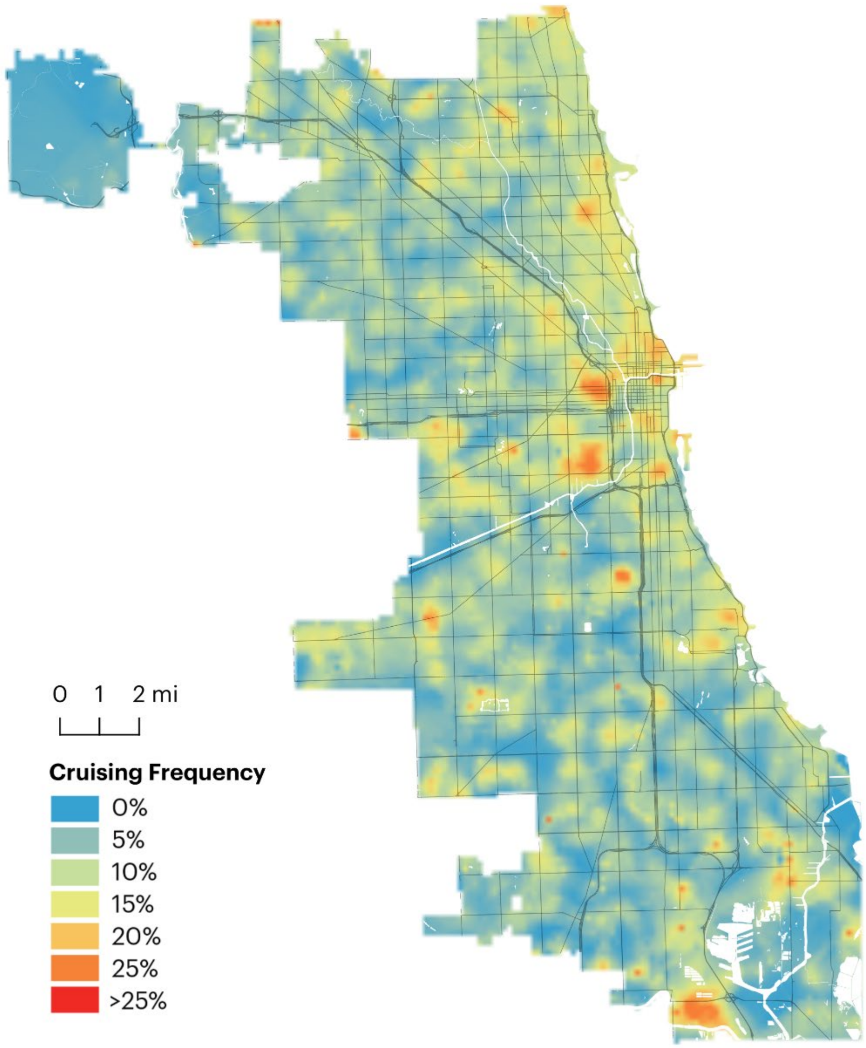
- More cruising in downtown Atlanta and Buckhead, relative to the rest of the city
- Shifts in trip destinations during the second period with far less intensity on the downtown
- Cruising hot spots do not always correspond with areas of greatest trip making
- Cruising hot spots during spring and summer 2020 migrated away from Buckhead and redistributed around downtown

CHICAGO, ILLINOIS: YEAR OVER YEAR AND TIME OF DAY

For the Chicago use case, raw location data were purchased for June 2019, 2020, and 2021. From the location data, trips were inferred and analyzed as described earlier in this report. Differences are expected from the pre-COVID to the early COVID periods and additional differences to late COVID. Unfortunately, the data for June 2021—the late COVID period—were of insufficient quality to include in the final analysis. This provides an important caution for users of the tool. The deficiency was not important for illustration of a use case, but cautionary where the analysis is centered on the geography, in this case Chicago. Additional data should be acquired to perform the additional desired or required analysis. The analysis proceeds here with a focus on the 2 years for which data are of sufficient quality.

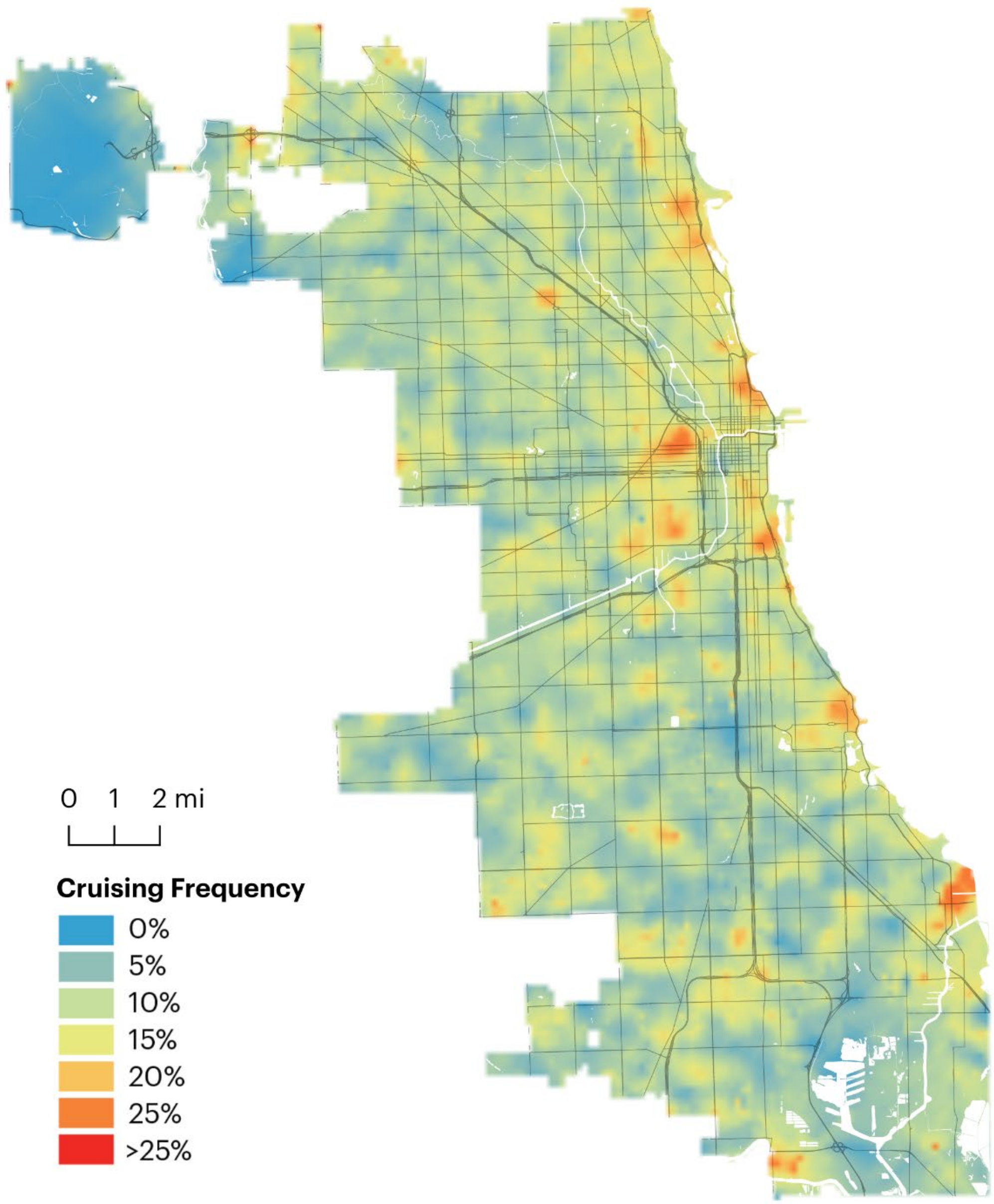
Where Cruising Occurs

With the full data set of mapmatched and cruising-identified traces, high cruising areas can be identified. Figure 34 and Figure 35 show the cruising rate for each street segment for the 2 months of data. In other words, the figures show for each trip that traveled along a street segment, what percentage of those were cruising trips. Overall, many of the same areas stand out, such as the West Loop, Pilsen, Lakeview, Hyde Park, and the area around the convention center. A couple high cruising areas located on the periphery of the city, such as the hot spots in South Chicago and Riverdale neighborhoods, appear to be noise due to a low quantity of trips in the data set.



Source: FHWA.

Figure 34. Map. Cruising 2019.

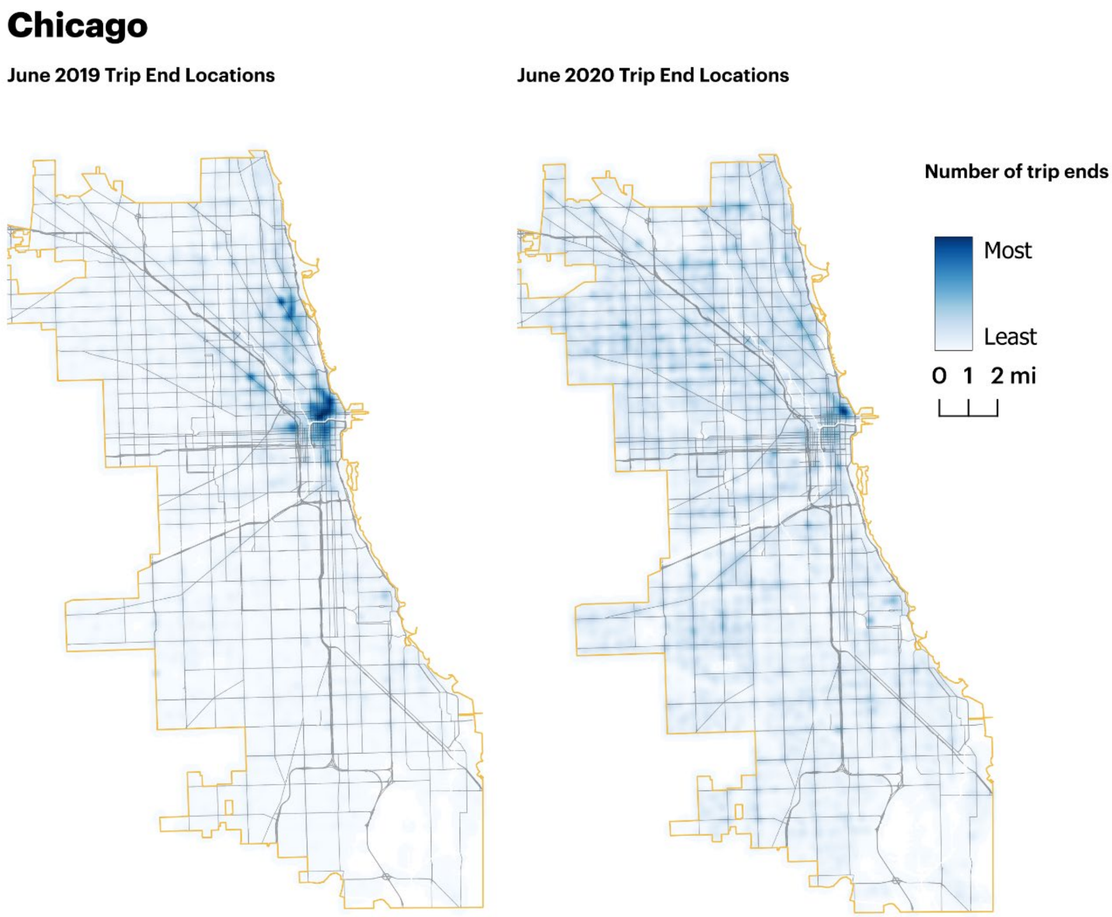


Source: FHWA.

Figure 35. Map. Cruising 2020.

The year-over-year comparison is complicated by the fact that the distribution of trips across the 2 years suggests a different geographic market penetration of the applications from which data are collected as well as differences in trip patterns. There are about 40 percent more trips in the 2020 data set (115,000 in June 2019 and 165,000 in June 2020). As Figure 36 shows, the location of trip ends is quite different. In June 2019, trips were heavily concentrated downtown, the Near North Side, and Northwest Side; all are predominantly white and affluent areas. While the pandemic may explain fewer trips into downtown or to points of interest in some North and Northwest Side neighborhoods, it would not explain why so many more trips are occurring in other neighborhoods. It is likely, therefore, that the year-over-year differences between June

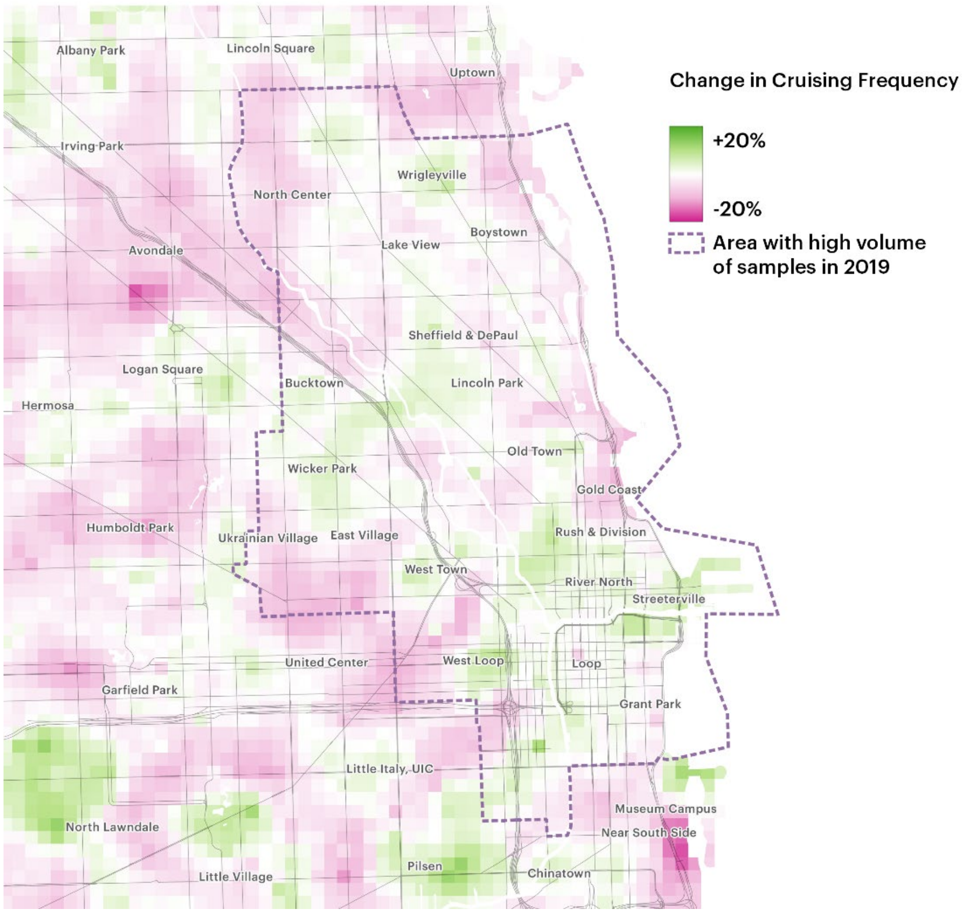
2019 and June 2020 are likely biased by the mix of unknown apps present in the data. The broader distribution of trips in 2020 suggests a more distributed data collection base.



Source: FHWA.

Figure 36. Map. Comparison of trip ends 2019 and 2020.

With the caveat noted, Figure 37 shows the neighborhood changes in frequency from 2019 to 2020.

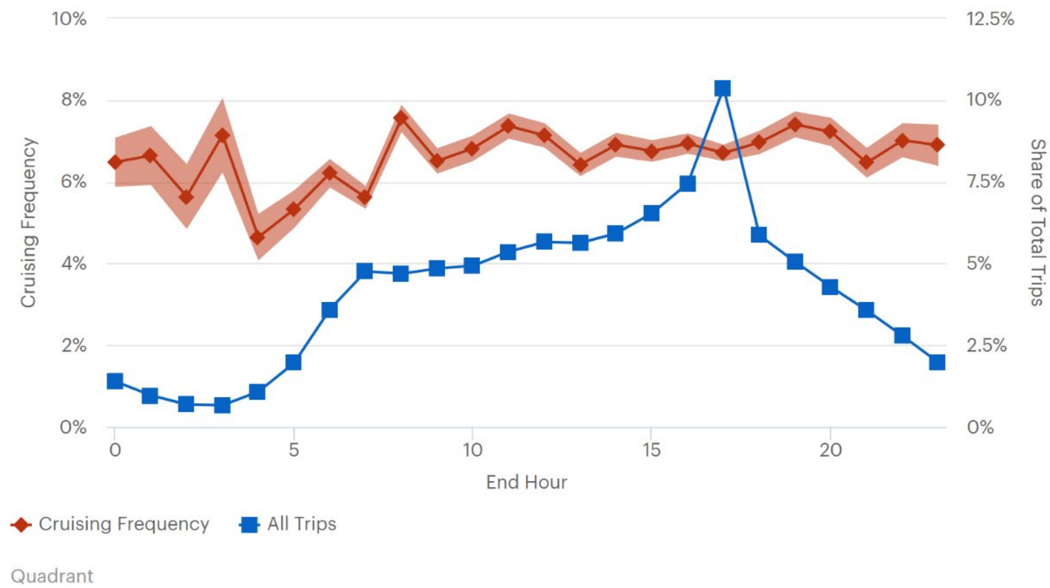


Source: FHWA.

Figure 37. Map. Change in cruising frequency.

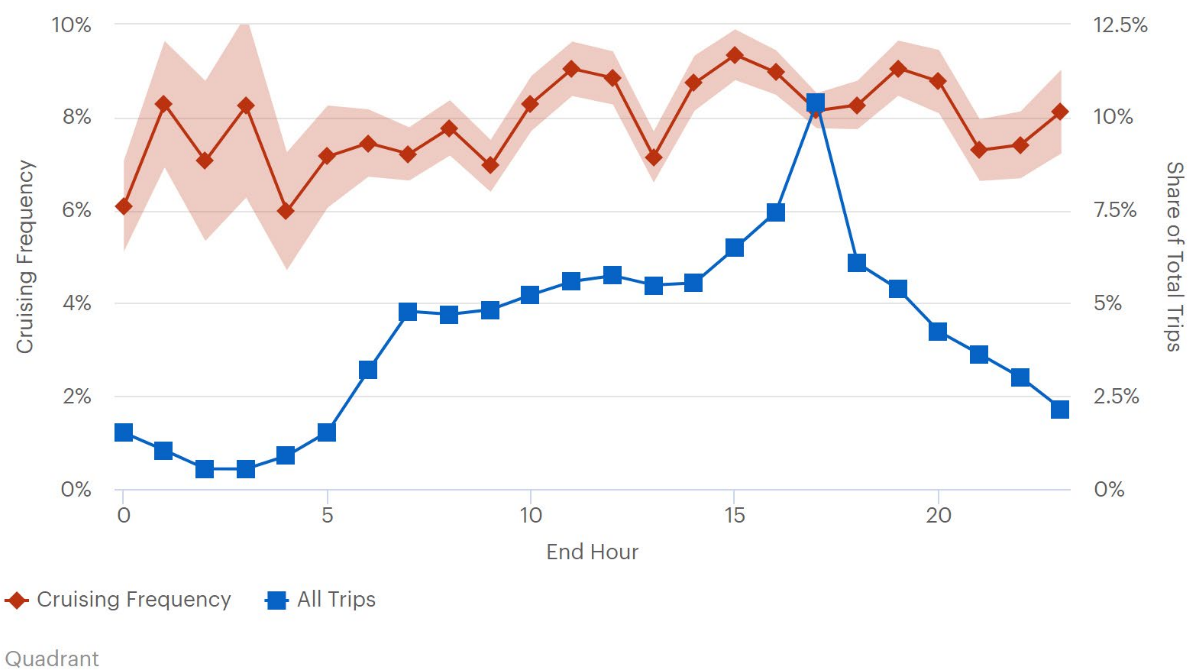
When Cruising Occurs

Citywide, cruising remains between approximately 6.5 and 7.5 percent for most of the day. For trips ending on metered streets, which was 67 percent of trips in 2019 and 60 percent in 2020, the rate is between 8 and 9 percent between 10 a.m. and 8 p.m., with a dip to 7 percent at 1 p.m. For trips ending on non-metered streets, after a peak of 7.5 percent cruising between 8 and 9 a.m., cruising stays between 5 and 6 percent for most of the day. The volatility observed in the early morning hours is likely due to the low number of samples during those times. The higher variance noted in Figure 38, Figure 39, and Figure 40 supports that hypothesis; that figure set illustrates cruising frequency and overall trip making citywide, on metered streets and on non-metered streets, respectively.



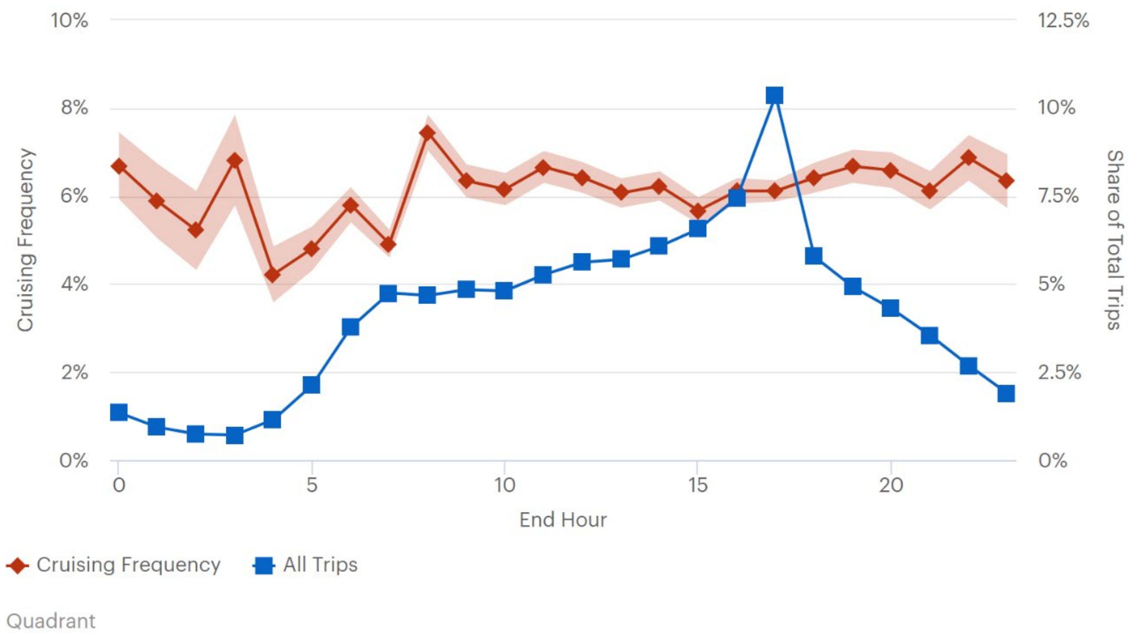
Source: FHWA.

Figure 38. Graph. Diurnal distribution of trips and cruising trips.



Source: FHWA.

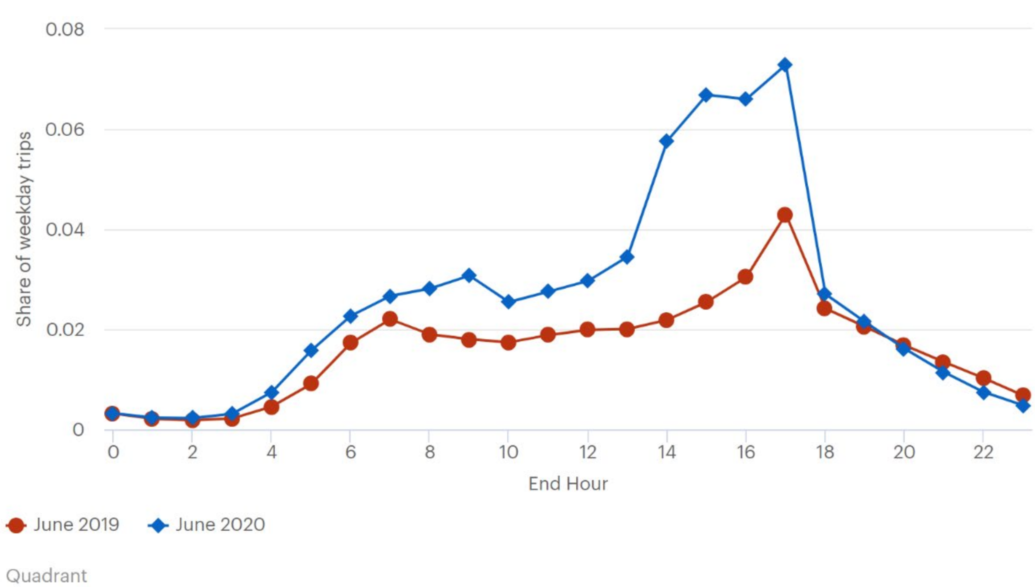
Figure 39. Graph. Diurnal distribution of trips and cruising trips ending on metered streets.



Source: FHWA.

Figure 40. Graph. Diurnal distribution of trips and cruising trips ending on unmetered streets.

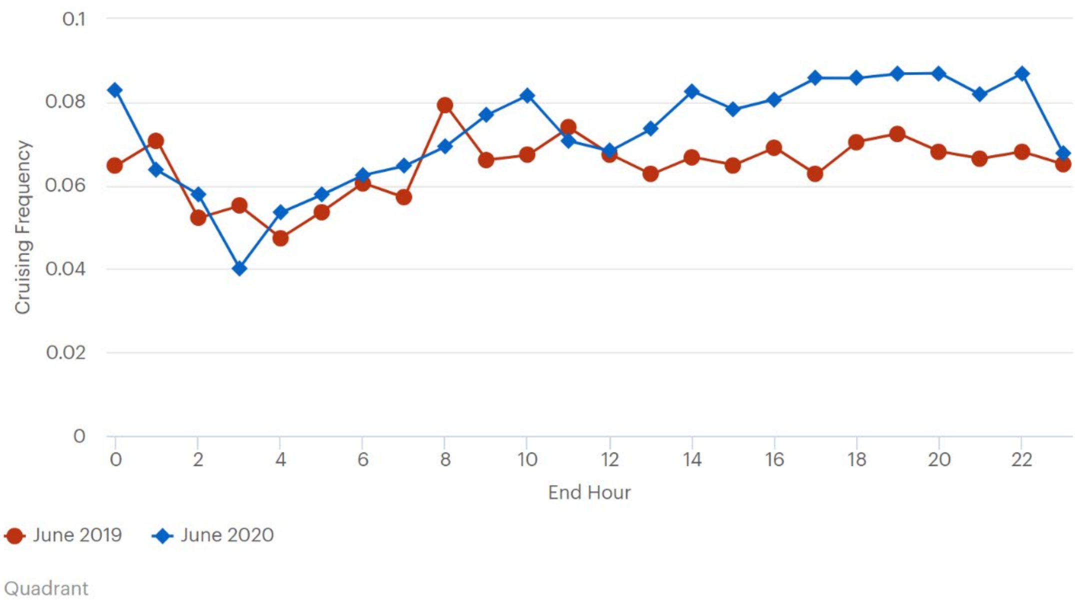
Just as with the geographic distribution of trips, the differences in the diurnal distribution of trips between June 2019 and June 2020 may be genuine or may be caused by differences in the underlying data sources. In June 2019, the data show a sharp peak in overall weekday trips at 5 p.m., while in June 2020, the peak is more spread out, from 2 to 5 p.m. (Figure 41).



Source: FHWA.

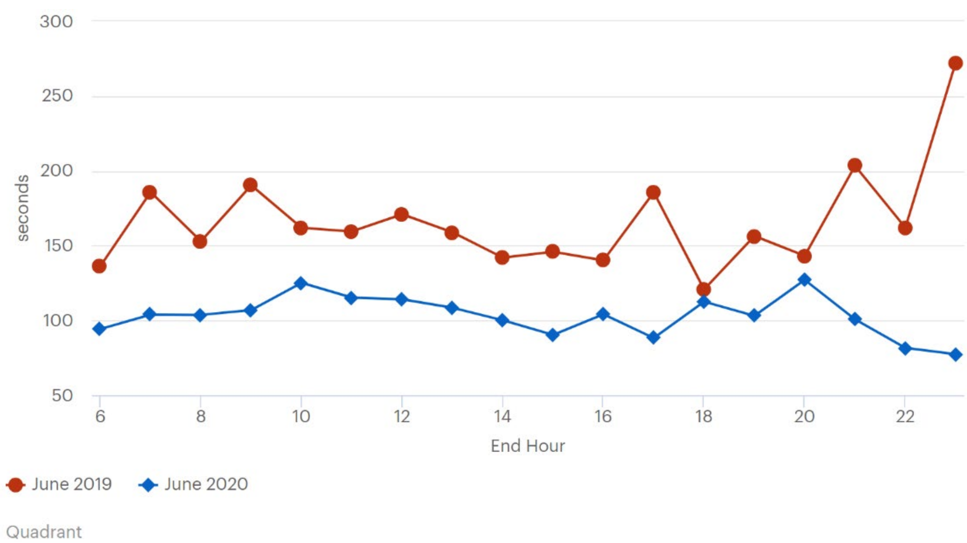
Figure 41. Graph. Diurnal distribution of weekday trips.

Cruising frequency remains relatively constant throughout the day in both June 2019 and June 2020, though it is slightly higher in June 2020 (Figure 42). Despite a lower frequency of cruising trips in June 2019, however, as shown in Figure 43, the mean cruising time is consistently higher in June 2019 than in June 2020. This finding suggests that, as trips are more distributed, cruising locations are more distributed and have less intensity.



Source: FHWA.

Figure 42. Graph. Cruising frequency by time of day 2019 and 2020.

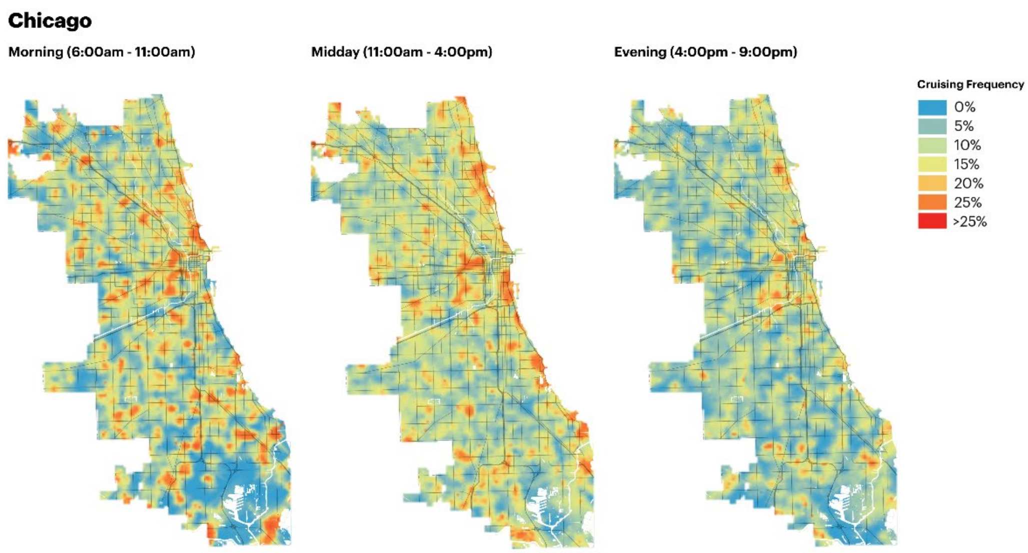


Source: FHWA.

Figure 43. Graph. Mean cruising time 2019 and 2020.

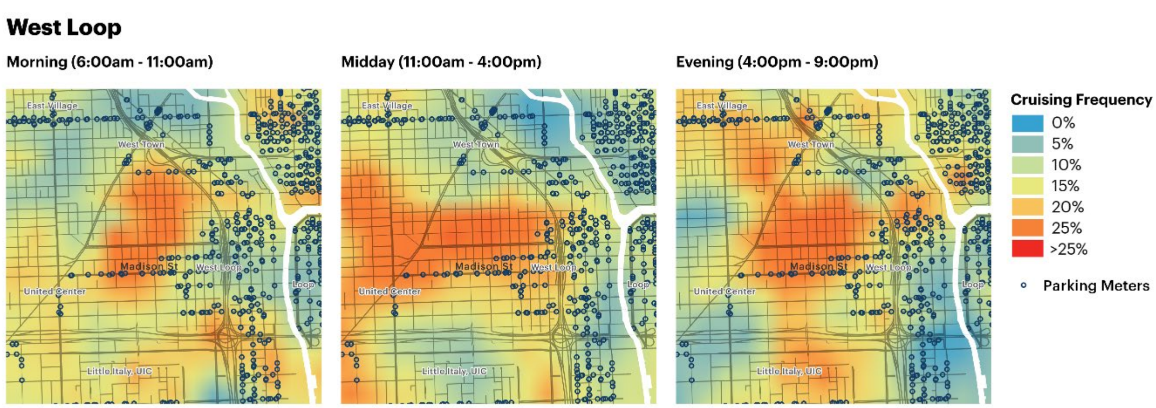
Do Cruising Patterns Change throughout the Day?

To mitigate concerns about the respective data sources for different years, the unaggregated data from Chicago allow for a high-resolution analysis of diurnal patterns within the same data set; the following analyses rely on the 2020 data set. Trips are classified into three time frames corresponding to traditional morning and evening peak periods and a midday period. The periods are: morning (7–10 a.m.), midday (11 a.m.–3 p.m.), and evening (4–7 p.m.). For the following analysis, the more evenly distributed June 2020 data are used. While some areas experienced similar levels of cruising throughout the day, in general cruising tended to be more concentrated to specific destinations in the morning, and most dispersed at midday (Figure 44). The same mapping analysis is shown below for the West Loop (Figure 45); River North (Figure 46) Hyde Park (Figure 47), and Lakeview (Figure 48).



Source: FHWA.

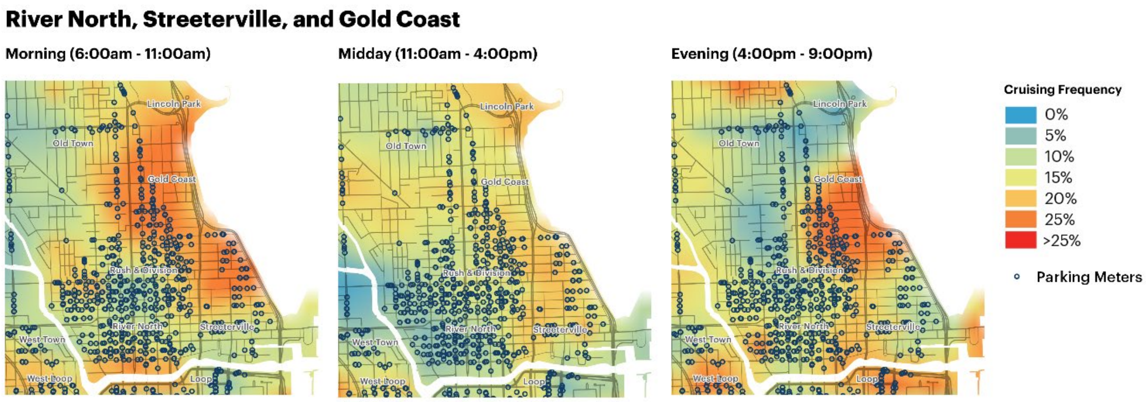
Figure 44. Map. Peak and midday comparison of cruising.



Source: FHWA.

Figure 45. Map. West Loop cruising peak and midday.

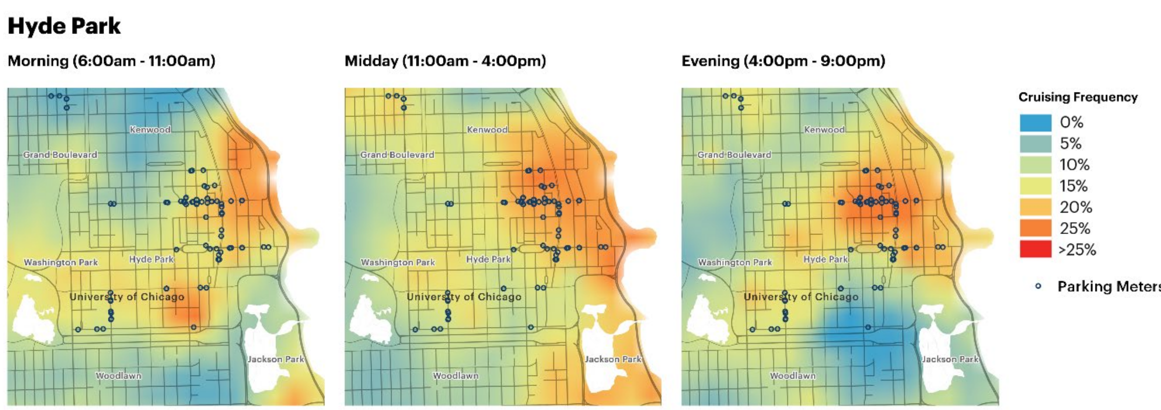
The West Loop, a neighborhood home to both wholesale food distributors and trendy restaurants and only one train stop, experienced some of the highest rates of cruising across the board. Parking is largely unregulated in the area, except along Madison Street, which can be identified by the series of meters running the length of the street, and in the southeast corner of the neighborhood, where cruising is lower.



Source: FHWA.

Figure 46. Map. River North cruising peak and midday.

The neighborhoods north of the Loop have some of the highest densities of retail, office, and residential space in the city. Most of these areas have metered streets, with the exception of the relatively more residential areas of Streeterville and the Gold Coast. The diurnal pattern of cruising here would be consistent with an influx of workers in the morning looking for free and/or all-day parking in non-metered areas near their workplaces, and, in the evening, Gold Coast residents returning home and competing over limited street parking.

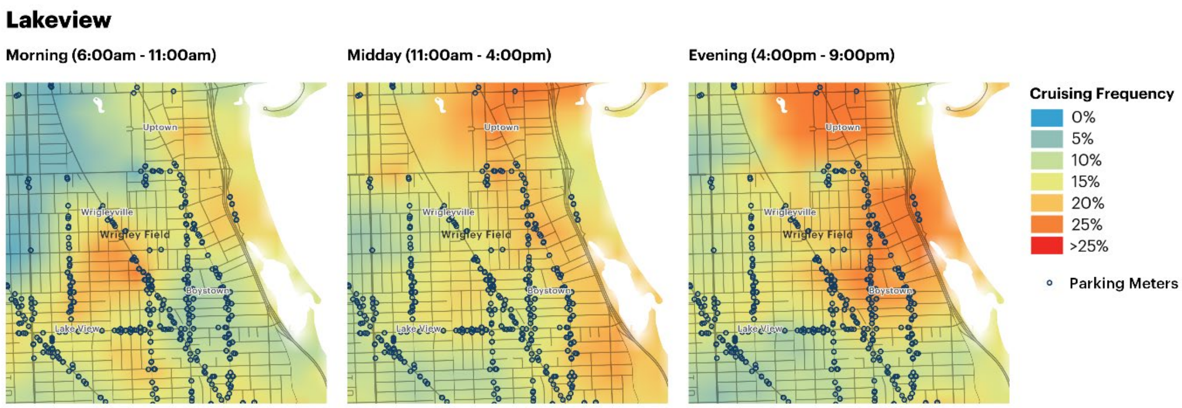


Source: FHWA.

Figure 47. Map. Hyde Park cruising peak and midday.

In Hyde Park, the diurnal patterns show that throughout the day, cruising remains high along the northeast lakefront section of the neighborhood—an area of concentrated high-rise apartments, in contrast to the three-story multifamily buildings found throughout most of the neighborhood. The commercial center of the neighborhood around 53rd Street, East Hyde Park Boulevard, and

Lake Park Avenue, also has high rates of cruising during midday and evening hours. In the morning, high cruising can be found in the southern part of the neighborhood near the University of Chicago, and in particular the University of Chicago Laboratory School, a private school serving students from kindergarten to 12th grade, which may reflect parents dropping off children, or university faculty and staff searching for parking.



Source: FHWA.

Figure 48. Map. Lakeview cruising peak and midday.

In Lakeview, cruising is highest in the evening near the busy entertainment corridor of North Halsted Street and North Broadway. Cruising is also high to the north in the Uptown neighborhood, where higher density housing is found.

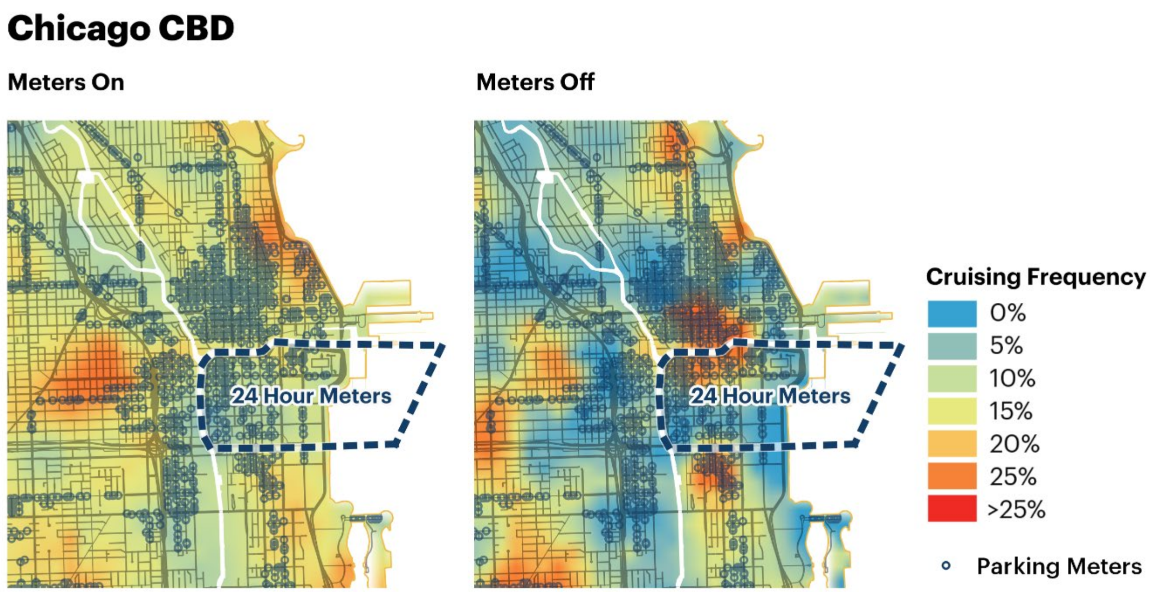
Metered Streets

Chicago has metered parking along most commercial corridors throughout the city. In the 2020 data set 60 percent of trips and 55 percent of cruising trips ended on metered streets. For those trips ending on metered streets, 55 percent of cruising vehicle miles traveled were done on metered streets. For cruising trips ending on non-metered streets, only 9 percent of cruising miles accrued to metered streets. This could indicate that cruising drivers with trips ending on metered blocks are looking for open metered spaces, and not necessarily searching for non-metered spaces. Likewise, cruising drivers ending their trips on non-metered streets are likely looking for non-metered spots.

At a citywide scale, the relationship between cruising and metered parking may depend on the neighborhood-specific land use context. In specific neighborhoods, such as the West Loop, Streeterville, and Gold Coast, areas with high frequency of cruising can be seen in unmetered areas adjacent to metered areas. These areas are both adjacent to, or even part of, the central business district (CBD), where the majority of streets are metered, rather than just the main commercial corridors. In neighborhoods farther out, such as Hyde Park, high rates of cruising along metered streets may indicate the high demand for parking that the meters are there to regulate.

Another temporal filter can be applied to examine cruising during hours when Chicago's parking meters are turned on and off. Chicago has different meter hours depending on the neighborhood, and parking meters in the Loop are in operation 24 hours per day. Figure 65 shows cruising frequency when trips end in places and at times meters are turned on, and in places and at times when they are turned off. When meters are turned on, cruising is highest in the two adjacent areas to the north and west of the CBD where there are fewer meters present. This could indicate people specifically avoiding metered areas and parking as close as possible to the core, or it could indicate that a lack of parking regulation in these areas is causing a higher demand than it might be if more meters were present.

When meters are turned off, the highest cruising is found in metered areas in River North and just south of the Loop that is not present when meters are turned on.



Source: FHWA.

Figure 49. Loop cruising meters on and meters off.

Summary

The Chicago case is based on raw location data that the project team analyzed directly. Having the individual trip trajectories allows a more complex study of the cruising paths taken, rather than simply basing findings on where trips end. The overall cruising rate in Chicago fluctuates between 6.5 and 7.5 percent, with higher concentrations in the denser and mixed use areas. The cruising rate is relatively stable throughout the day in both years analyzed, but shows some geographic variation across the day: it is more evenly distributed throughout the city in the morning period and more geographically concentrated in the afternoon. Finally, cruising has increased in duration in June 2020 relative to 2019.

Two important cautions arise from this part of the project. First, flexibility and adaptability in research design are a prerequisite for creating and presenting impactful analysis. The Chicago analysis was meant to be of 3 consecutive years' worth of data. Poor data quality in the final year prevented a complete analysis. Had this been a policy study, additional data should have been sought or a different time period substituted. Second, the close analysis of raw data over a relatively abbreviated time frame indicates there are likely biases due to data collection strategy. If collection is via particular applications that have more popularity among certain demographic groups that will likely also show geographic biases in the location of trip making and trip ends. With these kinds of biases an analyst may be unable to identify the worst locations for cruising, but could get a critical sense of cruising dynamics in particular areas. Apparent missing data could inform data acquisition strategies.

SEATTLE, WASHINGTON: TWO METER POLICIES

Seattle has adopted a performance pricing policy for its metered parking streets. Using annual surveys to estimate vehicle occupancy, the Seattle Department of Transportation (SDOT) raises, lowers, or leaves the same the parking meter prices in order to hit an occupancy/vacancy target.

The first Seattle case examines cruising before and after price changes to the city's metered parking. The business-as-usual case is examined wherein SDOT does a regularly scheduled meter price adjustment. SDOT made a price adjustment on January 28, 2020; the period of review is before and after the price change.

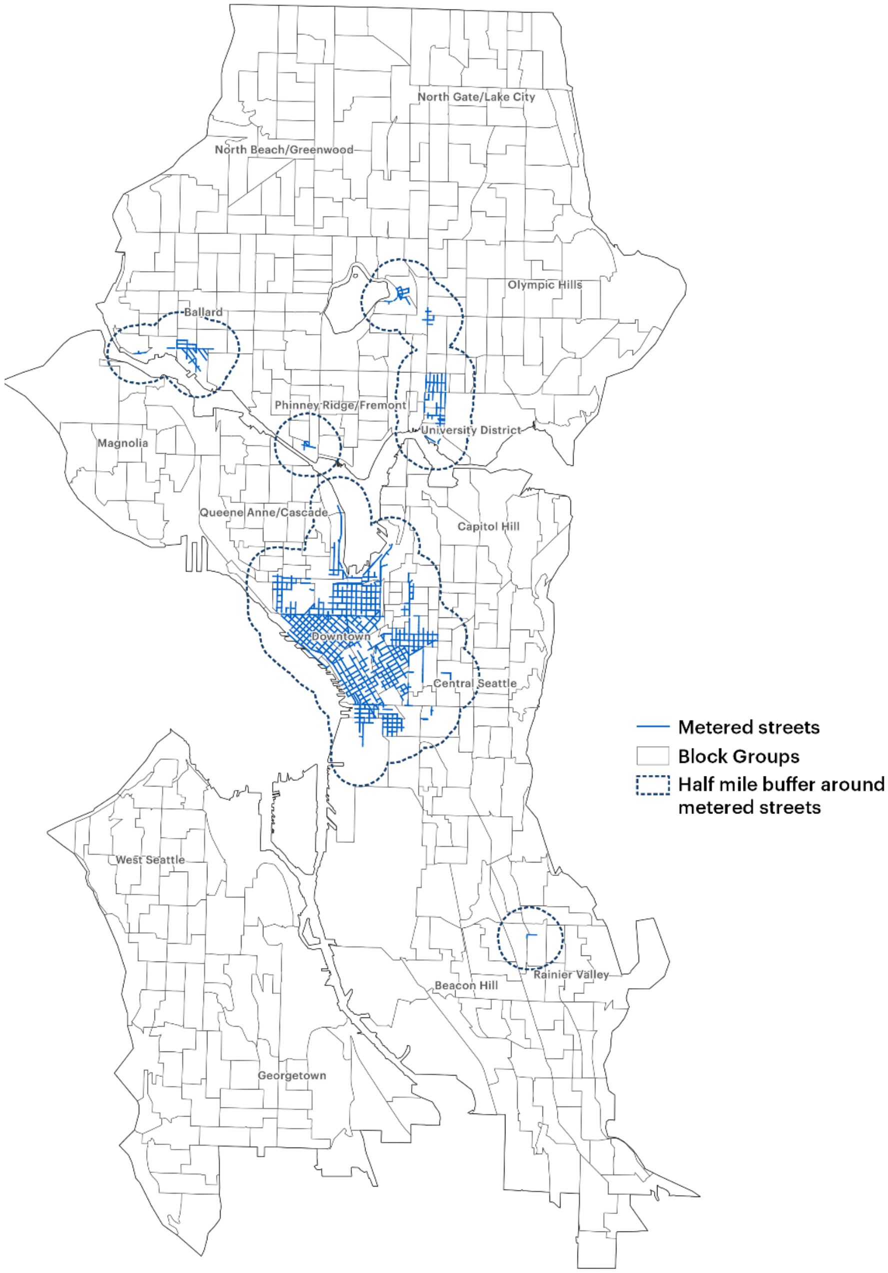
The second case examines cruising in the 2 weeks before and after SDOT temporarily suspended all parking meters on April 4, 2020. The city decided to suspend meters to ease the travel burden on essential workers.

For the purposes of both analyses the city was divided into metered streets, near-metered streets—on the assumption that meter policy can have spill-over effects on other streets—and non-metered areas. Due to the data agreement with the third-party processor, one of the Seattle data sources, the number of geographies was limited to 15,000, so trips not ending within 0.5 miles of metered streets were aggregated to the census block group level. Figure 50 shows Seattle's block groups along with metered and near-metered streets.

Most of the analysis in this case uses output created by the third-party processor. Raw location data for Seattle were also obtained and used in these use cases only where noted. Additional discussion related to the use of different data sources generally, and in Seattle specifically, is provided in Chapter 4 and Appendix A.

This section discusses the following:

- Baseline cruising and trip making in Seattle using data in the period January 6–February 28, 2020
- Before-after analysis of the business-as-usual meter price change that occurred on January 28, 2020
- Comparison of the baseline to data obtained for March 21–April 18, 2020
- Analysis of cruising before and after meter prices were suspended

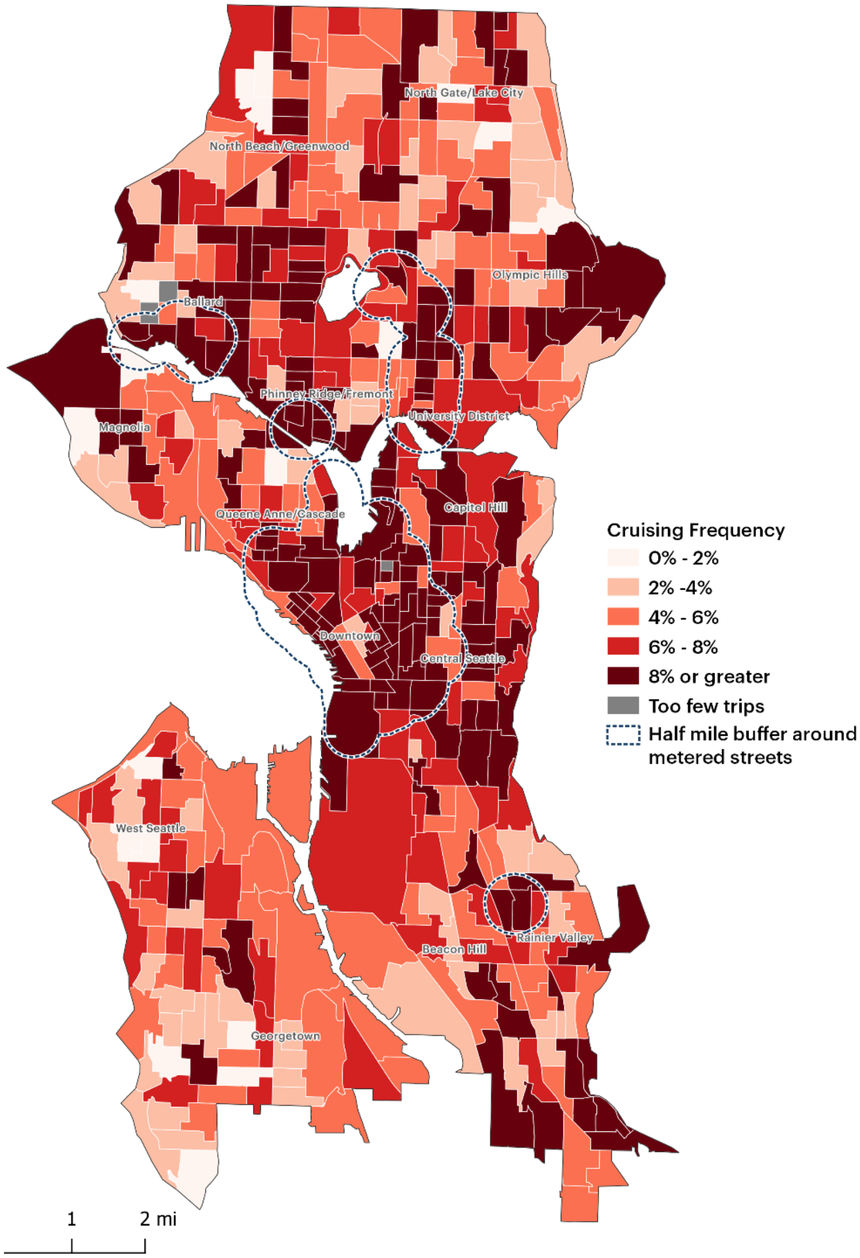


Source: FHWA.

Figure 50. Map. Seattle study area.

Where Cruising Occurs

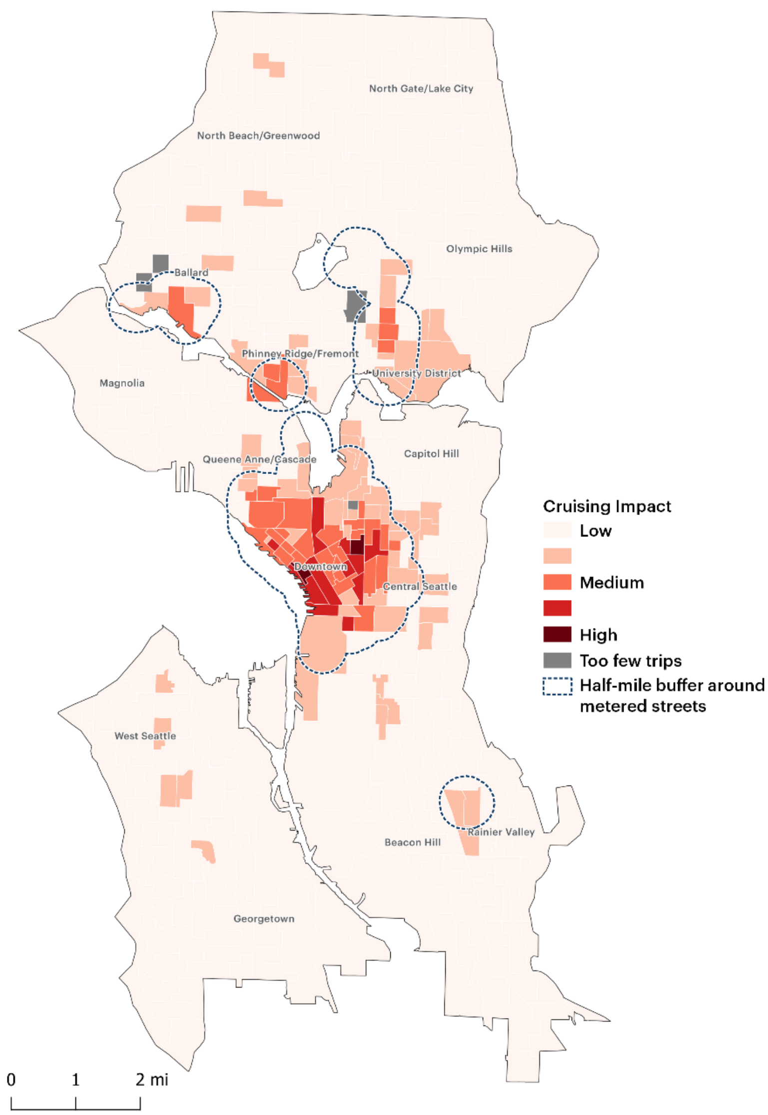
Census block groups with the highest density of cruising trips tend to be in metered districts (shown in outline) in or near the commercial business district, university district, and the neighborhoods of Adams, and Fremont. High rates of cruising are also found in parts of west Seattle, neighborhoods along Martin Luther King Jr. Way South, and in Lake City. Trips in these areas tend to be of shorter duration as proximate parking is likely easier to find (Figure 51).



Source: FHWA.

Figure 51. Map. Cruising frequency.

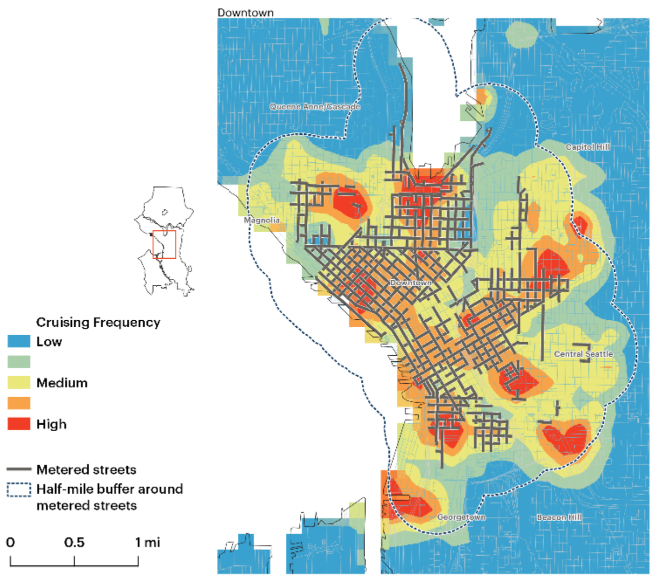
Not all cruising trips are the same. A cruising trip could take drivers a little out of their way or far out of their way; thus, time spent cruising should be considered along with cruising frequency. Figure 52 shows the aggregate level of cruising as aggregate time spent cruising for trips that end in each block group, normalized by the length of street in each block group. When considering total time spent cruising the problem areas align well with metered areas, suggesting that Seattle has appropriately placed its meters where pricing is needed as a curb management strategy. In this case, the map reflects where trips end, not the paths taken by drivers; though it appears counterintuitive, a plausible interpretation is that trips with a circuitous component are ending on metered blocks with greatest frequency. This could be that drivers are finding vacant spaces on metered blocks where they had not on other blocks. This is an affirmation of the meter policy that could be abstracted to the blocks where people prefer to park. It could also mean that drivers are looking for bargain parking, and when they cannot find it, drivers take paid parking as a second choice. Alternatively, this could be a result of cruising occurring in the metered areas where, policy goals notwithstanding, meter rates may have been too low to bring demand down to the level of supply.



Source: FHWA.

Figure 52. Map. Cruising impact area.

There is also a potentially important boundary effect. With the exceptions of cruising hot spots that are completely contained within the metered area, proximate to Pike Place Market and south of Lake Union, most of the commercial business district cruising is at the boundary of the metered and non-metered areas. This observation could warrant further thought regarding expansion of metered areas to discourage bargain hunting that may occur.

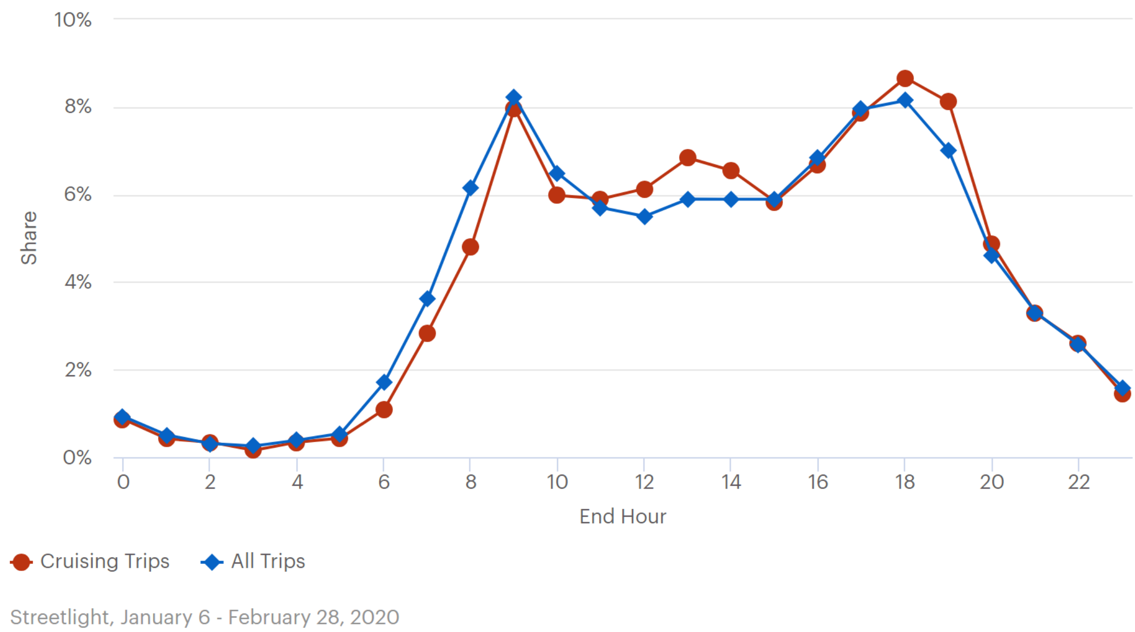


Source: FHWA.

Figure 53. Map. Cruising for parking boundary effects.

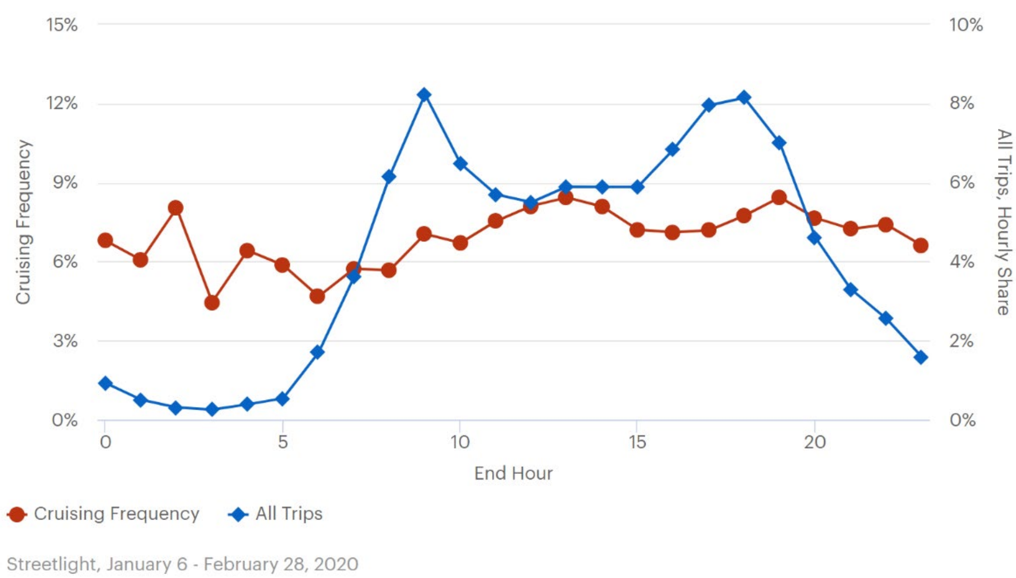
When Cruising Occurs

Citywide, cruising trips follow a similar diurnal distribution to overall trips (Figure 54), with morning and evening peaks. Cruising trips, as a proportion of all trips, ranged between 4.5 and 8.5 percent throughout the day, with peaks at midday and in the early evening toward the end of the evening peak travel period (Figure 55). Both peaks follow the two peaks in the overall trip numbers, suggesting that as morning commuters park near their workplaces and evening commuters park near their homes or near evening activities, available parking spaces fill up, leading to higher rates of cruising for parking.



Source: FHWA.

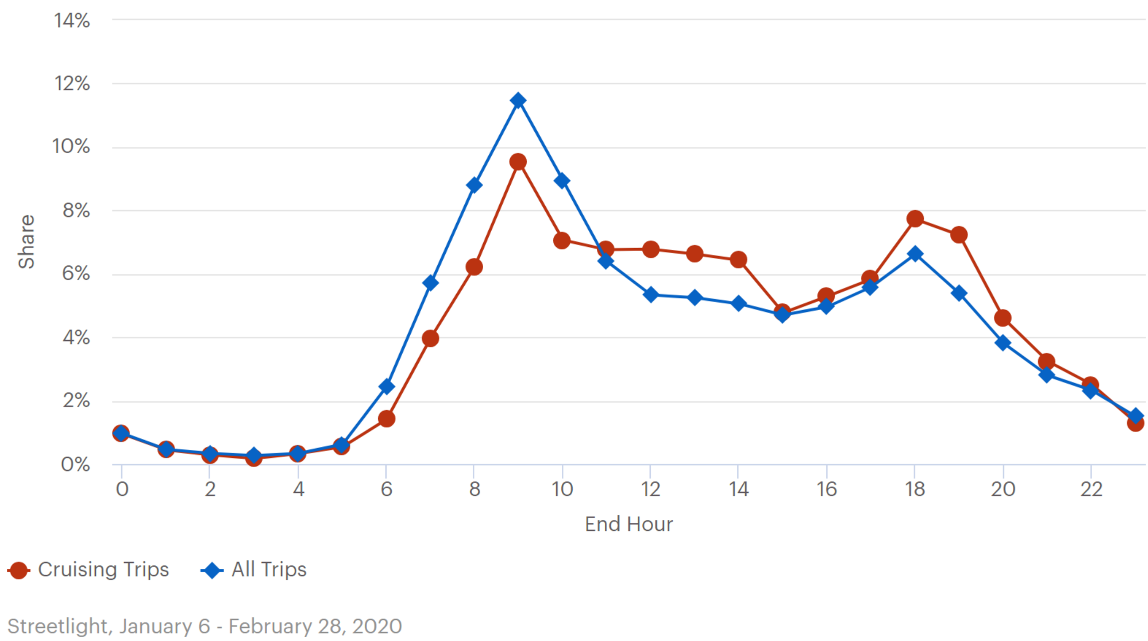
Figure 54. Graph. Diurnal distribution of trips and cruising trips.



Source: FHWA.

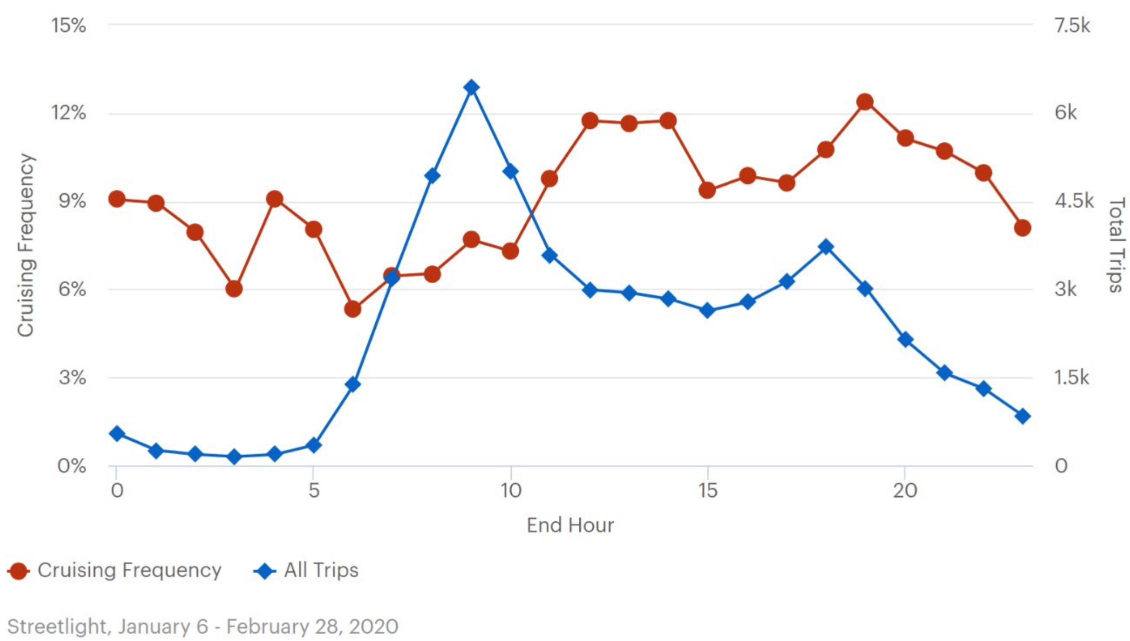
Figure 55. Graph. Diurnal distribution of trips and cruising as percent of trips.

In the metered and near-metered areas shown in Figure 56, the cruising lag is more pronounced than it is across the city. As shown in Figure 57, the rate of cruising is at its highest around noon, remaining high (between 9 and 12 percent of trips) until around 10 p.m.



Source: FHWA.

Figure 56. Graph. Diurnal trips and cruising on metered and near-metered streets.

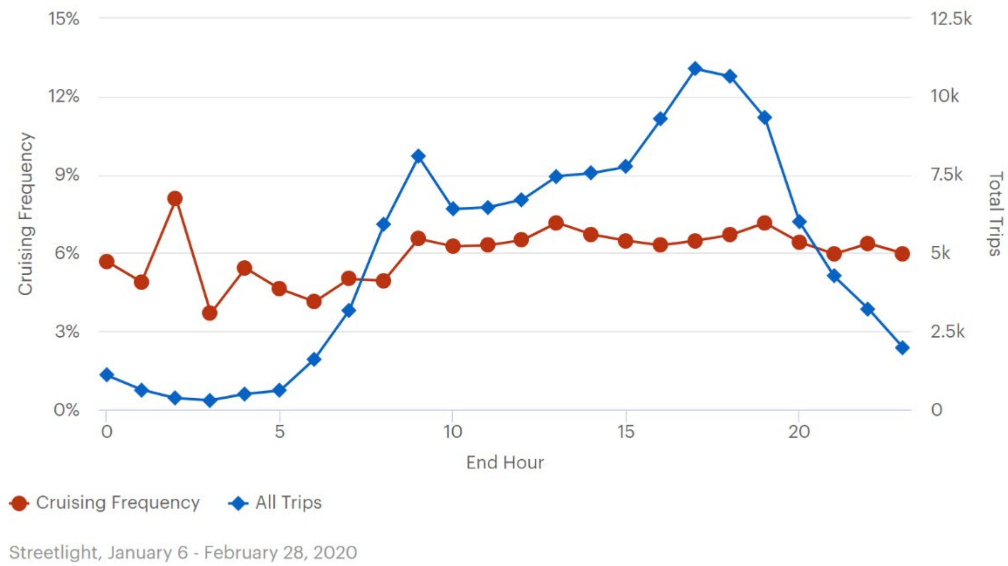


Source: FHWA.

Figure 57. Graph. Diurnal distribution of trips and cruising frequency on metered and near metered streets.

For trips that end more than 0.5 miles from metered streets (i.e., non-metered areas hypothesized to be largely immune to meter pricing policy and the demands of metered and near-metered areas), the midday and evening peaks observed in other areas do not materialize. Between 9 a.m.

and midnight, cruising frequency on non-metered streets hovers around 6 percent, varying only by just over 1 percent (Figure 58).



Source: FHWA.

Figure 58. Graph. Diurnal distribution of trips and cruising frequency in non-metered areas.

A disproportionate number of all trips, as well as cruising trips, end on metered streets (Table 2). Metered streets make up only 2 percent of overall streets in Seattle, yet account for 14 percent of trip ends and 18 percent of cruising trip end points. Near-metered streets are 10 percent of all streets, 19 percent of trip ends, and 24 percent of cruising end trips. Calculating the ratio of cruising trips to all trips, metered and near-metered streets show similar ratios of 1.24 and 1.22, respectively. This is unsurprising since metered streets are located where there is a higher density of destinations and a greater demand for parking.

Table 2. Trip intensity by area type.

Street Type	Share of Trips (%)	Share of Cruising Trips (%)	Share of Street KM (%)
Metered	14.2	17.6	1.9
Near-metered	19.3	23.5	9.9
Non-metered	66.6	58.9	88.1

As shown in Table 3, vehicles cruising in the non-metered area, a relatively rare event, spend, on average, under a minute searching for parking. On the other hand, a cruise trip which is more prevalent in the metered areas, takes longest there, with near-metered areas running a close second.

Table 3. Mean cruising time by time of day, in seconds.

Street Type	2–4 p.m.	6–8 p.m.	Other Times
Metered	148	140	113
Near-metered	110	117	111
Non-metered	57	49	56

Metered and near-meter streets have average cruising times 2–3 times higher than cruising trips that end on non-meter streets.

Comparison: Before versus after Business-as-Usual Meter Price Change

Consistent with SDOT policy, the January 28, 2020, meter price change entailed either a 50-cent increase, 50-cent decrease, or no change, depending on the observed occupancy on a particular block.[23] This case examines whether this price change had an effect on cruising behavior. The date range representing the before condition is January 6–27, 2020. The period of analysis representing the after condition is February 5–28. 2020.

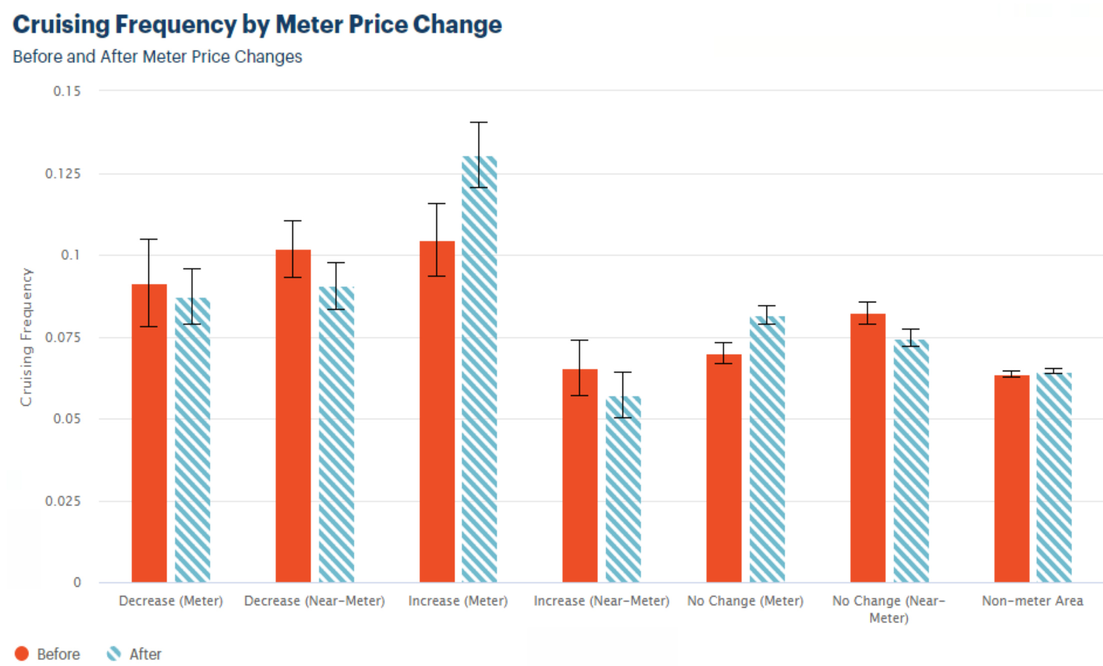
Figure 59 shows the frequency and changes in frequency of cruising on metered, near-metered and non-metered blocks. Metered blocks are divided according to whether the price was increased, decreased, or held constant. Near-metered streets were classified for price increases, decreases, or being held constant based on the policy treatment of the metered block to which they are nearest.

Figure 60 shows the time spent cruising in the metered, near-metered, and non-metered areas. The working hypothesis for non-metered areas (i.e., those beyond half a mile of a parking meter) is that travel behavior would not be affected by meter price changes. Supporting that hypothesis, Figure 60 shows there is no change in frequency of cruising trips ending on blocks in non-metered areas across the price change.

The changes in cruising on streets where prices either increased or decreased were small. Where meter prices were reduced in Seattle and on near-metered streets proximate to streets with metered price drops, the frequency of cruising trip ends also decreased. The decreases are small, and likely due to sampling error. The error bars in Figure 59 show the potential statistical overlap. On streets where the price was increased—in theory, creating more vacancies—the number of trips cruising also increased. This should not be interpreted to mean that price increases stimulated additional cruising, but rather that more cruising trips are ending on streets where prices were increased because there is more turnover and related availability on those streets. In both cases (i.e., whether meter prices were increased or decreased), the amount of time a driver spent cruising decreased. Limitations of the data only allow observation of where the trip ends. A plausible interpretation is that with increased vacancy, more trips that would have been cruising before the price adjustment no longer were—those cruising trips would have ended on other blocks or would have taken a longer time. The increase in cruising trips that ended on metered streets with price increases is statistically significant; this suggests a real change had

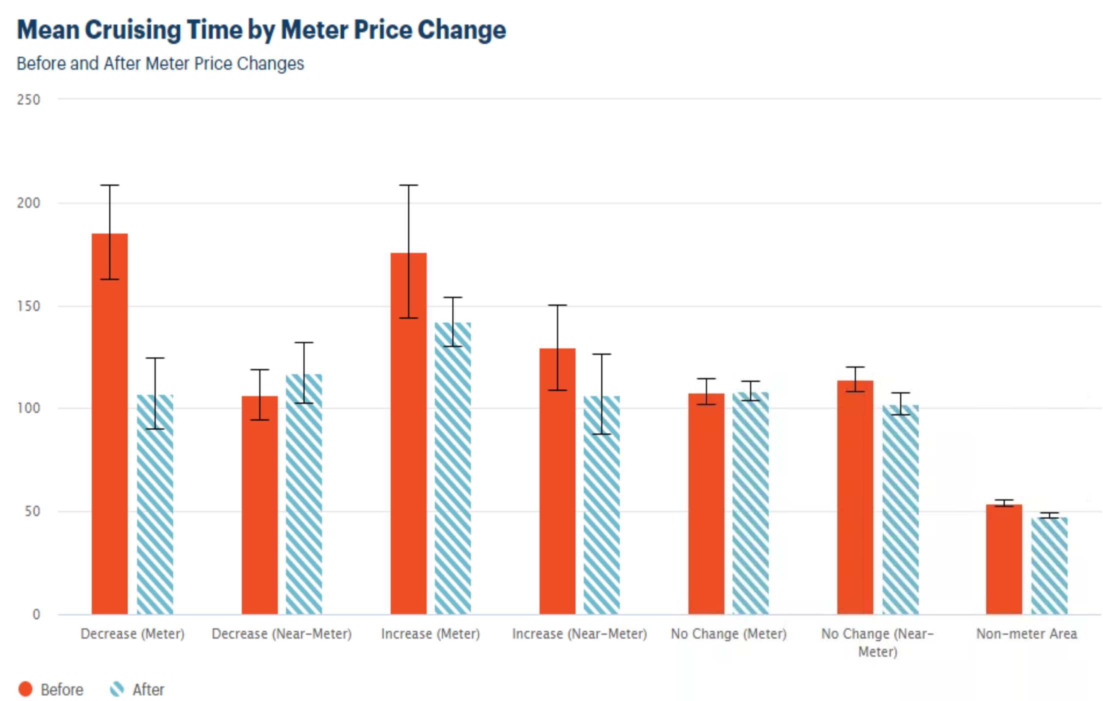
[23] S. Davis, Seattle Department of Transportation, SDOT Blog, "Paid parking rate changes are coming your way, January 31, 2020. Available at: https://sdotblog.seattle.gov/2020/01/31/paid-parking-rate-changes-are-coming-your-way/.

been measured. Streets proximate to metered streets that had price increases show a decrease in cruising trips, which, again, suggests parking demand is being better accommodated on metered blocks.



Source: FHWA.

Figure 59. Graph. Change in cruising by meter price change and area type.



Source: FHWA.

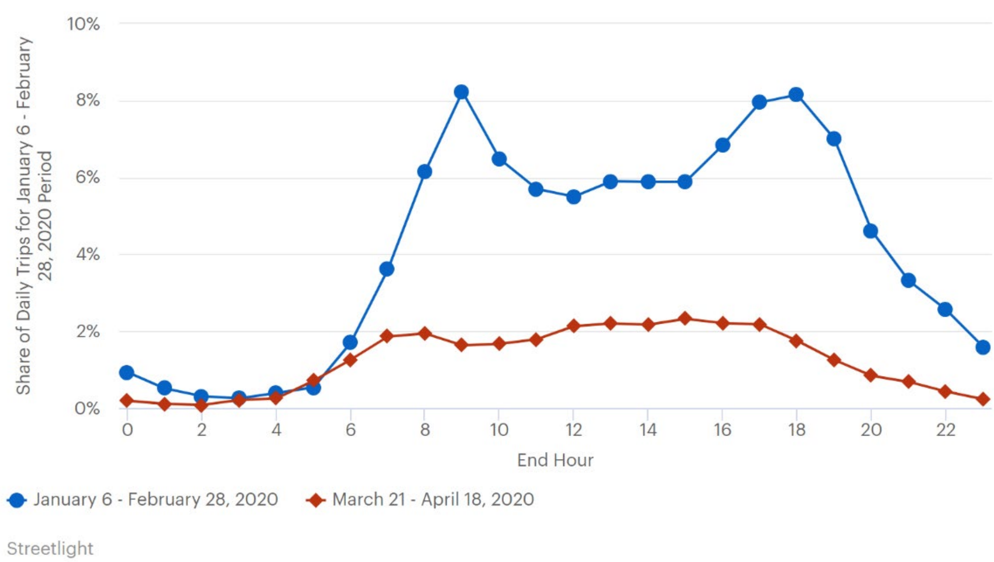
Figure 60. Graph. Time spent cruising by meter price change.

As the differences are small, albeit consistent, it can take several adjustments before a travel behavior change registers. A study of San Francisco showed a change in cruising behavior only after eight price changes.[24] Although the change in cruising frequency is not significant, the fact that cruising frequency is higher in areas that had a price increase confirms SDOT's information on where and when there is higher demand for parking.

Cruising Pattern Changes in Response to Meter Decommissioning

In the earliest days of the pandemic, travel patterns changed substantially. In the pre-pandemic period, trips followed the expected diurnal distribution with pronounced peaks in the morning and late afternoon. By late March–April 2020, however, travel was substantially curtailed and it also showed minimal peaking. Trips were low at night and in the early morning, but relatively flat between 8 a.m. and 3 p.m., dropping off sharply from there. In response to the COVID pandemic, SDOT temporarily suspended all parking meters and time limits, except for residential permit zones. This section focuses on an analysis of cruising and travel patterns in the 2 weeks before and after the meter suspension on April 4, 2020. To set the context for the meter decommissioning, this section first covers the changes in cruising behavior after the initial COVID-19 lockdown in March, 2020.

Figure 61 shows the diurnal distribution of trips before the Government's guidance to social distance and restrict travel and the distribution of trips after that guidance. Figure 62 shows the traditional morning and evening peaks for cruising in the before period and the reduced and flattened pattern in the after period.

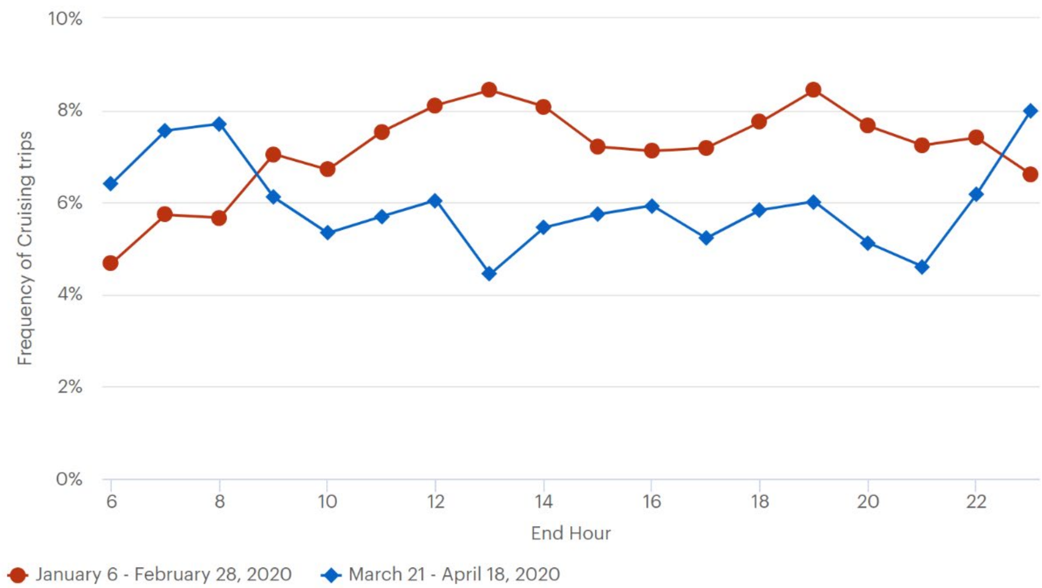


Source: FHWA.

Figure 61. Graph. Diurnal distribution of baseline trips and early lockdown trips.

[24] Adam Millard-Ball, Rachel Weinberger, and Robert C. Hampshire, "Is the Curb 80% Full or 20% Empty? Assessing the Impacts of San Francisco's Parking Pricing Experiment," *Transportation Research Part A: Policy and Practice* 63 (2014): 76–92.

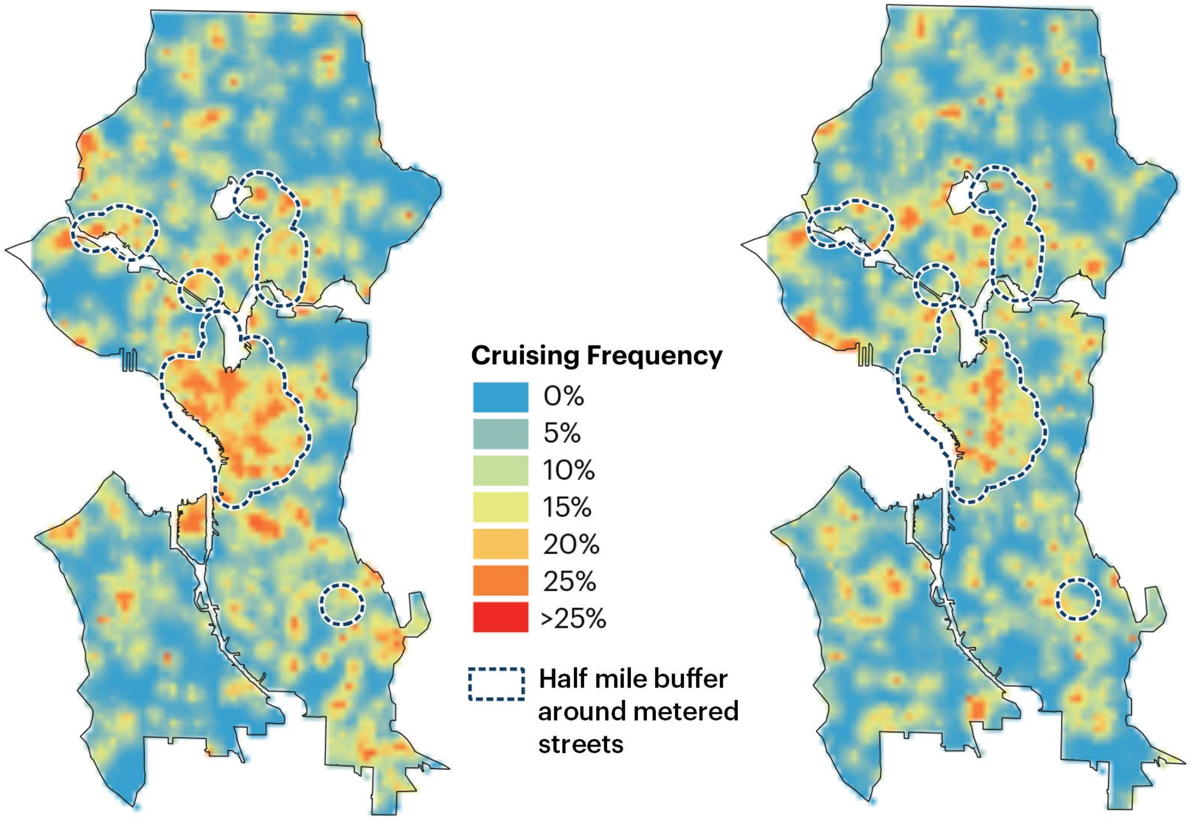
Even at one-third of pre-pandemic trips, cruising frequency was curiously consistent. The percentage of trips that included a cruising component in the January–February 2020 time period ranged from 4 to 8 percent, with an average daily rate of 7.1 percent. During the early pandemic, frequency of cruising trips ranged between about 4 and 8 percent, with an average daily rate of 6.1 percent. This represents a statistically significant decline, but only of 1 percent.



Source: FHWA.

Figure 62. Graph. Cruising frequency in early 2020 and in early spring 2020.

The disaggregated data allow for a detailed spatial snapshot of cruising patterns, and how they shifted between winter and spring 2020. Figure 63 shows the rate of cruising along street segments in the winter time period (January 6–February 28) and in the spring time period (March 21–April 18). Mirroring the aggregated output shown above, cruising rates are only slightly lower in the spring, despite the large decrease in overall trips. While many residential areas, in addition to areas near the University of Washington and east of downtown (home to several hospitals), maintained similar cruising rates, neighborhoods with more jobs than residents (downtown and the heavily industrial areas south of downtown) saw cruising decrease significantly.



Source: FHWA.

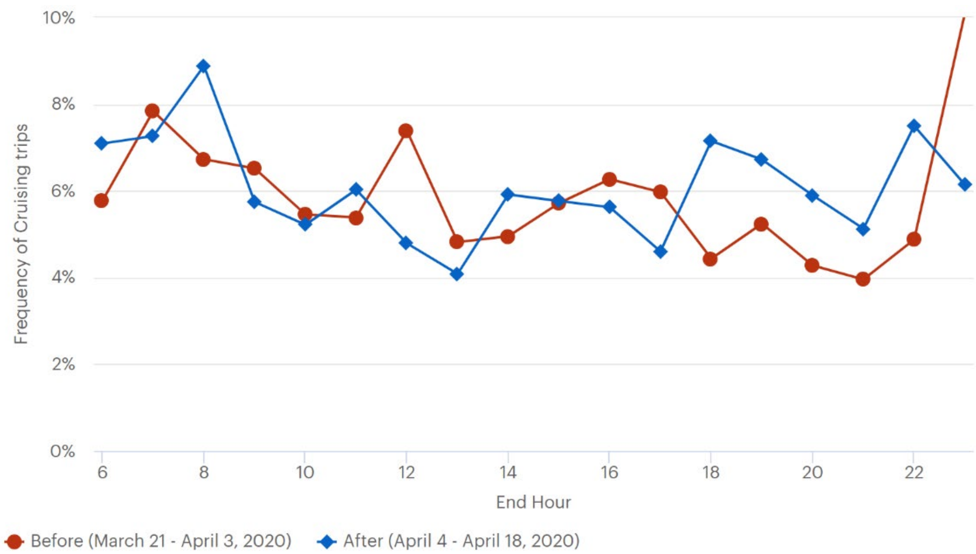
A. Seattle cruising hot spots, January–February 2020.

Source: FHWA.

B. Seattle cruising hot spots, March–April 2020.

Figure 63. Comparison of cruising hot spots.

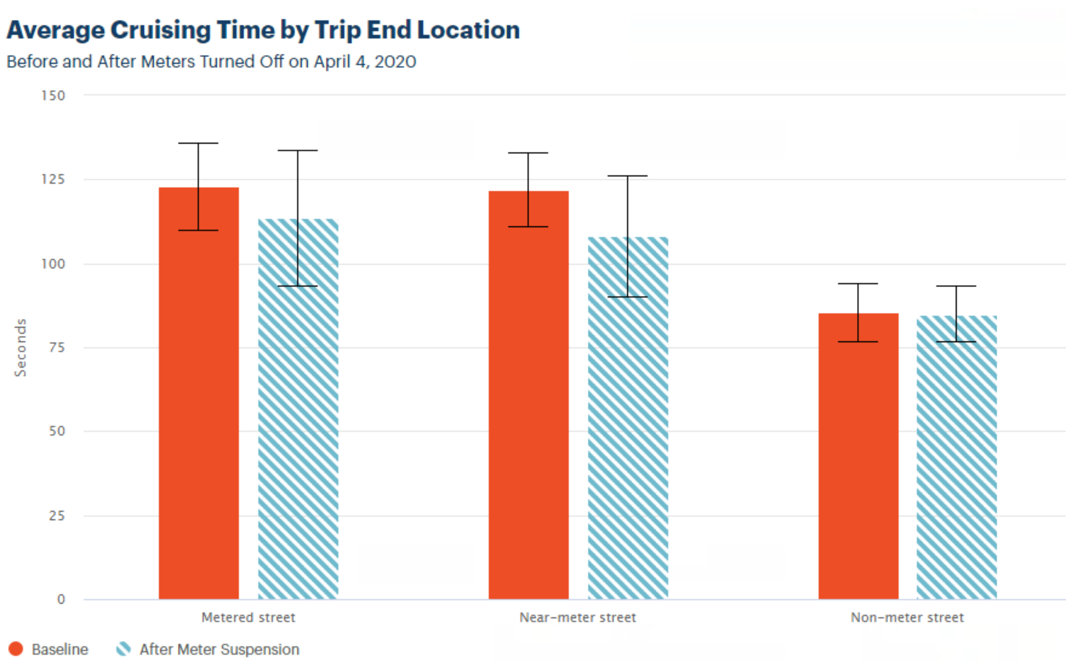
On April 4, 2020, SDOT temporarily suspended all parking meters as a relief measure for essential workers. SDOT also temporarily lifted existing time constraints on parking at the meters and generally throughout the city. The exception was in residential permit parking areas where time limits continued to be enforced.



Source: FHWA.

Figure 64. Graph. Cruising rates before and after meter suspension.

The frequency and time spent cruising before and after the suspension were compared. Citywide, the decision to decommission the parking meters in this period had no discernible impact on cruising frequency. As before, there was no change in average cruising time in the non-metered areas, which serves as a control. Average cruising time decreased slightly on both metered and non-metered streets once the meters were decommissioned. However, the difference is not statistically significant (Figure 65). It is possible that travel and cruising behavior were not responding to meter prices during such an acute point in the early pandemic.



Source: FHWA.

Figure 65. Graph. Average time spent cruising before and after meter suspension.

Summary

Two parking meter policies were analyzed in this section. First, a business-as-usual case was considered in which SDOT adjusted meter prices according to an annual occupancy survey. Second, meter suspension was implemented as part of the city's response to the pandemic. In the first case, there was a consistent decrease in the amount of time a cruising vehicle spent looking for parking after the meter rates had been adjusted. In the second case, even though trip-making rates had been substantially lowered, compared with the baseline, cruising was consistent, and differences before and after the meter suspension were indiscernible.

The Seattle analysis relies on aggregated data outputs of the third-party processor supplemented with raw location data from the data aggregator. The two approaches are taken to showcase the relative strengths of each. The third-party data are more abundant providing greater statistical confidence. The location data allow for more complex analyses of paths taken. Each has a potential function. A comparison of the data sources is provided in appendix A.

Finally, with respect to the apparent lack of difference in trip making and in cruising following the meter policy changes, it is possible that a 2- or 3-week period before and after a policy change may be insufficient time in which the market adjusts and differences can be observed.

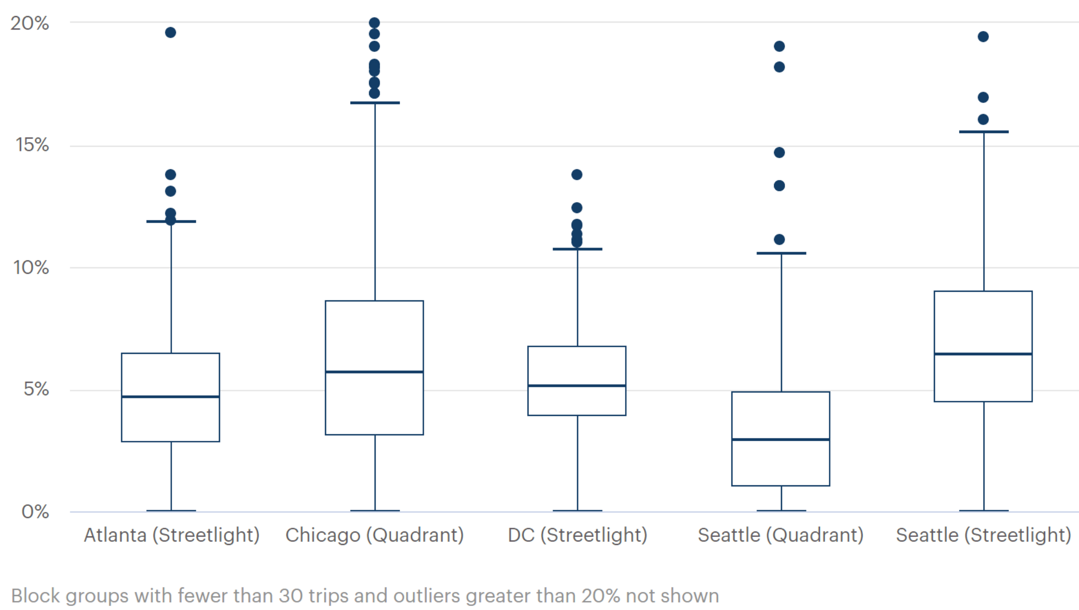
CHAPTER 4. LESSONS LEARNED

USE CASE SUMMARY

The project team presented use cases for Cruise Detector. All the cases were analyzed for time of day cruising and general geography, and, in all but one case, included a longitudinal analysis. The Seattle case analyzed two specific meter pricing policies and also, as briefly noted in Chapter 3, acquired data from two distinct sources for the analysis. The Washington, DC, use case illustrated different cruising patterns around different land uses, focusing on sports arenas/concert venues and rail transit stations. The Atlanta use case highlighted mixed use streets and the differences in trip destinations and cruising that arose from travel changes related to the pandemic. The Chicago use case presented a year-on-year longitudinal analysis.

Bringing all the cases together suggests that parking is hardest to find in the late afternoon/early evening. In Chicago, Seattle, and Atlanta the most cruising occurred between 4 and 6 p.m. (in Washington, DC, the most cruising occurred at noon). A general lag in cruising trips occurs shortly after the higher volumes of all trips likely due to earlier trips ending in the use of on-street parking, and the subsequent lack of availability of such parking leading to cruising. Cruising as a percent of trip making varies in a narrow band throughout the day and across cities. The latter fact is illustrated in Figure 66.

Seattle is shown twice in Figure 66, given the two different data sources.



Source: FHWA.

Figure 66. Cruising across geographies.

Table 4 summarizes the findings across the various use cases. Cruising here was found to add, on average, under 2 minutes to travel. In Chicago, in the base case, it added fewer than 3 minutes.

The highest rates of cruising were found in Seattle and Chicago where 7.3 and 6.8 percent of trips, respectively, showed some portion as cruising.

Table 4. Summary of data and cruising characteristics.

City	Data Type	Baseline Dates	Average Cruising Rate (%)	Average Cruising Time	Peak Hour for Cruising Trips
Chicago	Disaggregate	June 2019	6.8	Under 3 minutes	5 p.m.
Seattle	Disaggregate	January 6–February 28, 2020	3.6	Under 2 minutes	4 p.m.
Seattle	Aggregate	January 6–February 28, 2020	7.3	Under 1.5 minutes	6 p.m.
Washington, DC	Aggregate	January–December, 2018	5.8	2 minutes	Noon
Atlanta	Aggregate	October 1–November 25, 2019; January 6–March 31, 2020	4.9	Under 1.5 minutes	6 p.m.

CONSIDERATIONS

This section covers lessons learned on data quality and implementation of the tool.

Third-Party Processing or Raw Location Data

In this project raw location data were juxtaposed with processed data. Each approach has advantages and disadvantages. In terms of this project, using a third-party processor was costly, time consuming, and required a well-defined sense to begin with of how data should ultimately be aggregated. The delivery of point data (i.e., where cruising and non-cruising trips ended) prevented a detailed analysis of which streets had been traversed. In Seattle, where output showed more cruising trip ends on blocks where meter prices had increased, it was only by using the raw location data that the project team was able to show that those trips had traversed primarily metered streets. Hence, it is assumed drivers were looking for available parking and not necessarily looking for free parking. Relying only on trip-end data, the notion that the meter price increase meant accommodating more trips rather than causing more cruising (due to searching for free parking or lower-cost meters) is a plausible explanation rather than a provable or disprovable hypothesis. Using traces that show the entire cruising path would convert plausible into provable.

Another disadvantage of using the third-party processor is that once the data were run and aggregated, there were no opportunities to redefine the study areas or more deeply investigate questions that might have arisen from initial analysis.

The advantages of raw location data are the complements to the disadvantages of using the third-party processed data. At the same time, the raw location data have their own disadvantages.

These data were of varied consistency with fewer guarantees of their quality, primarily due to volume. They appeared to be sensitive to or biased by the times of day that applications are used, rather than the times of day that people travel. The processed data may have had similar shortcomings. The third-party data, being opaque to the analysts, could not be assessed in this regard.

Computing Resources

Cruise Detector requires a high-performance central processing unit and at least 32 gigabytes (GB) of random access memory. Parallel processing capability is recommended, and therefore a multicore processor with a minimum of eight cores is recommended. The tool was developed and tested using a machine with an Intel® Xeon® W-2265 processor* with 3.5 gigahertz and 12 cores. On that machine 20 GB of GPS point location data took approximately 10 days to process. Users should ensure they have enough hard disk space to store both the raw GPS data and the Cruise Detector database. When processing, Cruise Detector may need as much as twice the hard drive space as the size of the raw data. The amount of hard drive space can be reduced by running the data in smaller batches. Running Cruise Detector in smaller batches also reduces the risk of errors or crashes.

Data Quality Concerns

Cruise Detector relies on relatively high-resolution GPS traces (recommended minimum of 1 ping per minute; twice that density is preferred) that identify discrete vehicle trips. In-car navigation devices may be likely to provide the most reliable data, but many GPS data vendors offer only location data mined from smartphone applications. Often they do not specify the data source. Data quality can vary from vendor to vendor, from month to month from the same vendor, and across cities from the same vendor. For example, in this project the same vendor provided data for Seattle and Chicago. The Chicago data for June 2019 and 2020 were robust; Chicago data for June 2021 were of insufficient quality to use. Meanwhile, Seattle data for 2021 from the same vendor were highly reliable while Chicago data for 2021 were not. Seattle data in 2019 were of limited use.

When negotiating with GPS data providers, analysts should consider obtaining samples of data to assess the resolution, quality, and any steps that may be needed to turn the sequence of GPS points into discrete trips. Information on how the sample was collected (e.g., whether the GPS points are from particular applications) may help analysts assess potential biases. Where available, analysts should also consider using GPS data that have a known source and sampling mechanism, such as those collected as part of GPS-enabled household travel surveys.

Poor quality data, even if a seemingly large base, can yield too few usable trips. In this case and other cases where there may be an insufficient sample size, too few samples will produce unreliable results.

Results can be confounded by time of day use patterns for smart-phone applications. The applications-based data generally showed a sharper PM peak than would have been expected based on other sources of trip data. This may reflect the greater likelihood that people use their

* Intel, the Intel logo, and Xeon are trademarks of Intel Corporation or its subsidiaries.

applications more frequently later in the day. To the extent possible, trip data should be weighted against other sources. The rate of cruising, however, remained consistent regardless of the number of trips and regardless of the time of day, with the exception of early morning hours (1–4 a.m.) where cruising was a higher proportion of all trips.

Applications

Described below are potential applications of Cruise Detector:

- **Quantifying the extent of cruising for parking and identify hot spots.** Cities often try and manage cruising for parking based on perceptions of parking scarcity, or complaints from residents or business owners. In practice, however, cruising for parking may be prevalent in less obvious places, such as older residential neighborhoods with limited off-street parking or beachfront parks. Cruising may spike in neighborhood commercial areas after meters have been turned off for the evening. Cruise Detector provides a data-driven way to identify the locations and times of day where cruising is most prevalent.

- **Analyzing the impact of policy interventions.** Cities can address cruising by managing curb parking, such as installing parking meters, extending meter hours, or adjusting on- and off-street parking prices. Better traveler information on parking availability may also help to reduce cruising. By using before-and-after GPS data, Cruise Detector can help evaluate the success of these interventions on cruising, as illustrated in the Seattle use case. However, as in Seattle (and in earlier work in San Francisco[25]), the impact of a single policy change, such as a 25-cent increase in meter rates, can be too small to have a detectable impact on cruising. In San Francisco, it was only the cumulative effect of multiple price changes that measurably reduced cruising.[26]

CONCLUSIONS

Across all the cities in this analysis, the level of cruising is consistent, even when using different data sources. The estimates in this report are also comparable to earlier work using a similar methodology. Supplementing Table 4 with findings from San Francisco (4 percent or 6 percent cruising, depending on the source) and Ann Arbor (3 percent)[27] further illustrates the consistency. In those cases, cruising was found to occur for on average about 500 meters—as long as it would take a driver to access the top floor of a typical parking structure.

The consistency, even at times of day or in places where parking is readily available, suggests that many trips identified as cruising may not be people searching for parking, but rather people taking a longer route for other reasons. For example, longer trips may be due to people taking a

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[25] Millard-Ball, Adam, Rachel Weinberger, and Robert Hampshire, “Comment on Pierce and Shoup: Evaluating the Impacts of Performance-Based Parking,” *Journal of the American Planning Association* 79, no. 4 (2013): 330–36, https://doi.org/10.1080/01944363.2014.918481.

[26] Millard-Ball, Adam, Rachel Weinberger, and Robert Hampshire, “Is the Curb 80% Full or 20% Empty? Assessing the Impacts of San Francisco’s Parking Pricing Experiment,” *Transportation Research Part A: Policy and Practice* 63 (2014): 76–92, https://doi.org/10.1016/j.tra.2014.02.016.

[27] Weinberger, Rachel & Millard-Ball, Adam & Hampshire, Robert. “Parking search caused congestion: Where’s all the fuss?” *Transportation Research Part C: Emerging Technologies* 120, (2020). https://doi.org/10.1016/j.trc.2020.102781.

detour to pick up or drop off other passengers, missing a turn because of inattention or unfamiliarity with the route, or having arguments with other passengers about where to eat or park. Thus, estimates of cruising may overstate a potential parking problem.

Consistency in the cruising estimates also point to an equilibrium level of cruising. Other work indicates that where parking is perceived to be scarce, drivers will often park short of their destination, taking the first space they find.[28] Where parking is readily available, drivers may be more selective about their choice of a parking space. An analogy is how roadway congestion reaches an equilibrium as users switch modes or departure times based on their tolerance for traffic delay.

In general, cruising is a localized issue. Cruise Detector can identify hot spots, but even in these hot spots, the average time spent cruising is typically brief, and cruising only impacts a relatively small percentage of trips. Cruising in the peak city at the peak hour still affects fewer than 10 percent of trips. A car that parks on the top floor of a parking garage will spend more time finding parking than the average driver cruising for an on-street space, although congestion and other externalities may be greater for the latter.

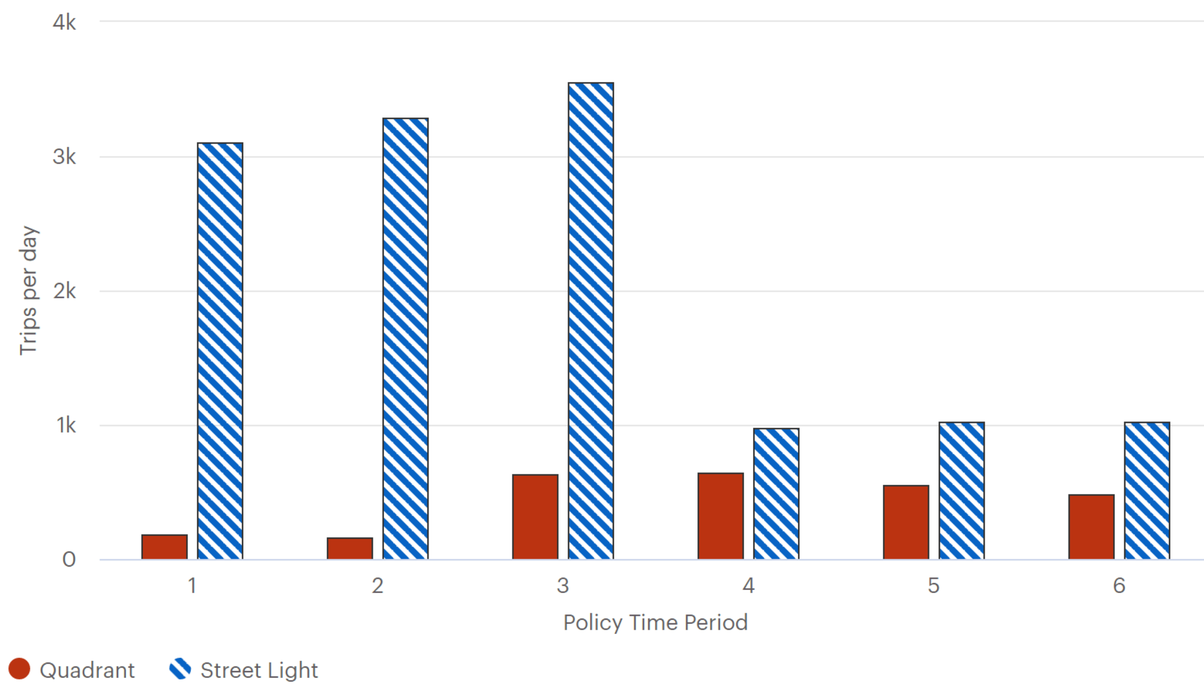
[28] Millard-Ball, Adam, Robert C. Hampshire, and Rachel R. Weinberger, "Parking Behaviour: The Curious Lack of Cruising for Parking in San Francisco," *Land Use Policy* 91 (2020), https://doi.org/10.1016/j.landusepol.2019.03.031.

APPENDIX A. DATA COMPARABILITY

COMPARISON OF DATA SOURCES

The project team acquired output analysis for Seattle from two different sources: proprietary data were processed by Cruise Detector, but behind a data secure firewall. Output was provided in the form of particular metrics, including number of trips, number of cruising trips, date, and time of day for 15,000 units of analysis. The units were a mix of metered streets, streets within half a mile of a metered street, and for census block groups beyond that. In addition, the research team acquired and processed raw location data for several of the same date periods. The outputs of the two sets were compared to understand comparability and whether the sets might be used interchangeably.

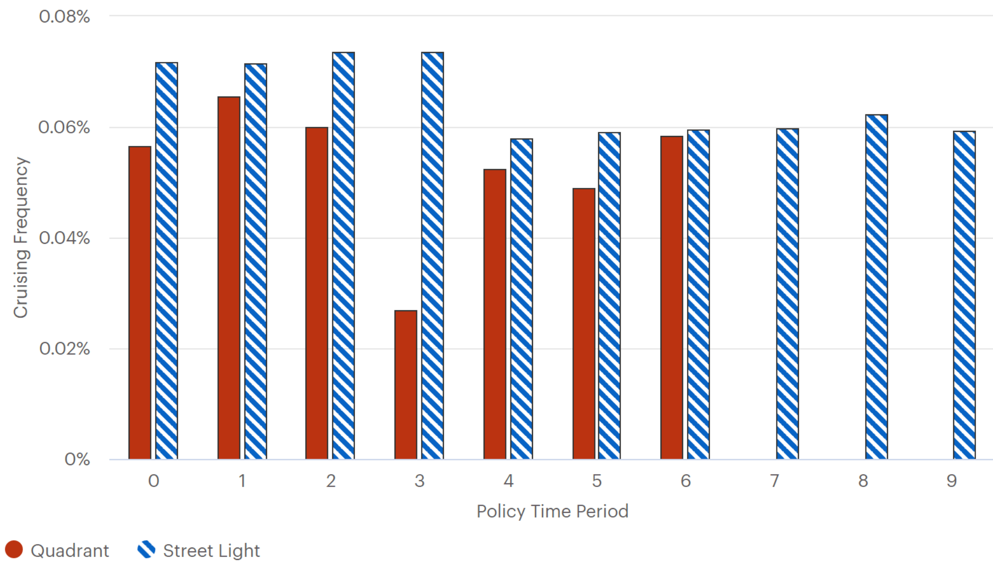
The pre-processed output was aggregated into nine policy time periods, six of which overlap with the second data source (i.e., the raw location data). The first three time periods correspond to most of January and February 2020, divided into before and after the price change. Subsequent periods correspond to late March and early April 2020 (before and after the Seattle parking meters had been temporarily decommissioned). The two data sets varied widely in terms of the volume of trips identified. Trips reported by the third-party processor gradually increased in the first three periods, then dramatically dropped for the remaining time periods—consistent with local stay-at-home orders. The number of trips per day in the raw location sample increased as users (new data sources) were added to their data collection base.



Source: FHWA.

Figure 67. Chart. Volume comparison.

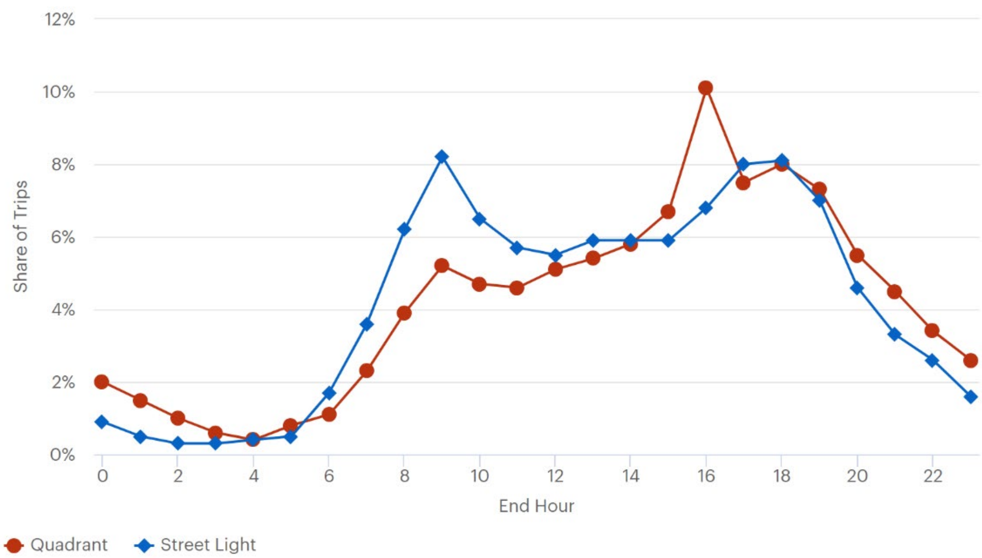
The frequency of cruising was also relatively consistent within each data source, but the raw location data showed consistently lower cruising than the processed data. There was also one notable drop in cruising in the third policy time period in the raw location data set.



Source: FHWA.

Figure 68. Chart. Cruising frequency by policy time period.

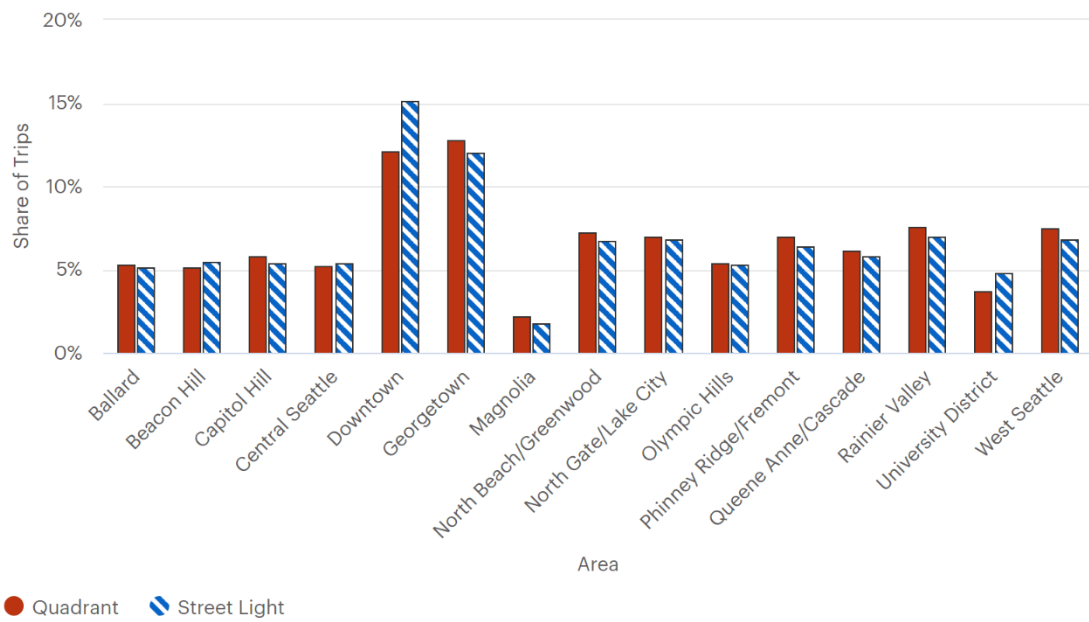
In terms of distribution throughout the day, both data sets show the bulk of trips between 8 a.m. and 8 p.m. but there are important differences between these extremes. The raw location data show trips climbing in the morning to an inflection point, after which they continue to climb but at a slower rate. There is a large spike in the afternoon. The processed data displays a diurnal pattern more similar to the expectation of a traditional morning and early evening peak.



Source: FHWA.

Figure 69. Graph. Time-of-day trip distribution Seattle data sources.

While the data sets differ temporally, spatially their distribution is much more similar. When the data were grouped by the neighborhood in which the trips end, the comparison is much more similar (Figure 70). This pattern suggests that both data sets are drawing from a similar cross section of Seattle neighborhoods, and the raw location set may be influenced more by when people use applications relative to the processed set, which may better describe when people make trips. The discrepancy is not important for some of the possible analysis, but it suggests the benefit of having independent trip counts in which to weight against. The need for such a step would depend on the kind of analysis required.



Source: FHWA.

Figure 70. Chart. Spatial distribution of trips Seattle data comparison.

These data sources offer policy analysts new opportunities to gain insights into trip making, cruising, and parking behavior. These analyses have demonstrated that although there is great potential, limitations in research design may arise from lack of data. Additionally, given the lack of transparency in how most data vendors obtain and process their data, researchers should use caution when drawing conclusions from any single data set. Nevertheless, Cruise Detector and location data can be used to identify potential issues that can be verified with additional data.

APPENDIX B. CRUISE DETECTOR USER GUIDE

INTRODUCTION

This manual describes how to use the GPS cruising identification model developed by FHWA. Any user with a working knowledge of GIS and simple database skills should be able to implement the system with the aid of information presented here. This tool uses GPS data to estimate the proportion of trips that are cruising for parking.

SOFTWARE REQUIREMENTS

Installation

Install PostgreSQL 13+, PostGIS 3.2+ along with pgrouting 3.3.0+. Using pgadmin 4 is also recommended. User will also need to install osm2po and Java 8+ to import a street network.

The following Python® packages must also be installed: numpy 1.11.3+ scipy 0.19.0+ pandas 0.19.2+ gpxpy 1.1.2+ psycopg2 2.5.2+ sqlalchemy 1.1.6+ docopt 0.6.1+

Create a base directory, and download the cruising and pgMapMatch repositories to that directory, and download the sample location data to the cruising folder. Add a folder titled "output" to store logs, and unzip the sampleLocationData folder if using. Download osm2po to a directory with no spaces in its path.

DATA REQUIREMENTS AND FORMAT

Street Network

The street network should be in pbf format. An extract for specific geographic areas can be obtained from geofabrik.de. The extract should be saved to the osm2po base path, if that is different from the project base bath.

Census Boundaries

Census tract or block group boundaries are used to aggregate results for analysis purposes after pgMapMatch has been run on the GPS trace data. Census geographies can be obtained in shapefile format from the U.S. Census Bureau's TIGERweb database.

Global Positioning System Data

Location Data

Data formats may vary by vendor, but the raw GPS location data must be a table containing a minimum of: device ID, timestamp, latitude and longitude, and horizontal accuracy. The cruising_importLocationData.py script is based on one specific vendor's data and may require alteration to match the format and data structure of the location data obtained.

The following is an incomplete list of possible location data vendors[*]:

- Vera set
- Quadrant
- Onemata
- Lifesight

Trip Data

Trip data that have been pre-processed into traces by the vendor can also be used. The imported PostgreSQL table must contain:

- **trip_id**: unique ID for each trace
- **lines_geom**: Linestring M geometry of the trace
- **start_geom**: Point M geometry of the start point
- **end_geom**: Point M geometry of the end point

The following is an incomplete list of possible vendors for trip data*:

- StreetLight
- AirSage
- INRIX
- TomTom

As with the location data, the list is not comprehensive, not an endorsement and not a guarantee the vendor will make usable data available. A collaboration with these firms may be necessary to access their data and information.

CONFIG FILE CHANGES

User will need to change the configuration settings for Postgres, pgMapMatch, osm2po, and the cruising tool itself.

Postgres. After setting up the postgres database, removing the password requirement allows the tool to run smoother. This can be done by changing authentication requirements in the pg_hba.conf file to trust.

Clone the cruising and pgMapMatch repositories, and add a folder titled "output" to store logs.

cruising. Configuration parameters are located in the cruising.py file. Open cruising.py and set the parameters for host, file paths, regions, spatial reference systems, and number of CPU cores used for processing. The config file also contains multiple parameters to calibrate trace generation from GPS data and identify cruising.

[*] The names of vendors in this list are included for informational purposes only and are not intended to reflect a preference, approval, or endorsement of any one product or entity.

pgMapMatch. Open config_template.py and make changes to the pgInfo parameter for the postgres database connection. If password has been removed, make sure requirePassword is set to False. Save the file as config.py.

osm2po. Use the osm2po tool to import the OpenStreetMap data into the database. Make a couple of changes to the osm2po config file to accurately reflect turn restrictions and one-way streets:

```
postp.0.class = de.cm.osm2po.plugins.postp.PgRoutingWriter
postp.1.class = de.cm.osm2po.plugins.postp.PgVertexWriter
graph.build.excludeWrongWays = true
```

LOAD THE DATA

To get started, create extensions for Postgis and Pgrouting by running the following query in the project's PostgreSQL database:

```
CREATE EXTENSION postgis;
CREATE EXTENSION pgrouting;
```

Next, run the following in Python IDE:

```
import sys
sys.path.append('[yourBasePath]/cruising') ## change this to your base path
sys.path.append('[yourBasePath]')
from cruising import *
from cruising_importLocationData import *
```

Import Street Network

Run loadTables(region='[yourRegion]') with the respective region as specified in cruising.py, which will import the osm street network and turn restriction table into the database. The field names for the streets table should match those in the pgMapMatch/config.py. Make sure the SRS of the streets table matches the SRS to be used for the location or trip data, and create indexes and spatial indexes have been created. Depending on the imported network, it may improve performance to clip the street network to a convex hull around the study area.

To run the sample data, user will need to download the Washington State osm.pbf file to the osm2po path and run loadTables(region='wa'). The sample data are comprised of GPS point data, which will be used to generate traces, that can then be analyzed for cruising.

Import Census Boundaries

Use PostGIS to import the census boundary files to database, and reproject the data to the SRS being used. Use a spatial join to add the tract or block group ID to the streets table.

Import Global Positioning System Data

The cruising_importLocationData.py script is based on a specific data vendor and may require alteration to match the format and data structure of the location data obtained.

To import the sample data, set the sample data directory and name for the imported location data table points_table and output trace table output_table.

Run the following code to import the table:

```
points_table = 'samplepoints'
trace_table = 'sampletraces'
iT = importTable(points_table, 'sampleLocationData', schema = 'public', region = 'wa',
forceUpdate=True)
iT.createTable()
iT.importCSV()
```

To generate traces from the sample data, run the following code:

```
pts = pointData(points_table, trace_table, schema = 'public', region = 'wa',
forceUpdate=True)
pts.geocodePoints()
pts.processPoints()
pts.generateTraces()
pts.generateUniqueIDs()
```

Map-Matching from User-Generated Traces

Once the trace table is created, from either the sample data set or the user's data, it can be mapmatched by running the following code:

```
trace_table = "[yourTraceTable]" ##same as the trace_table in the previous section
tt = traceTable(trace_table, schema = '[yourSchema]', region = '[yourRegion]',
forceUpdate=True) ## change the table, schema, etc.
tt.runall()
```

This may take several hours, even with the sample data.

RESULTS AND INTERPRETATION

Once the trips have been processed the data output can be analyzed with a spreadsheet, python, or any statistical package and GIS. See the data dictionary here: https://github.com/amillb/cruising/blob/master/data_dictionary.csv.

GLOSSARY FOR THE CRUISE DETECTOR USER GUIDE

breadcrumb	A trail or path made up of a collection of chronologically arranged GPS locations.
Mapmatch	A process to match a series of pings or traces to a street network or map.
Osm2po	Both a converter and a routing engine.
PgInfo	Displays information about processor groups hierarchy, its contents, and its characteristics.
Pgmapmatch	A map-matching algorithm.
Pgrouting	An extension that adds routing and other network analysis functionality to PostGIS/PostgreSQL databases.
PostGIS	A spatial database extender for PostgreSQL object-relational database.
PostgreSQL	Also known as Postgres, a free and open-source relational database management system emphasizing extensibility and SQL compliance.
Reproject	To change the projection (coordinate system) of spatial data with another projection.
Spatial join	Involves matching rows from the Join Features to the Target Features based on their relative spatial locations.
Trace	A related or connected group of pings.

APPENDIX C. GLOBAL POSITIONING SYSTEM-INDEPENDENT CRUISE ESTIMATOR MODEL ESTIMATION

OVERVIEW

The GPS-independent cruise estimator, or G-ICE, addresses an important question: In the absence of GPS data, can models be developed to estimate the probability of cruising and what data sources would prove useful for this endeavor? The rationale for this tool is that not every jurisdiction will be able to obtain GPS data. Thus, to support those places, can a tool be developed to estimate cruising even in the absence of GPS data, at least of sufficient quantity and quality? By calibrating estimates from cities where there are large samples of GPS traces, the objective is to enable a low-cost way for geographical areas that do not have access to these traces to estimate cruising with minimal data requirements.

The research team prioritized data sources that have already been cleaned and are ready to be processed and carried out for the analysis across multiple cities. This affords us access to a large sample of GPS traces that will be required for calibrating the estimates. Potentially, the model could provide an order of magnitude estimate of cruising with minimal data requirements. Given the availability of the explanatory variables and depending on the predictive accuracy, G-ICE could be used nationwide and was thought might hold the promise of significant utility particularly for cities without access to sufficient high-quality GPS data.

Using both regression and machine learning approaches, the models were structured with cruising as a function of:

- Vectors of covariates of the geographic area including the built environment,
- A vector of travel- or trip-related covariates including the parking variable, and
- A vector of temporal attributes such as time of the day and day of the week.

The research team implemented different structural forms of the regression and machine learning architectures to identify the one that provides the best predictive accuracy. Beyond the root mean square error and the mean absolute error, measures for the percentage of bad predictions were also provided using a 30-percent tolerance threshold value.

EMPIRICAL MODELS

To implement the models, the research team used StreetLight and Quadrant proprietary trip data from Seattle; Washington, DC; Atlanta; and Chicago with the analysis carried out at the census block group level. Explanatory variables include those with predictive power that are publicly available or easily accessible irrespective of the jurisdiction. Both regression methods and machine learning (multilayer perceptron[29] and generalized regression neural networks) approaches were employed for the data analyses.

[29] A perceptron is a linear classifier that takes input regressors and generates a single binary output via an activation function that is triggered when the cumulative sum of the weighted input regressors exceed a specific threshold.

Dependent variable is cruise—measured either by mean cruising distance or time and a categorical form of the cruise variable based on a 250-meter threshold. The categorical variable is 0 when the cruising distance is 0, 1 if there is cruising but the cruising distance is less than 250 meters, and 2 if the mean cruising distance is more than 250 meters.

Covariates include the following:

- wkdy: dummy variable that captures whether the trip happened during a weekday or weekend (True = Weekday, False = Weekend)
- peak: dummy variable based on the trip end – equals 1 if the time falls within the peak period and 0 otherwise
- r_den: housing units per acre on unprotected land
- j_den: jobs per acre on unprotected land
- p_den: parking meters per acre on unprotected land
- lnaadt: log of the average annual daily traffic (AADT) of all road segments within the CBG
- city_dummy: dummy for cities; for example, the Seattle dummy equals 1 for all trip records from Seattle and 0, otherwise
- d2a_ephhm: employment and household entropy calculations, where employment and occupied housing are both included in the entropy calculations

Interactions terms were also used. For example, a city dummy (e.g., for Seattle) was interacted with day-of-the-week dummy or if the trip ended during the peak hour. The variables above provide standardized and widely available data that could be used to develop and validate the model. Equally important, if G-ICE were to have enabled accurate predictions, it would have relieved cities of the need to purchase the data given that they are non-proprietary. It also provides a basis to carry out objective comparisons across jurisdictions. The comparative analysis component of the model provides us with the ability to generalize the process to additional cities.

RESULTS

Three analyses were carried out: multiple linear regression analysis with the cruising estimated using conditional expectations, generalized regression neural networks (GRNN), and multilayer perceptron. In the regression analysis, what is relevant is the model-explained portion of the regression or the explained sum of squares (ESS) relative to the total sum of squares given that the focus is on prediction. Consequently, the emphasis is on the ESS that explains the variation observed in the modeled values. This is the case whether the mean cruising is measured based on time or distance. There was no difference in the goodness of fit when the interacted terms are included as regressors.

Only a marginal difference was observed for the mean square error from the GRNN compared to that of the linear regression. The percentage of bad predictions (a 30-percent threshold) also buttresses the results obtained from earlier methods. The plot of residuals versus predicted values has very high positive values for the residual—an indication that the predictions were too low. Ideally, these values should be close to zero given that the residual, for each observation, is simply the actual minus the predicted cruising.

To expatiate on the previous analyses, the mean cruising distance was changed to a categorical variable using a 250-meter average cruising distance threshold. A multilayer perceptron (MLP) neural network was subsequently run with cruise as the dependent variable and with two hidden layers, each with a hundred nodes (neurons). Using the predict command where the predicted value defaults to the option with the highest probability, a predicted accuracy of 88 percent across all the cities that were featured in the analysis was obtained. This, however, inflated the goodness of fit given the number of observations with zero cruise. For cruises classified as moderate (cruise=1), only 4 percent of the predictions are right while none of the predictions for high cruising (cruise=2) is right. This is a source of concern given that these are instances when a false negative cannot be afforded—situations where there is cruising and there may be need to put countermeasures in place, but the predicted value says otherwise.

CONCLUSION

As mentioned, the 88 percent accuracy figure obtained for the MLP inflates the goodness of fit given that none of the specific instances of cruise=2 (high cruising) were predicted correctly. This is problematic given that it is in this situation that the public may be sensitive to Type II errors or false negatives (no cruising) when there is indeed cruising. The research team surmises that determinants of cruising are localized (temporally) events, which were not adequately reflected for the present analysis. For example, it is difficult to have decent predictive powers when covariates are based on average values over time—e.g., AADT—or when values used have no temporal association to the present. Policy effects are nuanced—for example, the research team found a statistically significant increase in distance cruised when the parking meters were switched off in Seattle though this happened at a time when total trips were about one third of prior trip making, between March and April 2020 when the city was on lockdown. G-ICE did not successfully project this outcome.

U.S. Department of Transportation
Federal Highway Administration
Office of Operations
1200 New Jersey Avenue, SE
Washington, DC 20590

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