Spatiotemporal comparative analysis of scooter-share and bike-share usage patterns in Washington, D.C.

Grant McKenzie

Department of Geography, McGill University, Montreal, Canada
grant.mckenzie@mcgill.ca

Abstract

The United States is currently in the midst of a micro-mobility revolution of sorts. Almost overnight, U.S. cities have been inundated with short-term rental scooters owned and operated by start-up companies promising a disruption to the urban transportation status-quo. These scooter-share services are presented as a dockless alternative to traditionally government-funded, docking station-based bike-sharing programs. Given the rapid rise of electric scooter companies, and how little is known about their operations, there is pressing public interest in understanding the impact of these transportation-sharing platforms. By exploring the nuanced spatial and temporal activity patterns of each of these platforms, this research identifies differences and similarities between dockless e-scooters and existing bike-sharing services. The findings from this research contribute to our understanding of urban transportation behavior and differences within mobility platforms.

Keywords: micro-mobility, scooter-share, bike-share, dockless, e-scooter

1. Introduction

We are in the midst of technology-induced paradigm shift in transportation. Ride-hailing services, short-term car rentals, and autonomous vehicles are altering the transportation landscape. Within this environment, electric, dockless, scooter-sharing services are experiencing explosive growth and adoption in urban centers (Brustein and Lanxon, 2018; Marshall, 2018a). Presented as a solution to the *last-mile* problem, privately funded scooter-share companies have inundated cities so quickly that municipal governments are struggling to evaluate the impacts on existing services, determine legality, and assess citizen safety.

First, a brief overview of how current scooter-sharing services works. A user accesses a map of available scooters via a service-specific application downloaded to their mobile device. After navigating to the available scooter, the user unlocks it by scanning a Quick Response (QR) code on the vehicle and begins their trip. Upon reaching their destination, the user parks the scooter on any public city property, clicks the trip completion button on their mobile app, and walks away. The trip is charged to the credit card registered with the mobile application. At time of writing, the cost to use a scooter in most U.S. cities is $1 USD to unlock and $0.15 per minute of usage (from `https://www.li.me/help`). A number of scooter-share companies are in service today. One of the dominant operators in the United States, and the source of trip data for this research, is *Lime* (a set of Lime scooters is shown in Figure 1a).

(a) Lime dockless electric scooters

(b) Capital Bikeshare docked bicycles

Figure 1: Two mobility services in Washington, D.C. *Docked* refers to programs that require vehicles to be docked at stations, as opposed to those that permit vehicles to be left in any public space (*Dockless*). Photographs published under Creative Commons License. Photographers (a) Grant McKenzie (b) Ben Schumin.

In much the same way that ride-hailing services recently forced citizens and governments to re-evaluate urban transportation, this new mode of short-trip travel is again causing heated discussions at a municipal level (Richter, 2018). One program most likely affected by the influx of these scooter-share services is government-funded bike-sharing. These two services likely appeal to a similar demographic of the urban population and bike-share programs often involve substantial financial investment in infrastructure and maintenance. For example, between 2011 and 2019, the City of Montréal, Canada, spent an estimated $62.2 million in taxpayer funds to support the BIXI bike-share program (Guénette and Doucet, 2017). Given the level of investment, and the desire of scooter-share companies to expand into new markets (Canadian Press, 2018), it is worthwhile investigating scooter-sharing services further and assessing the differences between them and existing, subsidized, bike-sharing programs.

One of the issues facing cities is that few studies were conducted prior to the introduction of these scooter-share services. Many of these vehicles showed up on city streets without warning (Lazo, 2018) and the proprietary nature of the companies operating these services has limited external research opportunities. Questions still remain as to how these services are actually used and the overall impact that these scooter-share companies are currently having, and will continue to have on cities. While existing research has focused on a number of facets ranging from regulatory (Anderson-Hall et al., 2019) and economic concerns (Smith and Schwieterman, 2018), to usage behavior (Todd et al., 2019) and environmental impact (Weiss et al., 2015) to the best of my knowledge, little research has investigated the nuances of when and where people are using these scooters. In this work I identify these spatiotemporal usage patterns and compare them to existing bike-share mobility services in a major urban center.

Figure 2: Location of study area, Washington, D.C.

The geographic setting for this work is Washington, District of Columbia (D.C.), in the United States (Figure 2). The city was chosen for this work as it is one of the few cities in North America that currently requires private micro-mobility companies to share their data publicly in order to receive an operating permit (DDOT, 2018). This, in combination with the recent inflow of scooter-share services into the city allows for the analysis of ridership patterns at a high spatial and temporal resolution within a major metropolis. Furthermore, comparison with existing mobility services is possible through open data efforts in the region. D.C.'s *docked* bike-share program, *Capital Bikeshare* (Figure 1b), is one of the largest, and most successful, government-funded bike-sharing programs in the United States (Lazo, 2017), and anonymized trip data are openly shared with the public. These factors combine to make Washington, D.C. an ideal region in which to analyze scooter-share spatiotemporal usage patterns.

Contribution

The primary contribution of this work is the identification and comparison of spatial and temporal scooter-share and bike-share usage patterns in Washington, D.C. To this end, the work presented here addresses the following four research questions (*RQ*). The first two pertain to a scooter-share service itself while the latter two involve comparative analysis with an existing bike-share service.

*RQ*1 What is the *temporal* distribution of scooter-share trips and how do they vary during the course of a day? Are there differences between weekdays and weekends?

*RQ*2 What is the *spatial* distribution of scooter-share trips and what is their land use distribution?

*RQ*3 Is there a significant difference in the *temporal* activity patterns of customers using a docked bike-sharing program and dockless scooter-sharing service?

*RQ*4 Are there *spatial* differences in the usage patterns of a dockless scooter-sharing service and a docked bike-sharing program?

These questions will be addressed in the remainder of this manuscript which is organized as follows. Related work is presented and discussed in

Section 2. An overview of the data is provided in Section 3 and the data cleaning process is presented in Section 4. The first two research question are addressed in Section 5 while Section 6 presents a comparative analysis with a bike-share program, addressing the remaining research questions. A discussion of the implications of these analyses are provided in Section 7 and conclusions are presented in Section 8.

2. Related work

Dockless scooter-share services are a new and rapidly emerging market (Clewlow, 2019), and as such, limited external research has investigated their impact on existing municipal services or transportation infrastructure. What research there is has primarily focused on the social impacts of these scooter services (Petersen, 2019; Loizos, 2018), parking placement (Fang et al., 2018), adoption rates (Riggs, 2018; Degele et al., 2018), and safety concerns (Allem and Majmundar, 2019). Additional research has centered on distribution optimization (Chen et al., 2018) and electrical engineering-focused efforts towards efficient batteries (Pellegrino et al., 2010). One recent scooter-share usage study based out of Chicago conducted analysis using hypothetical trips. The authors identified a number of ways in which scooter-share services could potentially augment existing public transit and reduce personal automobile usage (Smith and Schwieterman, 2018). In this case, however, no spatial or temporal analysis was done to identify the differences between any of these services.

While the body of literature related to scooter-shares is small, a substantial amount of research pertaining to bike-share programs, their impacts on existing transportation systems, as well as socioeconomic and environment effects exists (see Fishman, 2016 for an overview). Recent efforts have been exploring relatively new *dockless* bike-sharing services, though many of these have been replaced by scooter-sharing (Sussman, 2018) in recent years. Zhou et al. (2018) discovered that the introduction of dockless bike-sharing services produced a modal shift, reducing metro ridership in Shanghai, China. Research into the impact of bike-sharing services on traffic and congestion found that these services had a positive impact on large cities and negative impact on wealthier municipalities (Wang and Zhou, 2017). Similarly, Mooney et al. (2019) examined spatial equity of dockless bikes in Seattle, Washington finding that education level of residents correlated with a higher density of dockless bikes. Other work (Ricci, 2015) supports the notion that bike-sharing systems reduce travel times and cost, and improve health and travel experiences. Computationally, there is a substantial body of literature pertaining to optimization strategies for bike-share distribution (Pal and Zhang, 2017; Lin et al., 2018; García-Palomares et al., 2012). More recently, the spatial and temporal distribution of docked and dockless bike-sharing trips has been analyzes showing unique patterns within each service (McKenzie, 2018).

Probably the most similar area of research to scooter-sharing is *electric* bike-sharing. The introduction of these services have been found to have an impact on existing city infrastructure. Specifically, electric bike-shares have been shown to draw users from bus systems, taxis, and metro (Campbell et al., 2016) and the ride-hailing company *Uber* just reported that the electric bike-sharing program *Jump*, in which they are heavily invested, is cannibalizing riders from Uber cars (Rao, 2018). While electric bike-share services substantially overlap with scooter-share services, few research efforts have been made to quantify the difference in spatial patterns of the various mobility services.

3. Data

In this work, trips using two urban mobility services were analyzed, namely *Capital Bikeshare* (CB), the government-funded docked bike-sharing service, and *Lime* (LS), the dockless electric scooter-sharing company. An overview of the data collected is shown in Table 1.

Table 1: Descriptive statistics for Lime scooters and Capital Bikeshare programs. Median value in brackets. *The temporal resolution of data collection for Lime scooters was 5 minutes hence the median trip length of 5 minutes.

Platform	Lime eScooters (LS)	Capital Bikeshare (CB)	
Service	N/A	Members	Casual
Total number of trips	937,590	1,086,619	327,436
Mean trip distance (meters)	649 *(554)*	2608 *(2244)*	2698 *(2436)*
Mean trip length (mins)	5:19 *(5:00*)*	14:34 *(10:26)*	39:23 *(24:20)*
Mean num vehicles per day	287 *(325)*	1886 *(1919)*	1080 *(1143)*
Mean num trips per day	7050 *(7962)*	8170 *(8478)*	2462 *(2390)*

3.1. Lime

Lime scooter data were accessed at a 5-minute temporal resolution via the public accessible application programming interface (API) for the D.C.

region (https://ddot.dc.gov/page/dockless-api). Data were collected from June 13 through October 23, 2018. The result of a single API request is an array of *available* vehicles (those not currently in use). Each available vehicle includes limited attribute information such as the vehicle identifier and geographic coordinates. As the data were collected in real-time, a time stamp was assigned to each API request.

Data collection for scooters resulted in 15,960 *snapshots* of available scooters taken at 5 minute intervals over 133 days. A trip was identified as the time stamp and coordinates of when a scooter last appeared available in a snapshot, to the time stamp and coordinates of when the same scooter next appeared available in the set of incremental snapshots. The start of the next trip for the scooter was then identified as the stop location of the previous trip and the start time of the trip was identified based on when the scooter next moved. Only those scooters that moved more than 80 meters were considered trips. This was done primarily in consideration of GPS multi-pathing errors and vehicle location adjustment by non-users. Using this approach, 1,005,788 trips were identified in the scooter data before further cleaning.

3.2. Capital Bikeshare

CB trip data are freely accessible as monthly comma delimited text files from the Capital Bikeshare website (http://www.capitalbikeshare.com/system). Trip data were downloaded for the same time period as the scooter data. Each CB trip consists of a set of attributes including a bike identifier, trip start and end station identifiers, trip start and end time stamps, and duration of trip in seconds. The geographic coordinates of docking station locations were downloaded from D.C.'s Open Data portal (http://opendata.dc.gov) and mapped to bike trip start and end stations identifiers. The CB service region currently covers the greater D.C. metro area including parts of Virginia and Maryland, a total of 523 docking stations. For this study only those trips that both started and ended within the municipal boundary of D.C. were included, restricting analysis to 269 stations and 1,414,055 trips. The pricing structure for Capital Bikeshare includes two *plans*, *members* that pay an annual or monthly fee for unlimited access to the bike-share service, and *casual* riders that pay per trip (This includes riders that purchase 24 hour or 3-day passes). Provided this information, CB trips were further separated into two datasets, one for casual users (CB_{Casual}) and one for members ($\mathrm{CB}_{Members}$). Again, Table 1 gives a numerical overview of the services.

4. Data cleaning

Before analysis could be done with the data, I first identified potential issues such as falsely labeled trips within the scooter data.

4.1. Scooter-share juicing

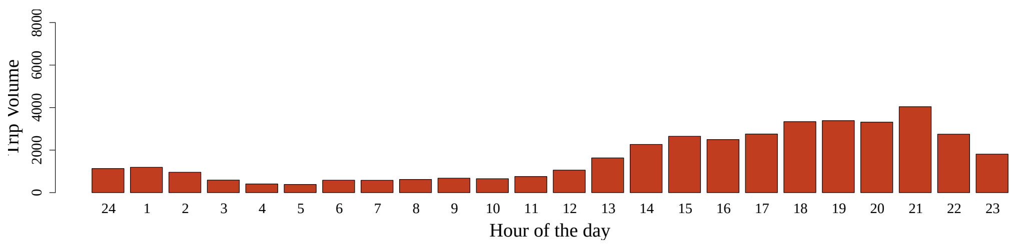
Under normal usage conditions, a typical electric scooter must be recharged at least once within a 24 hour period. To accomplish this, Lime developed a crowd-sourcing program called *Juicing*. Through the juicing program, Lime pays citizens to recharge electric scooters on their private property (`https://web.limebike.com/juicer`). Participants are instructed to pick up scooters that have low batteries at the end of the day and drop them off to specific locations the next morning. In order to analyze authentic trips within the dataset, *juicing trips* were first identified and removed.

As a first pass, all trips with a duration over 2 hours were identified. Given a average trip duration of roughly 5 minutes, it is highly unlikely that a trip lasting 2 hours is an authentic user trip. Furthermore, since an electric scooter can only run continuously for 2 hours (roughly 30 miles per charge at a speed of 15 mph) (Marshall, 2018b), a trip lasting 2 hours would likely involve a stop with a long duration and should not be included in analysis for this project. Two hours is also important as it is considered the minimum amount of time that a *juicer* can spend recharging a scooter in order to get paid (Ridester, 2018). Through this method 37,243 trips were identified as *juicing trips*.

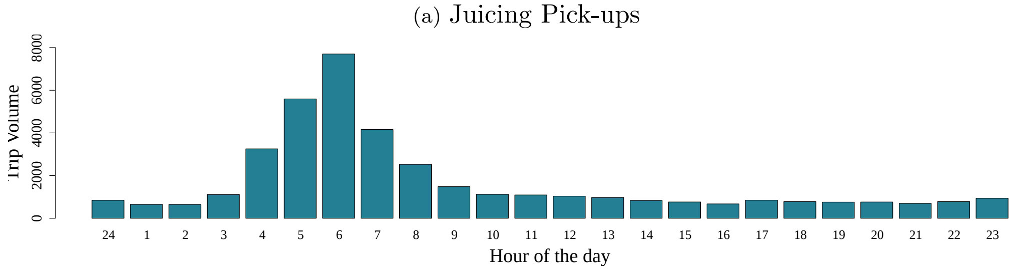
While it could be argued that removing all trips with a duration over 2 hours may falsely remove actual user trips, I chose to error on the side of removing false positives rather than include false negatives. Figure 3 shows the temporal distribution of scooter pick-up and drop-offs, trips identified as *juicing trips*, aggregated to a 24 hour period. This figure shows that most pick-ups related to juicing are distributed broadly in the evening hours which is a reflection of when the batteries on the scooters run low and juicing is requested by Lime. Comparatively, juicing drop-off times are much more specific with most of the drop-offs occurring between 4am and 8am.

4.2. Scooter-share redistribution

Aside from *juicing*, Lime also employs staff members to redistribute scooters that are in non-optimal locations (e.g., too many scooters in one location, or a scooter has not been used in 24 hours). The maximum speed of a scooter



(a) Juicing Pick-ups



(b) Juicing Drop-offs

Figure 3: Temporal pattern of *juicing trip* pick-ups and drop-offs over an aggregated 24 hour period.

is 15 miles per hour (Lime, 2018). Given this information, *redistribution trips*, were identified as any trip with an average speed faster than this as identified by the distance between the start and end points, as computed by the shortest path distance along the D.C. road network, divided by duration. These "faster than maximum speed" trips imply that the scooter moved by way of a redistribution vehicle. Notably, the majority of these *redistribution trips* occurred between 3pm and 4pm on weekdays, likely with the goal of redistributing scooters before peak commute times. Through this process I further identified and remove 15,791 trips leaving a total of 937,590 authentic scooter-share trips.

5. Spatiotemporal scooter-share usage patterns

In addressing *RQ1* and *RQ2*, I first identify the temporal and spatial usage patterns within the scooter trip data.

5.1. Temporal patterns

The 4 months of scooter trips were aggregated by hour of the day and day of the week and normalized to produce the temporal usage patterns shown in Figure 4. The start times of the trips are shown in this figure but given that the mean duration of trips is roughly 5 minutes (the temporal resolution of data collection), the end trip usage pattern is nearly identical. A mid-day peak is seen in both weekday and weekend usage with a smaller, and more pronounced peak on weekday mornings during peak morning commute, roughly 8am.

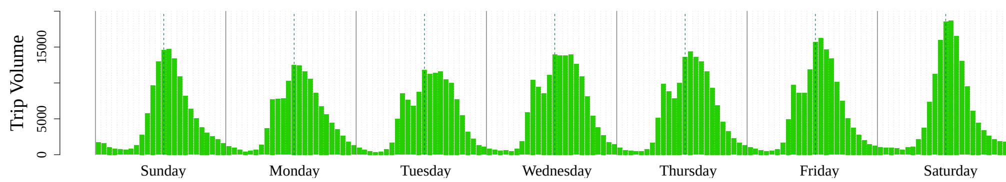


Figure 4: Scooter-share trip start times aggregated to hours of the week. Solid lines at midnight and dashed blue lines at 12 noon.

Cosine similarity (CosSim) was employed to statistically assess the degree of similarity between days of the week. CosSim measures the cosine angle of two inner product vectors and produces a similarity measure for each pair of temporal activity distributions allowing for statistical comparison between temporal usage patterns. While all combinations of days produced relatively high CosSim values (above 0.9), midweek days, Tuesday-Thursday, were determined to be the most similar followed by Saturday-Sunday. This approach also supports the visual estimation that the least similar scooter-share usage is between weekend and midweek days, addressing *RQ1*, that there are indeed differences in usage between weekdays and weekends.

5.2. Spatial patterns

While the previous section identified temporal patterns in the scooter-share data, this section presents the spatial distribution of scooter-share trips.

5.2.1. Land use

These activity patterns were then further analyzed by splitting trips based on *land use* of origin and destination with the goal of addressing *RQ2*. By separating the temporal usage patterns in this way, I gain a better understanding of potential trip purpose, at least as it can broadly be identified through the proxy of land use. The most recent land use spatial data for D.C. was downloaded, all scooter trip start and end locations were intersected with the dataset, and the nearest land use code was assigned to each start and end point. Land use types were grouped into broad categories. Low, medium, and high density residential were categorized as *Residential*, all office and commercial types were designated as *Commercial*, and all recreational, federal public, and quazi-public land were designated as *Recreational/Public*. Trips starting or ending in mixed-use, industrial, or schools were removed from analysis in this work as together they accounted for less than 10% of all trips. Of the remaining three land use categories, trips that started in *Recreation/Public* accounted for 40.6% of all trips, *Commercial* accounted for 36.3%, and *Residential* 23.1%. Breaking this down further, all combinations of origin and destination land use were tabulated. Overall, 60% of these trips started and ended in the same land use type (e.g., Commercial → Commercial). Table 2 shows the breakdown of trips.

Table 2: Origin and destination of scooter-share trips by top three land use types.

Trip Start	**Trip End**	**Percentage**
Public/Recreation	Public/Recreation	28.2
	Commercial	8.2
	Residential	4.2
Commercial	Commercial	19.5
	Public/Recreation	8.6
	Residential	8.2
Residential	Residential	11.4
	Public/Recreation	4.2
	Commercial	7.5

The land use of the origin of each trip was further examined by hour of the week. The percentage of trips split by land use type are shown in Figure 5. Notably, the number of trips starting in *Residential* areas did not change much between weekdays and weekends, 24.1% to 23.0% respectively. The largest difference between weekdays and weekends was found with both *Commercial* and *Public/Recreation* land use types. On weekdays, 38.9% of trips started from *Commercial* areas compared to 32.1% on weekends. In contrast, 37.1% of *Public/Recreation* origin trips occurred on weekdays increasing to 44.9% on weekends. This is a significant shift in both cases.

5.2.2. Traffic analysis zones

The origin locations for all scooter-share trips were next intersected with the traffic analysis zone (TAZ) polygon dataset for D.C. and trip density was calculated for each TAZ (Figure 6a). Visually, we see a clear cluster of trips near the downtown core of the city with far fewer trips originating

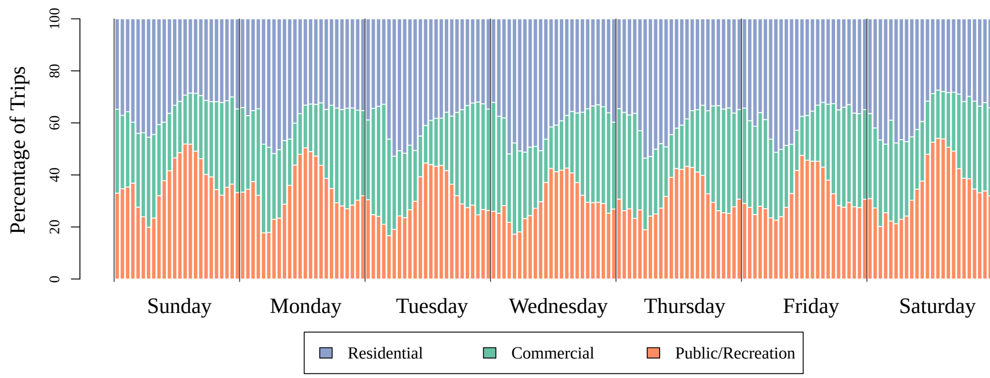
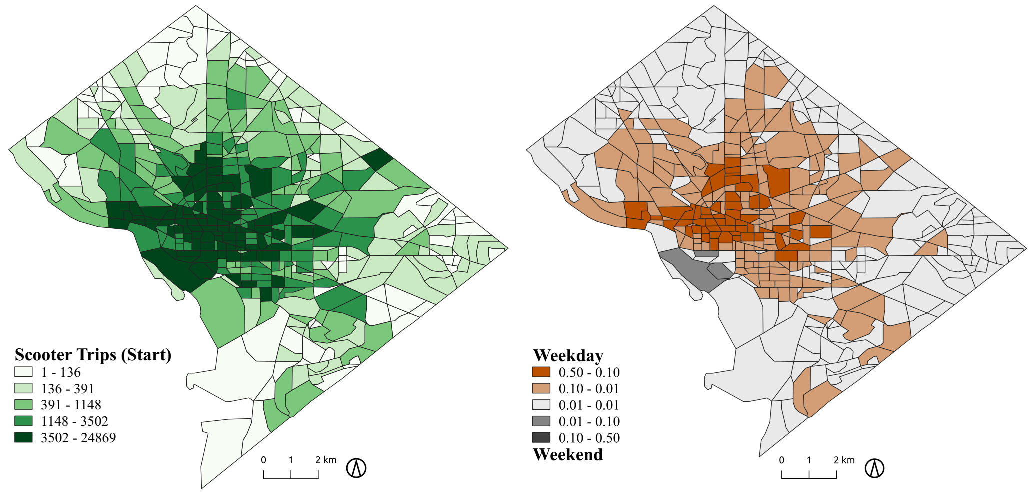


Figure 5: Percentage of trips by hour of the week split by land use of where the trip originated.

on the outskirts of the region. Given that analysis of the temporal patterns identified differences in trip volume between weekends and weekdays, I next computed *Global Moran's I* (Moran, 1950) for the two patterns in order to identify differences in spatial autocorrelation. The results demonstrate that the trip volume patterns are both non-spatially random with weekday trips (0.170) showing a higher degree of spatial clustering than those on the weekends (0.121). Both analyses had an expected value of -0.0022 and standard deviation of 0.0033. Calculating the weighted standard deviation distance from the mean weighted TAZ centers identified weekends a having a larger radius distance than weekdays. In response to the spatial dimension of *RQ1*, this indicates that weekday trips are generally more centered in the downtown city core of D.C. relative to weekend trips which show greater spatial dispersion.

The differences in regional trip density are shown in Figure 6b. Normalizing trip volume to allow for comparison, weekday trips were subtracted from weekend trips resulting in a map showing the regional dominance of trips based on day of the week. Notably, weekday trips dominate the majority of TAZs, especially around the downtown city core whereas weekend usage is relatively greater than weekday usage in regions near the National Mall and along the Potomac River. There is negligible difference in scooter usage on the outskirts of the district.



(a) Scooter trip density (b) Normalized weekend vs. weekday trips

Figure 6: Spatial distribution of trips aggregated by traffic analysis zone. Figure 6b ranges from Weekday to weekend dominance.

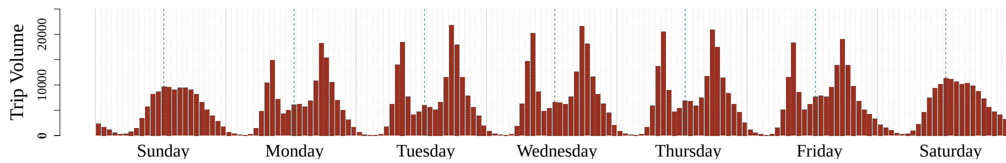
6. Contrasting scooter-share and bike-share usage patterns

In this section I address *RQ3* and *RQ4* by comparing scooter-share spatiotemporal usage patterns with those of D.C.'s bike-share program.

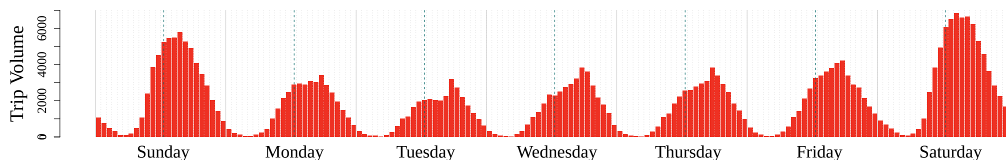
6.1. Temporal activity similarity

Similar to the scooter temporal patterns introduced in the previous section, bike-share trips were aggregated by hour of the day and day of the week to produce an averaged temporal vector of 168 values. Split by membership type, the two temporal signatures for trip start times are shown in Figure 7.

There is a striking difference between the two CB patterns shown in these Figures. Figure 7a clearly shows increased trips during typical commute times on weekdays while Figure 7b shows increased usage on the weekends and no clear commuting behavior during weekdays, aside from a slight increase in usage around 5pm. This is in line with previous findings comparing these two bike-share types (Buck et al., 2013). By comparison, the scooter-share temporal pattern (Figure 4) is visually similar to *casual* CB ridership, more so than *member* CB usage. To assess the similarity of these patterns statistically, *Watson's* U^2 *two sample test for homogeneity* (Watson, 1961) was applied with the goal of identifying any significant differences between



(a) *Member* Capital Bikeshare trip start time



(b) *Casual* Capital Bikeshare trip start time

Figure 7: Temporal patterns for Capital Bikeshare trip start times aggregated to hours of a week. Solid lines at midnight and dashed blue lines at 12 noon.

the services and membership types. This test is a variation on the Cramér–von Mises test (Cramér, 1928) and provides a criteria to test whether two circular distributions, such as these temporal patterns, differ significantly from one another. The test starts with the null hypothesis that the two distributions being sampled are drawn from the same population distribution. Setting a significance value of 0.01, which in turn sets a critical value for the 168 element distributions of 0.268, this approach recommends rejecting the null hypothesis for the pair of CB_{Member} and scooter temporal trip patterns. This suggests that these two patterns are not drawn from the same overall temporal distribution and are in fact quite dissimilar. The results of Watson's U^2 test for the other pairs, at the same significance value (0.01), namely CB_{Member} vs. CB_{Casual} and CB_{Casual} vs. scooters, suggest not rejecting the null hypothesis, meaning they are much more similar to one another. A more detailed investigation of these values finds a significance value of $p < 0.001$ for the CB_{Member} and scooters pair, $p < 0.05$ for the CB_{Casual} and scooters pair, and $p > 0.1$ when comparing the two bike-sharing temporal patterns. This indicates that, according to this method, the bike-share platforms are more similar to one another than to the scooter-share service.

While a useful measure, the results of Watson's U^2 test really offers two possible outcomes, either the distributions are significantly similar or they are not. To supplement this measure, *CosSim* was again used to assess the degree of similarity between temporal patterns, allowing for a more nuanced comparison between the services and membership types. The CosSim between CB_{Casual} and CB_{Member} was 0.756 whereas CB_{Casual} to scooters was 0.886, and scooters to CB_{Member} was 0.809. These values again support the hypothesis that trips performed by casual bike-share users are more similar to scooter-share trips than membership based bike-share trips. In addressing *RQ3*, I can state that there are statistically significant differences between bike-share and scooter-share temporal usage patterns. Membership based bike-share clearly reflects standard commuting patterns while scooter-share does not.

6.2. Spatial activity similarity

Having compared temporal patterns, I next turn focus to assessing the spatial differences between scooter-share and bike-share services (*RQ4*). The primary difficulty in comparing two spatial datasets such as these is that bike-share trips are restricted to a set of static locations (269 docking stations) while dockless scooter trips are not. This complicates spatial analysis that requires two datasets to be represented at the same spatial resolution for comparison. To mitigate this issue, a Voronoi polygon tessellations (Voronoi, 1908) was constructed for D.C. based on the point locations of CB docking stations. The purpose of this tessellation approach was to assign each docking station to some region within D.C. The assumption being that any individual interested in starting a CB trip would navigate to a bike docked at their closest station. Figure 8 shows the overall volume of trips by region for the CB_{Member} service. This Voronoi tessellation approach serves another purpose in that it provides a contiguous set of polygons to which each scooter trip start and end can be assigned. Using a spatial intersection, each scooter-share trip start and end is assigned to a CB docking-station-based Voronoi polygon and trip volume is calculated for each region and each service.

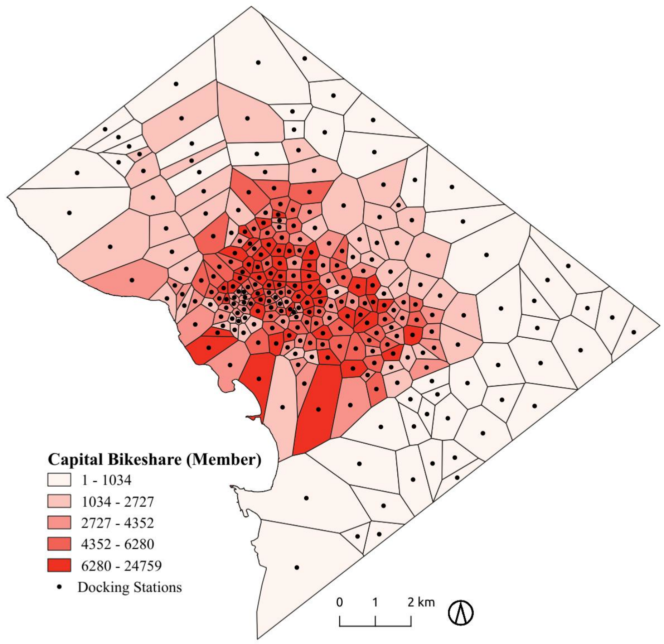
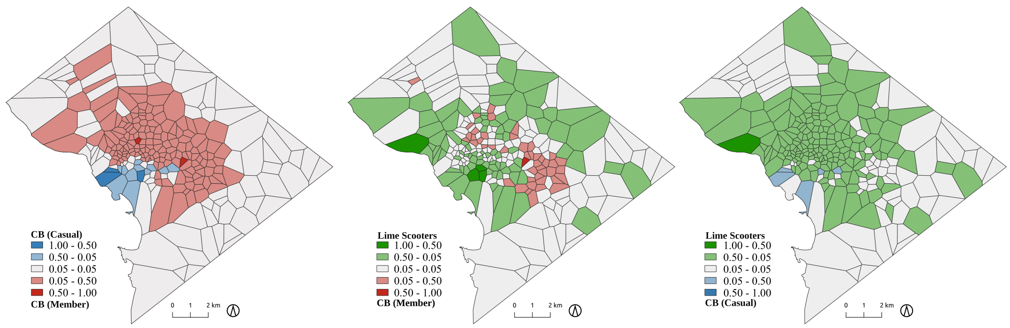


Figure 8: Voronoi polygons built around Capital Bikeshare docking stations. Color intensity reflects number of trips started by bike-share members.

Next, I calculate the difference in the spatial distribution between the services and membership types. Each service is normalized providing a value between 0 and 1 for each docking station polygon. This normalization allows each service to be compared to each other service in the spatial dimension, with respect to trip density. Figure 9 shows a set of maps produced by subtracting trip density of one service from another. These maps show variation in service dominance. Notable observations from these maps are that CB_{Member} trips appear to dominate the downtown core of D.C., with higher relative usage around the *Capitol Hill* neighborhood when compared to either LS or CB_{Casual} trips. On the other hand, scooter-share appears to have broader regional adoption outside of the downtown core with greater trip volume relative to CB on the outskirts of the district. The only region that appears to show higher than average trips for CB_{Casual} is along the *Potomac river waterfront* whereas scooter-share usage is dominant around *Georgetown* and the *National Mall*.

The similarity of these spatial distributions is statistically tested using a two dimensional Earth Mover's Distance (EMD) approach (Rubner et al., 2000). EMD calculates the similarity between two equally sized multi-



(a) CB_{Member} vs. CB_{Casual} (b) CB_{Member} vs. Scooters (c) CB_{Casual} vs. Scooters

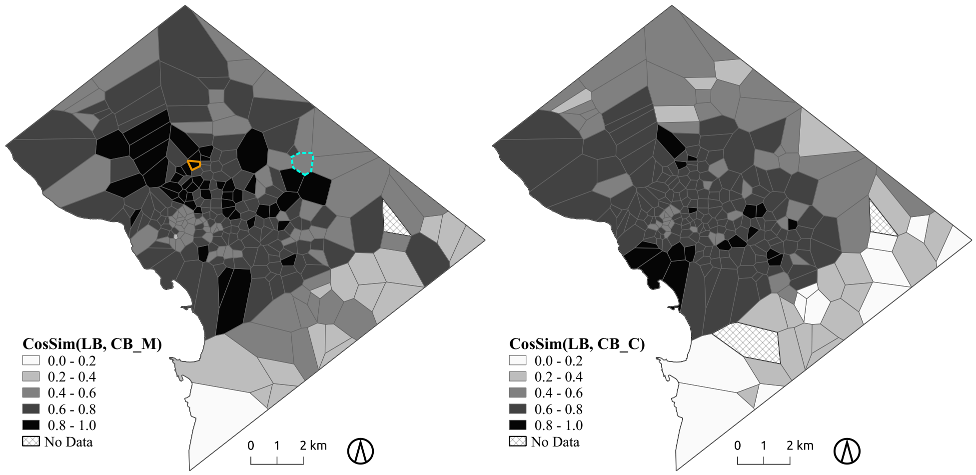
Figure 9: Normalized trip volume for one service compared to another.

dimensional matrices by computing the cost of converting one distribution into the other. The cost in this case is based on the difference between normalized trip volume in a region, and the minimum "distance" needed to travel. The results of the EMD analysis indicates that the highest level of spatial similarity is between CB_{Member} and CB_{Casual} (0.13) whereas the least similar spatial distributions are CB_{Casual} and scooters (0.50). A comparison of scooters to CB_{Member} demonstrates an EMD similarity value roughly between the two at 0.37. In other words, while casual bike-share usage is similar to scooter-share usage in the temporal dimension, it is quite *dissimilar* in the spatial dimension.

6.3. Temporal similarity within regions

Temporal activity patterns are next computed for each of the 269 docking-station based regions independently within the dataset, one for each of the three services. CosSim is computed between all pairs of temporal patterns within each individual region. This analysis allows us to determine which regions of the city demonstrate the highest degree of temporal trip similarity and which show the least. Figure 10 presents the CosSim of temporal patterns by region for each bike-share and scooter service.

In Figure 10a we see that the highest levels of similarity are in the regions between the downtown core and the peripheral neighborhoods in the city. The orange solid bordered region shown in this figure is the region with the highest cosine similarity. In this case both of the temporal patterns appears to mirror the commute pattern indicative of the district-level CB_{Member} temporal usage. The light blue dashed bordered region on the other hand



(a) Cosine similarity of CB_{Member} and Lime Scooters

(b) Cosine similarity of CB_{Casual} and Lime Scooters

Figure 10: Cosine similarity between bike-share and scooter-share trip temporal patterns by region. Orange solid bordered region shows the highest cosine similarity and blue dashed border region shows one of the regions with the lowest cosine similarity between services.

reflects two substantially different temporal patterns with CB_{Member} showing a prominent commuting pattern with very high trip volume during the weekday morning commute compared to the scooter data which shows the standard scooter-share pattern with high activity on the weekends and little to no indication of weekday commuting behavior.

Figure 10b shows the CosSim comparing CB_{Casual} to scooters. The regions with the highest similarity between these two services are found along the *Potomac River* and the *National Mall* as well as a few regions within the downtown city core. Exploration of these similar regions in the downtown core show that neither service portrays commuting patterns but instead the high degree of similarity could be attributed to their non-commute trip patterns. A notable limitation of visualizing the data in this way is that cosine similarity decreases as the sparsity of the trips increases. This means that polygons in the Southeast of D.C. may be seen as less similar simply because they lack a large enough trip volume on which to produce an accurate cosine similarity measure.

7. Discussion

The overall goal of this research is to identify similarities and differences between existing docked bike-sharing and this new service of dockless scooter-sharing. The results of the analyses presented in the previous sections demonstrate that there are clear differences both in the temporal and spatial dimensions. Not only are ridership patterns different within Washington, D.C. as a whole, but these results indicate that there are nuanced regional differences within the district. Splitting bike-share trips into those taken by members and those that use bike-share casually allows for a more detailed comparison of the services. The results indicate that while both bike-share modes show similar spatial distribution of trips, they vary substantially in their temporal patterns. When compared to the new scooter-share service, the results show that casual bike-share is similar temporally but varies greatly in spatial distribution. Membership bike-share, on the other hand, is generally dissimilar to scooter-share usage in both dimensions.

The primary take away from these results is that these two services are used for different purposes. Member bike-share in Washington, D.C. is predominantly used by those commuting to and from work while scooter-share does not reflect this standard commuting behavior. While the purpose of the trips conducted by users of these services is not explicitly clear, the analysis in this work suggests that causal bike-share usage and scooter-share trips support leisure, recreation, or tourism activities, more so than commuting. Reasons as to why these services are used in these ways was not explored in this work but I theorize that much of this has to do with the length of time the two services have been in operation. Capital Bikeshare has been in use, in some form, since 2008 and over the years has proven to be a robust and trustworthy service on which both residents and visitors to D.C. can rely. Furthermore, the Capital Bikeshare program is funded through tax dollars and supported by local governments. In contrast, Lime's scooter-share service is roughly one year old. The service has not had time to build trust within the community and to many residents these scooters remain a novelty. It is therefore not surprising that residents prefer to rely on the membership-based Capital Bikeshare program when commuting to and from work and likely use scooter-share when the cost of failure (e.g., not making it to work on time) is low.

7.1. Biases

Though this work focuses solely on the spatial and temporal distribution of trips within Washington, D.C., there is a clear discussion to be had pertaining to the demographics of scooter-share and bike-share users. While *Capital Bikeshare* conducts and publishes regular user surveys, little information is available regarding the demographics of scooter-share users. What is notable however, is the regions of the city that show little to no scooter-share activity. Wards 7 and 8 in the Southeast of D.C. report the fewest number of scooter-share and bike-share trips and are also home to the lowest income families and largest percentage of African Americans in the district. This suggests one of two things, either these mobility services only appeal to a small socio-economic subset of the population, or these new services are contributing to a further socio-economic divide fueled by technology-based transportation. Regardless, further investigation into the demographics and socio-economic status of the users is necessary to understand why there is a lack of urban mobility service usage in these regions.

7.2. Data limitations and future work

Though analysis in this work relied solely on scooter-share trips from one of the largest providers in D.C., *Lime*, other scooter-share services may depict different patterns. While unlikely to be substantially different from the results of this analysis, further research should investigate the variation between services. In addition, the five minute temporal resolution of data collection limits the analysis and comparison of trip duration, given that many trips are shorter than five minutes. Future efforts will increase the temporal resolution of data collection.

Next steps on this research topic will compare these results to spatial and temporal patterns of scooter-share services in other cities and involve examining regional variability in scooter usage. Land use will be further examined with the goal of identifying differences within land use types (e.g., High density vs. low density residential). Similarly, the impact of regional climate, seasonal changes, and hyper-local weather will be assessed. Finally the results of these analyzes will be compared to other existing modes of transportation including traditional automobile, ride-hailing services, and public transit.

8. Conclusions

The rapid influx of scooter-sharing services in U.S. cities has caught many municipal governments by surprise. One of the first steps towards understanding the impact of these new micro-mobility services is to identify how they are used within a city. In this work I explored the spatial and temporal patterns of dockless scooter-share trip origins and destinations and compared these patterns to those of traditional docked bike-sharing services. The results indicate that there are important differences between the two services. Bike-sharing services within the city of Washington, D.C. are primarily used by individuals commuting to and from work while scooter-share is not. These findings offer novel insight into how these services are used in an urban setting and provide a foundation on which public policy and transportation infrastructure decisions can be made.

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