Urban mobility in the sharing economy: A spatiotemporal comparison of shared mobility services

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Abstract

The influx of micro-mobility services, such as dockless scooter-share and e-bikes, in many cities are contributing to a substantial change in urban transportation with adoption rates reminiscent of other shared-mobility services, such as ride-hailing, years prior. Touted as a solution to the last mile problem, a multitude of micro-mobility companies have situated themselves in urban centers promising low cost alternative transportation options for short, urban travel. The rapid arrival of these companies, however, has left little time for city officials, transportation planners, and citizens to assess the demand for these services and compare them to existing transportation options. In this work, we investigate two key aspects of these micro-mobility services. First, we identify the spatial and temporal differences between these mobility companies and highlight the nuanced differences in usage patterns. Second, we compare these new services to an existing mode of transportation, namely automobile-based ride-hailing, with regards to differences in travel time within a city. The results of these analyses indicate that while many micro-mobility companies are spatiotemporally similar, there are notable differences in where and when these services are used. Similarly, we find that automobile travel is not always the fastest means of transportation within an urban setting. During periods of heavy traffic congestion, e.g., rush hour, micro-mobility services offer a faster means of travel within the city. The findings presented in this work offer evidence on which to inform urban planning and transportation policy with respect to shared mobility services, free floating vehicles, and alternative urban transportation.

Keywords: shared-mobility, micro-mobility, scooter share, bike share, dockless, ride-hailing

1. Introduction

In March of 2018, a new form of urban transportation appeared on the streets of Washington, D.C. Dockless, electric scooter and bike companies descended on the city, as they have in many other urban areas, distributing vehicles-for-hire and promising a novel solution to the *last-mile* problem. While the introduction of these new platforms lead to mixed reactions from citizens (Richter, 2018; Trivedi et al., 2019), they came into use so rapidly, that city planners and transportation engineers had little time to assess their impact on existing infrastructure and municipal services (Lazo, 2018). In fact, many municipalities have struggled with the legality and regulations of these services (Bergal, 2018) with some implementing pilot programs to further assess their impact (DDOT, 2018) and others establishing outright micro-mobility bans (Camozzi, 2018). Given the confusion driven by the rapid influx of these platforms, it has become increasingly apparent that comprehensive research is necessary to truly evaluate the effect that these services are having on our cities. One approach is to compare these new platforms with existing urban transportation options. It is through a comparison to existing services that we may begin to identify the nuanced difference between platforms and determine if, and how, these services are addressing a population whose travel demands have not previously being met.

Though the term *micro-mobility* has been used for a number years now, its definition still remains vague. We use the term in this work to describe both dockless scooter-share (Figure 1) and dockless electric bike-share services. These services work by first using the mapping interface of a mobile application to find an available vehicle. Once a suitable vehicle is found, the user unlocks it through scanning a QR code thus beginning a *trip*. Once the trip is

Figure 1: Examples of dockless electric scooter-share (`Lime` and `Bird`). Photograph CC-BY-SA-4.0.

complete, the user parks the vehicle on any public city space, locks the vehicle through her mobile device, and walks away. The typical charge for use of an e-vehicle is $1 USD to unlock and $0.15-$0.30 per minute of use, depending on the city. At the time of writing, micro-mobility companies are operating in over two hundred cities world wide with many investors valuing these of these companies in the billions of dollars (Wiggers, 2019). The number of micro-mobility companies in operation is substantial, with new platforms entering the market monthly (see Crunch Base (2018) for an up-to-date list). In Washington, D.C., for example, there are currently 6 micro-mobility services in operation (DDOT, 2018). The District Department of Transportation (DDOT) requires that each operating company holds a permit restricting them to a maximum of 600 vehicles of any time (e.g., bike or scooter). Washington, D.C. was one of the first metropolitan regions to require that these services publicly share their data in order to be granted an operating permit. Though other municipalities have quickly followed suit, this DDOT requirement offered us, as researchers, an early opportunity to analyze these micro-mobility data and report scientific findings on which to inform public policy.

From a urban research perspective, the rapid adoption of these new transportation technologies has given rise to a burgeoning new sub-field with numerous avenues of exploration. In this work we chose to concentrate our efforts on two facets of these new services. The first focuses on identifying the spatiotemporal differences and similarities between the micro-mobility companies that operate within Washington, D.C. With six different companies providing very similar services using virtually the same technology, we question if there are significant differences between the activity patterns of these services and whether or not these differences are reflected through their regions of operation or popular times of day. *Induced demand* would suggest that these services were established based on an outstanding need for short distance travel options and that the user base has grown to meet the volume, and spatial distribution, of these micro-mobility services. Building on this notion, we analyze the user activity data provided by these services with the goal of identifying the dimensions through which these services differ from one another.

The second facet of these services to be examined is *travel time*, specifically how trips using this new mode of transportation compare with automobile travel times in an urban setting. Automobile transportation within a city is often viewed as the fastest mode of travel between two locations. As automobile traffic volume continues to increase in most metropolitan areas, however, questions begin to arise as to what, if any, transportation alternatives may surpass automobile travel with respect to travel time. Micro-mobility services are challenging this notion, forcing us to re-evaluated urban travel time and compare these new services to automobile travel. Access to robust, high resolution automobile travel time datasets on which to conduct comparative analysis have historically been difficult to ascertain. The recent availability of ride-hailing travel time data offers one possible solution allowing us to address this dynamic. The transportation network company *Uber* recently began publishing travel time datasets providing average trip duration between numerous sub-regions in cities around the world. These data offer an unprecedented opportunity to compare automobile and micro-mobility travel times throughout a major metropolis.

Given these two focal areas of research, we have outlined four specific research questions (*RQ*) below that will be addressed in the remainder of this work.

*RQ*1 Is there a difference between the *temporal* usage patterns of micro-mobility services? We construct temporal signatures based on user activity patterns and compare micro-mobility services to one another.

*RQ*2 Is there a difference between the *spatial* usage patterns of micro-mobility services? The regional dominance of each platform is examined and a number of spatial analysis techniques are used to compare and contrast the services.

*RQ*3 Is there a difference between the average travel time of micro-mobility and ride-hailing services over the same distance in an urban setting? If so, does this difference vary by time of day or day of the week?

*RQ*4 Similarly, if a difference in travel time between micro-mobility and ride-hailing services does exist, does it vary *spatially* within the city?

The remainder of this manuscript is organized as follows. An overview of existing work in this domain is presented in Section 2 followed by introduction of the data and data cleaning process in Section 3. Temporal and spatial comparative analyses between micro-mobility services are presented and the results are shown in Section 4. This is followed by Section 5 comparing these micro-mobility platforms to a ride-hailing service and reporting on spatiotemporal differences in travel times. Finally, a broader view of this work is discussed including limitations and future work in Section 6. Finally, Section 7 summarizes our findings as conclusions.

2. Related work

Micro-mobility services are a new and rapidly expanding sub-field of urban transportation research. As datasets are just now becoming available, limited research has examined the spatial and/or temporal aspects of scooter-share and dockless e-bike usage, a gap that the research presented here aims to fill. A considerable body of literature, however, has explored the social implications of these services, namely safety concerns (Badeau et al., 2019; Allem and Majmundar, 2019; Loizos, 2018), adoption rates (Riggs, 2018; Aono and Bigazzi, 2019) and regulatory / policy implications (Fang et al., 2018; Petersen, 2019). For instance, work by Degele et al. (2018) focused specifically on scooter-share *users*, clusters them based on activity patterns ranging in scope from geographic to behavioral. These findings demonstrated that there are differences between users, producing cluster labels such as *power users* and *casual users*. An interesting finding, but one that does not address the spatiotemporal patterns of usage within an urban setting.

Though done using *hypothetical trips*, other existing research has explored scooter usage in identifying how scooter-share services might supplement public transit and automobile trips (Smith and Schwieterman, 2018). The results suggest that scooter-share could be a strong alternative to short private automobile trips and potentially enhance access to metro services. This is supported by a small sample qualitative study observing everyday e-scooter usage in Munich, Germany (Hardt and Bogenberger, 2019) with results indicating that e-scooters trips have the potential to replace local automobile trips. Again, these findings suggest that e-scooters are having an impact on our cities but do not speak to the nuanced difference between these services and fall short of directly comparing travel times between automobile and micro-mobility services.

Since scooter-share literature is still quite limited, we also look to a similar and more established domain of research, namely *bike-sharing*. There is a large body of work contrasting bike-share services with other means of urban transport (see Fishman (2016) for a review). The introduction of *dockless* bike-share systems, the predecessor of scooter-share in many urban settings, have been shown to impact existing city services (Zhou et al., 2018) both negatively (Wang and Zhou, 2017) and positively (Ricci, 2015). Furthermore, the distribution of these dockless bicycles in some cities is shown to be related to neighborhood equity characteristics (Mooney et al., 2019). Research specifically on electric bike platforms (Campbell et al., 2016) determined that these types of services do in fact draw users from public transit and taxis. All of this research demonstrates that there are indeed differences in mobility services across cities as a whole, but does little to investigate either the spatial or the temporal differences within a city.

Existing work by McKenzie (2018) identified how the introduction of dockless bikes may have an impact on city-funded docked bike-share programs, investigating the spatial differences within the city of Washington, D.C. This work suggests that e-scooters may exhibit similar spatiotemporal patterns to those demonstrated by dockless bike-share riders. Regarding travel times, Faghih-Imani et al. (2017) compared duration of taxi trips to docking station-based bike-sharing in New York City. The authors found that during times of heavy congestion, bike-share was faster or competitive with taxi travel. While docked bike-share usage has been shown to be substantially different from scooter-share with regards to land use (McKenzie, 2019), these results suggest the potential for similar findings when comparing dockless scooter-share to ride-hailing services. Similarly, in commercial transport research, Gruber and Narayanan (2019) discovered that *Cargo Cycles* had the potential to be faster than some commercial trucks in regions within German, again supporting the notion that travel time largely depends on the spatial and temporal characteristics of the platform and the environment.

In recent years there has been a plethora of work related to transportation network companies, or ride-hailing services more generally (see Clewlow and Mishra (2017) and Chan and Shaheen (2012) for an overview). Much of this work has focused on issues related to route optimization (Agatz et al., 2012; Bimpikis et al., 2019), safety (Feeney, 2015; Goel et al., 2016), and the impact of hide-hailing services on existing urban infrastructure. For instance, work by Young and Farber (2019) found that an increase in ride-hailing trips had a negligible impact on public transit, negatively impacted taxi ridership, and contributed positively to active modes of travel such as biking. Further work by Contreras and Paz (2018) supports this finding of a negative impact on taxis but shows that ride-hailing services in Los Vegas, Nevada complement public transit. Though little research has investigated the effect that micro-mobility services are having on ride-hailing, some preliminary (internal) work from Uber's data science team suggests that users of Uber's electric bike-share platform, `Jump`, are actually cannibalizing trips from Uber's automobile ride-hailing service (Rao, 2018). From a spatiotemporal perspective, existing literature has explored both the spatial and temporal activity patterns of ride-hailing services. A study by Calderón and Miller (2019) found that there was a wide distribution of ride-hailing service throughout the greater Toronto, Ontario area with a consistent balance between trip origin and destination zones. Temporally, a survey of users in San Francisco, California by Rayle et al. (2016) discovered that wait times for ride-hailing services were actually much shorter and more reliable than traditional taxi services, a finding that leads nicely into our work comparing ride-hailing travel times with new mobility services. To the best of our knowledge, no work has continued on this vein, comparing travel times between these two distinct modes of urban transportation.

3. Data

The analysis presented in this manuscript was performed on data collected from two different modes of transportation, namely dockless electric micro-mobility services and an automobile ride-hailing platform.

3.1. Micro-mobility

First, dockless electric scooter-share and bike-share availability data were accessed via public application programming interface (API). A current list of APIs is curated by the District Department of Transportation and is available at `https://ddot.dc.gov/page/dockless-api`. In total, data for six micro-mobility sharing services were accessed, namely `Bird`, `Lime`, `Lyft`, `Skip`, `Spin`, and `Jump`. The first five of these platforms offer electric scooter-share services, while the last platform, `Jump`, provides electric-assist bike-sharing. Notably, `Lime`, `Spin`, and `Jump` offer both dockless scooters and non-electric bikes in other cities, but the data used in this work is restricted to those vehicle types listed above.

A request to any of the service APIs returns a list of currently available vehicles including the following attributes: Vehicle identifier, geographic coordinates, and time stamp of request. Requests were made to the six platform APIs every minute over the course of four months starting in December 2018. Provided these *snapshots* of available vehicles, trips were constructed for each service based on the following methodology. The start of a trip was determined as the time and location of a vehicle before moving more than 100 meters. The end of the trip was determined as the next time stamp that the vehicle re-appeared as available in the dataset. Only those trips with a road network distance greater than 100 meters and duration longer than one minute were kept in our study dataset. These restrictions were made to account for vehicle GPS multipathing errors, repositioning of vehicles, or short trips conducted by users simply testing out the service.

The data were cleaned by removing all trips that lasted longer than 2 hours, the maximum battery life of a scooter given continuous movement. Any trip lasting longer than 2 hours implies that the vehicle was offline for some period of time (e.g., recharging or in a truck for relocation). Similarly, those trips that reported an average speed greater than 15 miles per hour (maximum speed of a scooter) were removed from analysis as they were likely relocation trips involving redistribution via automobile. Lastly, those trips with average speeds lower than 2.2 miles per hour were removed as this is considerably slower than the average human walking speed and likely reflects a significant stop within a trip or error in the data. In many of these cases, our data cleaning approaches were overly conservative, as we chose to error on the side of removing a small number of actual user trips instead of including false positives in our analyses.

3.2. *Ride-hailing*

The second source of data for this analysis was provided by the *Uber* transportation network company, colloquially referred to as a ride-hailing platform. The company offers public assess to their *Movement* dataset (`https://movement.uber.com/explore/washington_DC/travel-times/`) which, among other information, reports mean travel times between all Traffic Analysis Zones (TAZ) in a number of cities including Washington, D.C. The highest resolution of temporal data available is travel time by hours of the day on either weekdays or weekends. The data used for this research was the mean travel time between TAZs for all ride-hailing trips that took place in 2018.

4. Spatiotemporal similarity of micro-mobility services

The first step in this research was to examine the similarities and differences between micro-mobility services in Washington, D.C. A basic descriptive overview of these six mobility services are presented in Table 1. Overall, the five scooter-share services are similar in total number of vehicles in operation, average number of vehicles in operation per day, and total number of trips within our study window. `Skip's` fleet of vehicles is the largest, leading to the highest number of trips overall. `Lime`, while similar to the other services in the first three values is very different with respect to average trip distance and duration. The mean distance traveled per trip for a `Lime` user is 874 meters with a duration of just under 5 minutes. Compare this to an average distance of over 2,000 meters and a duration of roughly 12 minutes for the other scooter-share services. `Jump`, on the other hands operates an electric bicycle service with a far smaller vehicle fleet and a much longer average trip distance and duration. Some possible reasons for these differences in trip lengths are presented in Section 6. The remainder of this section divides the analysis by the temporal and spatial dimensions of the activity data.

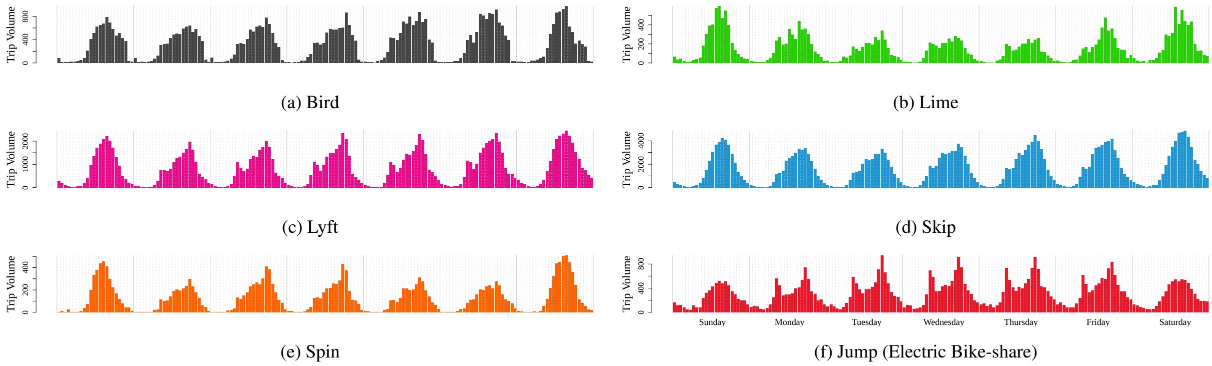
Table 1: Descriptive statistics for the six micro-mobility services in Washington, D.C. Averages show the mean with median in parentheses.

Service	Type	Num. Vehicles	Avg. Vehicles/day	Total Trips	Avg. Distance (m)	Avg. Duration (min:sec)
Bird	eScooter	2,328	134 *(129)*	20,475	2,382 *(2,081)*	14:35 *(11:01)*
Lime	eScooter	2,573	131 *(115)*	25,787	874 *(405)*	4:47 *(2:01)*
Lyft	eScooter	3,765	342 *(315)*	100,215	2,159 *(1,789)*	12:19 *(10:59)*
Skip	eScooter	5,953	489 *(516)*	178,531	1,797 *(1,485)*	10:56 *(08:01)*
Spin	eScooter	1,333	99 *(63)*	13,866	2,274 *(1,859)*	13:48 *(10:59)*
Jump	eBike	467	141 *(138)*	39,112	4,251 *(3,671)*	24:11 *(19:00)*

4.1. *Temporal activity similarity*

In addressing *RQ1* we first constructed *temporal signatures* from trips conducted by users of each mobility service. The start times of trips were aggregated by hour of the day and day of the week producing the typical weekly patterns show in Figure 2. While the temporal signatures for each service show different trip volumes (note the the y-axes), the general patterns depict similar temporal activity behavior. One service that sticks out from the others with regards to the temporal signature shape is `Jump` (Figure 2f). While most of the scooter-share services demonstrate a slight increase in trip volume around 5pm on weekdays during the evening commute, `Jump`'s e-bike service additionally presents a peak between 8am and 9am on weekdays during the morning commute. `Lyft`, `Lime`, and `Bird` also appear to show small trip volume increases during the morning commute, relative to nearby hours, but trip volume during these hours is much less pronounced.

These temporal signatures shown in Figure 2 are informative in that they allow for visual comparison between the different services. The similarities and differences between these services were also measured statistically. *Watson's non-parametric two sample test of homogeneity* (Watson, 1961) is used to assess the similarity between each pair of



(a) Bird (b) Lime (c) Lyft (d) Skip (e) Spin (f) Jump (Electric Bike-share)

Figure 2: Temporal signatures aggregated to hours of a week for the six dockless electric micro-mobility services in Washington, D.C. Notably each y-axis is different as the trip volume differs between services. Plot colors are based on the dominant colors of the service logo.

services. Watson's U^2 statistic offers a criterion on which to test whether two sample distributions are drawn from the same population distribution. A variation on the *Cramér-Von Mises criterion* (Cramér, 1928), Watson's U^2 test is specifically suited to *circular* distributions. The U^2 statistic is not dependent on the starting point of the measurement scale but rather the relative ranks of the observations in the two sample distributions. This makes it particularly well suited for the temporal signatures (hours of the week are circular) presented here. Prior to applying Watson's U^2, each temporal signature was normalized to produce hourly values between 0 and 1 allowing for a test of the relative temporal popularity between services rather than comparing raw trip volume. The results of these analyses are shown in the middle column of Table 2.

While Watson's U^2 test is one approach for assessing similarity between temporal signatures it is primarily useful in determining the significance of the similarity (or dissimilarity in this case). Another approach, namely *Cosine Similarity (CosSim)* was applied to these same mobility service pairs. CosSim measures the cosine angle of two inner product vectors producing a similarity measure for each pair of temporal activity signatures. The resulting measure is more nuanced than Watson's U^2 approach producing numerical values between 0 (most dissimilar) and 1 (most similar) for each service pair. These CosSim values are presented in the last column in Table 2.

Table 2: Two statistical approaches for measuring similarity between temporal signature pairs. Watson's non-parametric two sample test of homogeneity (middle column) reports criteria on which to test whether two temporal signatures are drawn from the same distribution. Cosine similarity (last column) measures the cosine angle of two inner product vectors, or temporal signatures.

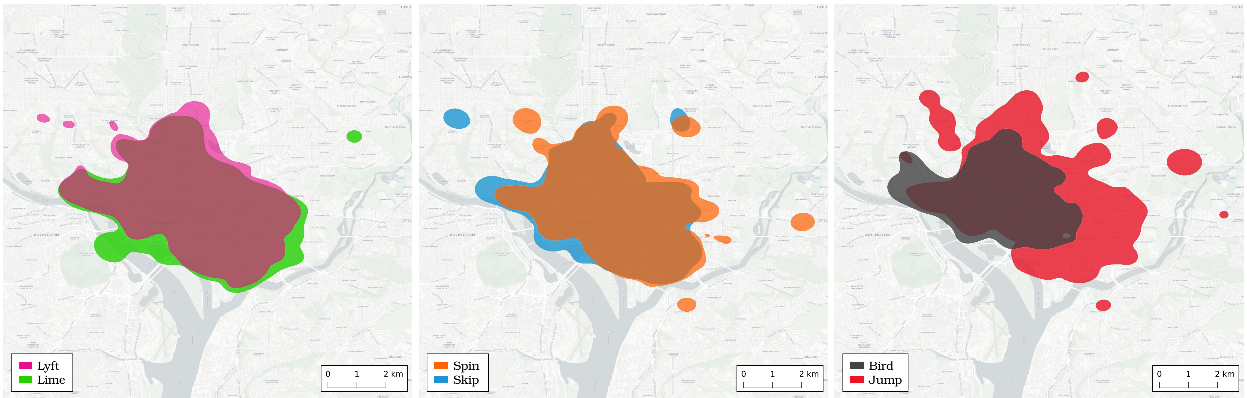
Service Pairs		Watson's U^2	CosSim
Bird	Lime	1.0518 *($p < 0.001$)*	0.924
Bird	Lyft	0.1607 *($0.05 < p < 0.10$)*	0.976
Bird	Spin	0.3272 *($0.001 < p < 0.01$)*	0.978
Bird	Skip	0.1521 *($0.05 < p < 0.10$)*	0.948
Bird	Jump	1.0973 *($p < 0.001$)*	0.938
Lime	Lyft	0.3798 *($0.001 < p < 0.01$)*	0.954
Lime	Spin	0.2677 *($0.01 < p < 0.05$)*	0.948
Lime	Skip	0.4155 *($p < 0.001$)*	0.949
Lime	Jump	0.1449 *($p > 0.1$)*	0.889
Lyft	Spin	0.1145 *($p > 0.1$)*	0.989
Lyft	Skip	0.0195 *($p > 0.1$)*	0.971
Lyft	Jump	0.5356 *($p < 0.001$)*	0.957
Spin	Skip	0.1429 *($p > 0.1$)*	0.962
Spin	Jump	0.3689 *($0.001 < p < 0.01$)*	0.939
Skip	Jump	0.5737 *($p < 0.001$)*	0.908

The application of two very different similarity assessments allows for a broader perspective on the differences between micro-mobility services. In analyzing the values presented in Table 2 we can identify which of the services are most similar and which are least. Jump, the electric bike service, is identified as the most dissimilar mobility service when compared to all scooter-share services. Specifically, the Watson's U^2 test supports rejecting the null hypothesis with a high degree of significance ($p < 0.001$) when comparing Jump to Bird, Lyft, Skip and Spin (with $p < 0.01$). There is disagreement in the results of the two statistical approaches when comparing Lime to Jump, however, with Watson's U^2 test indicating that the two temporal signatures are likely drawn from the same distribution ($p > 0.1$) and CosSim producing the lowest (most dissimilar) value across all service pairs. This notable difference between the temporal patterns of scooter-share services and electric bike-share services is supported by the previous finding that scooter-share and *non-electric* bike-share services exhibit very different temporal activity patterns (McKenzie, 2019). Within the scooter-share based transportation options, further examination of these results highlights that trips taken by Lime users are more temporal dissimilar to all other services than most of the other scooter-share platforms. This reflects the substantial dissimilarity in the average distance and duration of Lime trips as compared to other micro-mobility services. Lastly, Lyft and Spin report the highest degree of similarity across the two approaches presented in this work and generally do not show a high degree of dissimilarity with any of the other scooter-share services. This is noteworthy in that, with respect to trip volume, these two services are on opposite ends of the spectrum. Spin has by far the lowest number of trips and smallest fleet of vehicles whereas Lyft reports one of the highest trip volumes.

4.2. Spatial activity similarity

In the previously section we explored the temporal similarity of micro-mobility services. Here we investigate the spatial distribution and similarity of these services, again comparing and contrasting activity patterns of micro-mobility companies in Washington, D.C.

In exploring the spatial dimension of these micro-mobility services, our first goal was to identify the *core operating regions* for each service. In addressing *RQ2*, we intended to determine if, and where, these core operating regions overlapped between services. Trip starting locations for each of the services individually were extracted and a set of two-dimensional kernel density estimations (KDE) were constructed. A kernel bandwidth of 1km was used with a quartic shape producing a raster dataset at a spatial resolution of 5m by 5m for each micro-mobility service. A threshold value was calculated above which a pixel was considered part of the *core* operating region for that specified service. This threshold was specified as the mean value of each individual service. By setting this different threshold value for each KDE, we allowed for regional popularity comparison between services, ignoring the effects of trip volume. This meant that the size and shape of a region were not punished or enhanced purely due to one service providing a larger number of trips than another. The six core operating regions are shown in Figure 3.

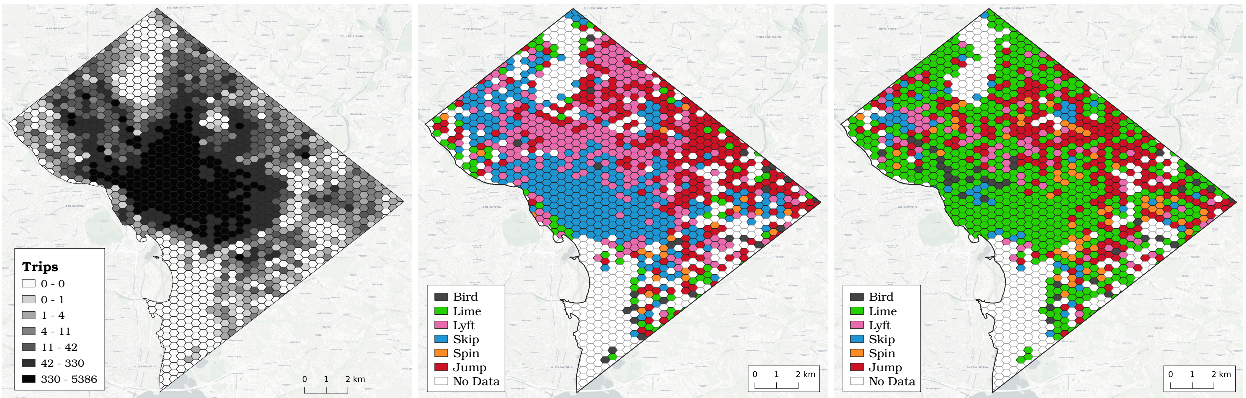


(a) Lyft and Lime (b) Spin and Skip (c) Bird and Jump

Figure 3: Core regions of the six micro-mobility services. These were constructed by setting a value threshold of a two dimensional kernel density estimation. Three separate maps are shown simply for readability.

As one might expect there is substantial overlap in the downtown city core with many of the core operating regions expanding West. Bird, Lyft and Lime have more of an operating presence in the *Georgetown* and *Potomac Waterfront* regions while Jump's region expands further East and North. Aside from Bird, many of the services show small satellite hot spots throughout the District. This visualization approach provides an informative *first step* in understanding the spatial distribution of these micro-mobility services, the degree of overlap, and spatial uniqueness of each service.

We next assess spatial similarity through the lens of *service dominance*. We generated a 500m radius hexagonal grid across the Washington, D.C. region and aggregated trip origin locations by grid cell. For reference, Figure 4a shows a choropleth map of trip volume for all services merged into one layer. Next, the same hexagonal grid was intersected with each of the six micro-mobility services in our dataset individually. Figure 4b was then generated by coloring each grid cell based on the dominant service as determined by raw volume of trips. As one can see, the downtown core is predominantly dominated by `Skip` followed by `Lyft` in the regions of D.C. directly North of downtown. While visually informative, this is not surprising given that `Skip` and `Lyft` boast the largest number of trips in our study. As an alternative approach we then normalized the trip count per grid cell and service meaning that all cells ranged between 0 and 1 for all services. Again, the dominant service per cell was calculated producing the map shown in Figure 4c. We see a very different pattern of service dispersion here with `Lime` dominating the majority of the map. This indicates that `Lime` actually has more of a relatively even distribution across the region than do the other services. By comparison, `Skip` shows a small number of cells with very high trip volume and a steeper drop off in trips outside of these areas. Notably, `Jump`'s spatial activity patterns remain relatively consistent between the two dominance-based approaches.



(a) Trip volume across all services

(b) Dominant service by raw trip volume

(c) Dominant service by normalized trip voume

Figure 4: Hexagonal grid cells (500m radius) showing density of trips and dominant micro-mobility service.

As conducted in the *temporal analysis* section, we next quantify the spatial similarities and differences between these services. Given a common geospatial resolution and extent, as provided by the hexagonal grids, *Earth Mover's Distance (EMD)* (Rubner et al., 2000) was used to compute the spatial similarity between the different services. EMD is a method commonly used in image retrieval that calculates the similarity between two multidimensional matrices. This is done by computing the cost of converting one matrix into the other, where the cost in this case is based on both the normalized trip volume in a grid cell, and the minimum spatial distance needed to travel. Table 3 presents the results of the spatial similarity analysis. The raw EMD cost values themselves are not particularly useful on their own so they have been normalized by the maximum (most dissimilar pair of services) EMD value, producing a set of *relative* (r)EMD measures.

The final column in Table 3 reports *Road Segment rEMD*. While assessing similarity of trip volume based on density of trip starting points is an effective approach to assessing spatial similarity, an alternative method explores the actual density of trips on individual segments of the Washington, D.C. road network. Given that the data accessed from the micro-mobility service APIs only included point data representing trip origin and destination locations, the actual path of an individual trip must be estimated. This was achieved by calculating the shortest path along the road network using *Dijkstra's shortest path first algorithm* (Dijkstra, 1959), producing road density datasets for each of the mobility services. For example, the road density for `Spin` is shown in Figure 5a. While there is no guarantee that mobility service users traveled along the optimal route, this approach presented one possible option for estimating

Table 3: Relative Earth Mover's distance between each pair of micro-mobility services both for noramlized trip volume aggregated to hexagonal grid cell and road segments. A value of 0 means the spatial distribution of services are identical and a value of 1 indicates the highest degree of dissimilarity in our dataset.

Service Pairs		Hexagon Grid rEMD	Road Segment rEMD
Lime	Bird	0.023	0.529
Lime	Spin	0.053	0.090
Lime	Jump	0.054	0.517
Bird	Spin	0.059	0.608
Bird	Jump	0.145	1.000
Spin	Jump	0.204	0.471
Lime	Lyft	0.254	0.137
Skip	Lyft	0.359	0.787
Lime	Skip	0.417	0.270
Lyft	Jump	0.437	0.392
Bird	Lyft	0.582	0.484
Lyft	Spin	0.641	0.394
Skip	Jump	0.796	0.078
Bird	Skip	0.941	0.213
Skip	Spin	1.000	0.316

road network density.[1] The D.C. road network was then converted to a point dataset by creating points every 10 meters along each road producing a road-point dataset containing 582,289 points. Each of the micro-mobility service traffic volume datasets were then intersected with this road point dataset assigning a traffic density value between 0 (no traffic) and 1 (highest traffic volume) to each point. The purpose of converting these line data to points was to allow for the use of the matrix-based EMD approach in calculating the spatial similarity between the road-point densities. The results of this analysis are show in the last column of Table 3.

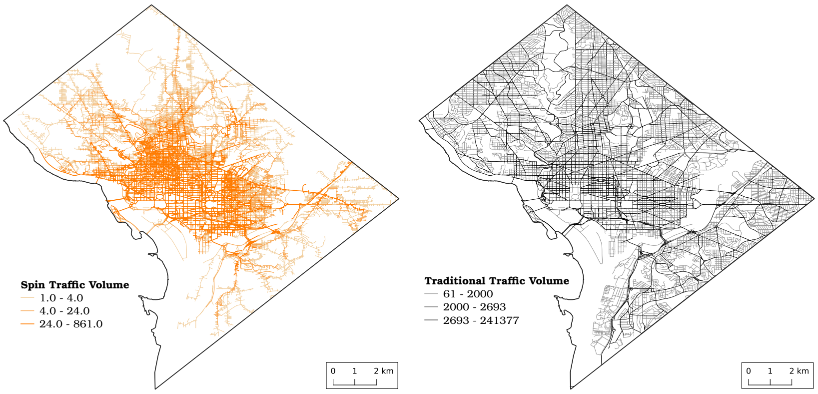
There is disagreement between the two rEMD approaches. In fact a Spearman's rank assessment shows no correlation between the two columns. This is not surprising given that one approach purely focuses on the origin of trips while the other takes into consideration the entire trip. Notably, `Lime` appear to be the most similar to all other services in the origin-only based approach with `Skip` being the most dissimilar. From a road density perspective there is less consistency with both `Skip` and `Lime` reporting a mediocre degree of similarity with other services and `Bird` showing the overall largest amount of spatial dissimilarity with all other micro-mobility services. It general, these findings speak to the fact that there are indeed differences in the spatial distribution of services with respect to both trip origins and actual trips themselves.

Lastly, in conducting spatial analysis of these micro-mobility services, we were interested in assessing the similarity of micro-mobility network volume to traditional automobile traffic volume in the region (Figure 5b). DDOT published a traffic volume spatial dataset for the year 2016 reporting the volume of traffic on every road in D.C. over the course of one year. This dataset was normalize to between 0 and 1 allowing for a density-based comparison with our mobility service datasets. An EMD comparison of each mobility service to this automobile traffic dataset showed `Bird` scooter-share service to be the most dissimilar with `Jump` electric bike-share service being the most similar. Importantly, however, if we take the dissimilarity between `Bird` and the automobile traffic volume as our most dissimilar pair (rEMD = 1.000), the most dissimilar pair of services within the micro-mobility set remains `Bird` and `Jump`, but with an *adjusted* rEMD value of 0.413 (formerly 1.000), demonstrating that there is a much higher degree of similarity within the micro-mobility services than with the automobile traffic dataset.

5. Micro-mobility vs. ride-hailing: A travel time comparison

The previous section compares and contrasts micro-mobility services with one another. In this section we compare micro-mobility travel with traditional automobile travel, using data provided from the ride-hailing service, *Uber*. Our

[1]Both the city and micro-mobility service companies require/suggest that users travel on the roads and bike lines (not sidewalks).



(a) Road network volume for Spin scooter-share (b) Road network volume from traditional automobiles

Figure 5: Road network volume from different sources. The `Spin` scooter-share traffic is estimated based on shortest path along the road network from each trip's origin to destination location. The *traditional* road network volume is based on a year's worth of automobile traffic published by the District Department of Transportation.

interest here, as outlined in *RQ3*, was in identifying variations in travel time between the two modes of transportation. The spatial resolution of the data used for these analyses, as supplied by the ride-hailing dataset, is traffic analysis zones, a set of 458 polygons covering the entire region of Washington, D.C.

5.1. Temporal differences

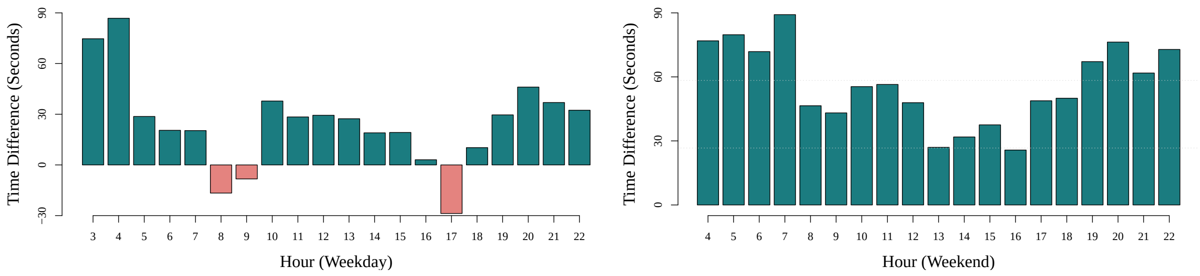
First, we explored the average travel time from each TAZ to each other TAZ for both our micro-mobility and ride-hailing services. The ride-hailing dataset is already in this format reporting a mean travel time between all pairs of TAZ split by hour of the day and either weekday or weekend. The micro-mobility service data was converted into this format by intersecting the origin and destination points of each trip with the TAZ dataset and calculating the mean travel time, split by hour of the day, weekday or weekend, and service provider. This produced seven similarly formatted datasets, one for our ride-hailing platform and one for each of the micro-mobility services. While the ride-hailing data reports mean travel times for all possible pairs of TAZs, the micro-mobility data is much sparser, especially as the distance between TAZ pairs increases. To account for this, all micro-mobility service data were aggregated to a single dataset by taking the mean travel time between TAZ across all available services.

We then performed a comparison of average travel times by hour of the day split by weekday or weekend. Importantly, the same pairs of TAZ were used for both datasets meaning that if the micro-mobility dataset did not report a travel time for a pair of TAZ at a certain time of day, the corresponding ride-hailing pair of TAZ were also excluded from analysis. This was done to ensure that there was a direct comparison and that the ride-hailing platform was not penalized as a result of longer distance trips. The comparison between the two transportation modes was then done by subtracting the mean ride-hailing travel time from the mean micro-mobility travel time. The results of this analysis are shown in Figure 6.

The bar plot displayed in Figure 6a shows a striking pattern. For the majority of the day, ride-hailing services are much faster than micro-mobility services with a peak average difference of 1.5 minutes in the early morning. In contrast, micro-mobility services are faster on average than ride-hailing services during regular weekday commuting hours, namely 8-9am and 5pm. This demonstrates that during times of heavy automobile traffic congestion, it is often faster on average to take a scooter or e-bike. The weekend bar plot shown in Figure 6b shows a different pattern with ride-hailing services offering faster travel in D.C., regardless of the hour of the day. This aligns with standard traffic volume expectations for a weekend in Washington, D.C. given the lack of congestion during weekday commuting hours. Overall this finding addresses *RQ3*, demonstrating that during specific time periods electric scooter-share and dockless e-bikes are faster, on average, than automobiles in the city.

5.2. Spatial differences

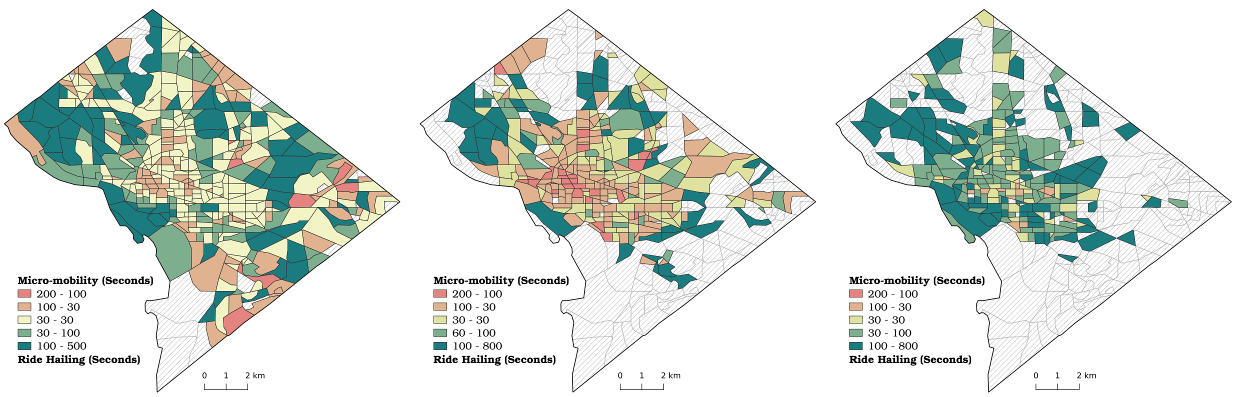
While the previous section looked purely at the average travel time in the temporal dimension, here we investigate these travel time patterns within the spatial dimension. With the goal of addressing *RQ4*, the mean travel time from



(a) Weekday (b) Weekend

Figure 6: Mean ride-hailing travel time subtracted from mean micro-mobility travel time aggregated by hour of a standard weekend or weekday. Travel time is calculated between the same set of TAZ for both micro-mobility and ride-hailing services. Note that early morning and late evening hours are not shown due to sparsity in the data.

each TAZ to all *adjacent* TAZs was calculated for both micro-mobility and ride-hailing services. The service values for each TAZ were subtracted from one another and Figure 7a was produced showing the difference in travel time. This figure only demonstrates a comparison between adjacent TAZs given that the vast majority of micro-mobility trips are within 2km. The sparsity of micro-mobility trips greater than this distance was too high to conduct further comparative analysis with ride-sharing services. Within the adjacency TAZ pairs, 91% of the TAZ pairs included two trips or more and the mean standard deviation between these trip pairs is 21.6 seconds (SD = 40.3).



(a) Mean difference in travel time to adjacent TAZs (b) Difference in travel time at **5pm** on a **Weekday** (c) Difference in travel time at **5pm** on a **Weekend**

Figure 7: Spatial comparisons of travel time based on mode of transportation. Darker green indicates regions where ride-hailing automobile service is faster. Red indicates regions were micro-mobility services are faster.

This Figure demonstrates that, averaging across time, there are regions of the city where micro-mobility services are faster than ride hailing and vice versa. In much of the downtown core and business areas it is either faster, or similar in travel time, to travel to nearby regions of the city using a scooter or electric bike than an automobile. The yellow color indicates regions where the time travel is roughly the same (30 seconds either way). Outside of the downtown core trips made via ride-hailing platform tend to be faster with a strong mixture of optimal travel options in Southeast D.C. Notably, Figure 7a does not take into consideration different times of day or weekday/weekend variation and reflects only those trips to adjacent regions.

Expanding this approach to include the temporal dimension, this analysis was repeated specifically for 5pm on a weekday, the time with the highest difference in travel time in favor of micro-mobility services, and 5pm on a weekend, a time in which ride hailing services are shown to be faster on average. Figures 7b and 7c present these results respectively. Again, Earth Mover's Distance was computed for all combinations of hour and weekday/weekend with the purpose of determining which spatiotemporal patterns are more similar and which are most dissimilar. Not surprisingly, the times of day close in temporal proximity are most similar (e.g., 5am and 6am on weekends). Statistically however, the most dissimilar patterns are during hours of a weekday with 9am to 8pm being the most dissimilar across all spatiotemporal pairs followed by 6am to 5pm. These findings roughly mirror the purely temporal patterns shown in Figure 6 and help us to identify the ways in which urban transport patterns change within the city over time.

6. Discussion

This work focuses on two key facets of urban transportation, namely the identification of spatial and temporal differences a) between individual micro-mobility services and b) between micro-mobility as a whole and ride-hailing services. The findings of the analysis presented in the previous sections detail some of the nuanced differences between these services and transportation modes. A general trend seen in these analyses is that `Lime` scooter-share and `Jump` electric bike-share demonstrate the highest degrees of spatiotemporal dissimilarity when compared to the other micro-mobility services. One finding that requires further discussion is the difference between the `Lime` scooter-share service and the other four scooter-share services, namely the difference in average trip duration and distance. As shown in Table 1, the average `Lime` trip is roughly one third the length of any other scooter-share services, even though the pay structure for `Lime` is virtually identical to the other mobility services. Existing reports pertaining to these services, both from inside (Lime, 2018), and outside the company (PBOT, 2018; Griswold, 2018; Irfan, 2018) support this finding. Aside from the difference in distance and duration of each trip, `Lime`'s service demonstrates a relatively high degree of spatial dispersion compared to other services, as reported by our *service dominance* analysis. The temporal activity patterns of `Lime` users, however, demonstrate high similarity with other scooter-share services. Without much detail on the demographics or the users, the underlying reasoning for this is difficult to ascertain. One possible reason is that `Lime` was the first scooter company to enter the Washington, D.C. market, with `Bird` entering the market roughly 8 months later. It is possible that the novelty of scooters is most reflected in `Lime` user behavior with many users testing out the service through short trips. The barrier to entry, namely downloading the mobile application and providing credit card details, could lead early adopters to remain with `Lime` as a service, even after new scooter-share services entered the market. Further research, specifically on the demographics of the users and purpose of their trips is necessary in order to full understand the reasoning for these differences in trip length.

An additional notable finding is the difference between scooter-share services and `Jump`, the sole electric bike-share service in our dataset. This difference can be more easily explained given the clear modal difference. Even though `Jump` offers electronic-assist bicycles for use, it is still necessary to pedal the bike in order for it to operate. This is a significant barrier to entry for some users, limiting the target user base to those willing to exert some degree of physical effort. Existing research on station-based bike-sharing services in Washington, D.C. (McKenzie, 2019) supports this finding that bicycle travel is associated with longer trips, more often during commuting hours, than scooter travel. It is important to note, however, that in our analysis, only the `Jump` bike-share services was analyzed meaning that these results may not be generalizable to all dockless, electric-assist bicycle services.

In examining the comparison between micro-mobility and ride-hailing, the finding that automobile travel is not always the fastest means of road network travel is compelling. This demonstrates that traffic congestion within a city such as Washington, D.C. can fluctuate substantially and that while micro-mobility services share the same road network (i.e., bike lanes), these services are less susceptible to congestion delays. This is most apparent on weekdays during rush hour commuting times in the downtown core of the city. The extent of this temporal benefit is limited, however, by the range of these micro-mobility services. Since most trips are below 2km in distance, clearly ride-hailing automobile travel is still the optimal choice for longer travel and travel outside of the congested downtown region. There are other factors such as availability and accessibility of each of these service that were not analyzed. This work did not take into consideration the wait time for a ride-hailing vehicle nor the walking time to the nearest dockless micro-mobility service. Similarly, group travel, safety concerns, and financial cost were not included in this analysis. The results clearly indicate however, that in some cases, micro-mobility services are faster in the city than ride-hailing automobiles.

A question remains as to the generalizability of these analyses and applicability of the results to cities other than Washington, D.C. Given that these services are still new, the results presented in this work serve two purposes, 1) To provide an overview of these new micro-mobility services and how they are used in a large metropolitan city and 2) To compare their usage to an existing mode of urban travel. While activity patterns may vary slightly between cities, at a minimum, transportation planners and policy makers from other cities can gain preliminary insight into how these services are used within a city, how their usage might compare to other modes of travel in their city, and given the usage patterns observed in the U.S. Capital, infer micro-mobility activity patterns in other, similarly sized, urban regions. From a policy perspective, city officials should be aware the majority of trips taken by users of these services are quite short, tend not to reflect commuting behavior, and are spatially dominant in the downtown city core. Given these findings and the recent surge in service adoption, efforts should be made by officials to restrict micro-mobility parking (e.g., geo-fencing), regulate where these services can be operated (e.g., in bike lanes), and invest heavily in operation and vehicle awareness campaigns.

6.1. Limitations

One limitation of this work is based on the temporal resolution at which the micro-mobility data were collected. While data collection at one minute intervals over the course of four months was suitable for the analysis conducted in this manuscript, a finer resolution would permit more detailed analysis of trip duration and a better understanding of the data collection frequency of the services themselves. Cleaning the micro-mobility data required certain assumptions to be made of the underlying platforms, such as no trips over a certain speed, etc. The approach used in this work was overly conservative likely erroneously removing actual trips from analysis in order to not include redistribution trips, for example. This was an unfortunate necessity which could be rectified by the data providers tagging trips as either *user* trips, or *administrative* trips. Given that the service-provided data only include origin and destination locations, routing between these locations was estimated in this work using a shortest-path algorithm. The actual routes taken by uses should be identified (perhaps through interviews) in order to assess deviation from this shortest-path estimation. From a user-based analysis perspective, further details pertaining to the socio-demographics of the users of these services would have been useful allowing for more detailed analysis based on attributes such as gender, age, or income. Similarly, demographic information of the ride-hailing users would have allowed for more detailed analysis. The spatial resolution of the *Uber Movement* data was limited to traffic analysis zones. In order to compare micro-mobility services with these ride-hailing data, they had to be aggregated to TAZ resolution, thus reducing the spatial precision of the trips. TAZs were suitable for this research but more nuanced spatial analysis will require block-level resolution.

6.2. Future Work

Future work in this area will explore the temporal and spatial activity similarities of these services at a much broader scale (e.g., seasonal effects, variation between cities) and with much more data. An increase in data collection will allow for a more robust comparison between mobility services over longer distances. Additional shared mobility datasets such as car-share and public transportation data such as metro ridership will be included in the analysis as will a detailed investigation of the the impacts of land use. Our near future work will involve examining the relationship between metro stations and micro-mobility trip origins and destinations in order to determine the limits of these services in addressing the *last mile* problem. Additional efforts are underway to conduct socio-demographic surveys of micro-mobility users in the region with the goal of identifying trip purposes and spatial equity of scooter-share distribution in the District. Many of the scooter-share companies are aware of the equity issues related to this new transportation technology and have programs in place to address the issue. Our future work aims to assess the impact of these programs over space and time.

7. Conclusions

Micro-mobility services are an emerging mode of urban transportation that are of increasing interest to transportation planners and urban analytics researchers. Though cities have experienced a substantial inflow of micro-mobility companies in recent years, surprisingly little is known about the differences between these platforms, let alone how they fit into the existing transportation landscape. In this work, we investigated the spatiotemporal differences and similarities between micro-mobility services in Washington, D.C. We found that while many of the services operate in the same spatial and temporal regions, there are nuanced differences between the services which are reflect in the trip duration and spatiotemporal signatures. In comparing micro-mobility services with traditional automobile trips, provided via ride-hailing data, the results indicate that there are substantial differences in travel times. During periods of high congestion, micro-mobility services offer faster trips than ride-hailing services, on average. Spatially, the downtown region of the city demonstrates a higher degree of similarity in travel times between the two modes of transportation, with ride-hailing proving to be much faster outside of the downtown core. As users continue to rely on these new mobility services, the results of this research aim to inform city regulators, transportation planners, and everyday citizens.

Acknowledgments

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