A spatiotemporal analysis of e-scooters' relationships with transit and station-based bikeshare

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Abstract

To address the policy question of how e-scooters interact with existing public mobility options, we conduct a spatiotemporal analysis of e-scooters' relationships with public transit and station-based bikeshare. Results suggest that e-scooters have both competing and complementary effects on transit and bikeshare. The service areas of the three modes largely overlap, and a majority of e-scooter trips could have been made by transit or bikeshare. A travel-time-based analysis further reveals that when choosing e-scooters over transit, travelers pay a price premium but save some travel time. The price premium is greater during COVID-19 but the associated travel-time savings are smaller. This implies that public health considerations rather than time-cost tradeoffs are the main determinant of travel behavior during COVID-19. In addition, we find that e-scooters enhance mobility services for some underserved neighborhoods. Before COVID-19, about 10 percent of all e-scooter trips were taken to connect with the rail services.

Keywords: Micromobility, e-scooter, public transit, bikeshare, spatiotemporal analysis, COVID-19

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1. Introduction

As a new form of micromobility, e-scooters (i.e., shared electric scooters) quickly emerged as a popular travel mode among urban residents. In 2019, just the third year after e-scooters first appeared on urban streets, the number of e-scooter trips (88.5 million) was more than double that of station-based bikeshare trips (40 million) in the U.S. (National Association of City Transportation Officials (NACTO), 2020). Some have predicted the e-scooter market to further grow, as evident by the billions of venture capital being poured into major e-scooter startups such as Bird, Lime, and Spin. This prediction is supported by travel-behavior findings from the 2017 U.S. National Household Travel Survey data, which showed that almost half of personal trips are three miles or less and that a large majority (more than 70%) of these short trips were made by cars (U.S. Department of Transportation (USDOT), 2017). E-scooters, if priced properly and supported by both government policies and adequate infrastructure, have a great potential to replace short car trips.

The popularity of e-scooters and their rapid expansion across cities lead to mixed reactions (Gössling, 2020). Some acclaim the invention of a new form of urban mobility, seeing the petrol-free e-scooters as an enabler of sustainable travel and lifestyles. Supporters of e-scooters believe that they can reduce car use and traffic congestion, facilitate transit access by expanding the catchment area of transit stops, and promote accessibility for people living in communities with fewer travel options (Clewlow, 2019). However, critics raise a variety of concerns including improper parking (Brown et al., 2020), travel safety, vandalism, and the lack of infrastructure to accommodate e-scooter use. In addition, it is possible that e-scooters mainly replace walking, bikeshare, and transit trips, thus undermining other sustainable modes of travel. These concerns suggest the need for policy guidelines and measures to ensure that micromobility can better fit into a city's transportation ecosystem.

As cities around the world deliberate how to manage and regulate e-scooters, there is an urgent need to learn how e-scooters interact with existing public mobility options including public transit and station-based bikeshare (to be referred to as bikeshare for simplicity). On the one hand, e-scooters are close substitutes to these options. An important concern among transportation professionals in the U.S. is that e-scooters may attract away transit riders, further exacerbating the trend of declining transit ridership (Berrebi and Watkins, 2020; Wasserman et al., 2020). On the other hand, e-scooters may be complementary to public transit by facilitating first-/last-mile connections to transit stops (Oeschger et al., 2020). In addition, affordable e-scooters services may enhance transportation for neighborhoods that receive inadequate transit services and lack convenient access to bikeshare systems.

To shed light on whether e-scooters substitute existing public mobility options or fill the mobility gaps left out by them, this paper presents a spatiotemporal analysis of the relationship between e-scooters services and two public mobility options (i.e., public transit and bikeshare) in Washington DC based on open big data. We address the following research questions:

RQ1. How much does the supply of e-scooter services overlap with that of transit and bikeshare services?

RQ2. To what extent do e-scooter trips substitute or complement transit and bikeshare services?

RQ3. For e-scooter trips that potentially substitute transit use, how do their travel times compare with those of the transit alternative?

Answers to **RQ1** and **RQ2** reveal the competing and complementary relationships between e-scooters and existing public mobility options from both supply and demand perspectives. As we discuss below in the literature review section, a supply-side analysis of this topic is rare, which is a novel contribution of this paper. A further examination of travel-time differences between observed e-scooter trips and their fastest transit alternative (**RQ3**), similar to what Young and Farber (2019) have done to understand the relationship between Uber and transit services, helps determine the degree to which observed e-scooter trips competes with public transit from a traveler's (consumer's) perspective. Our study context is Washington DC, which has robust transit and bikeshare systems and a mature e-scooter market. Since the recent COVID-19 pandemic has greatly disrupted how people travel and caused significant disruptions to public transit, we conduct the analysis for two periods of time: before and during COVID-19. The results can not only inform policymaking on how to better integrate e-scooters into the existing transportation system but also shed light on how e-scooters may enhance the resiliency of public transportation in a time of crisis.

2. Literature Review

In this section, we first discuss existing research on characteristics of e-scooter users and e-scooter trips. We then review studies that compare the spatiotemporal patterns between e-scooter trips and bikesharing trips. Finally, we summarize empirical evidence on the relationship between e-scooters and public transit.

2.1. E-scooter Users and Trip Characteristics

E-scooters were first launched in the city of Santa Monica, California in late 2017 and were quickly expanded to other cities such as San Francisco and Washington DC in early 2018 (Clewlow, 2019). By 2020, hundreds of cities worldwide have e-scooters on their streets. Researchers from both public and private entities have conducted surveys to collect the demographic and socioeconomic information of the e-scooter users. The survey results generally reported that a higher proportion of e-scooter users were male; and compared to the general population, they tend to be younger, college educated, and have higher income (Kopplin et al., 2021; Lyft, 2021; Mobility Lab, 2019; Nikiforiadis et al., 2021; North American Bikeshare Association (NABSA), 2020; Portland Bureau of Transportation (PBOT), 2019; San Francisco Municipal Transportation Agency (SFMTA), 2019). Minority populations including Blacks, Hispanics, and Asians appeared to be underrepresented groups of e-scooter users (Mobility Lab, 2019; PDOT, 2019; SFMTA, 2019), but this may result from survey sampling bias.[1]

Analysts have found that, on average, e-scooter trips are quite short. According to NACTO, for e-scooters trips made in U.S. cities in 2019, the average trip distance was one mile, the average trip duration was 12 min, and the average trip cost was between $2.8 and $4.5 (NACTO, 2020). The trips were even lower in cities such as Washington DC, and Austin where e-scooters were disproportionately placed at tourist attractions (Bai and Jiao, 2020; Merlin et al., 2021; Zou et al., 2020), possibly due to the use of e-scooters for leisure trips. Nonetheless, a majority of e-scooters trips were made for utilitarian purposes such as commuting, shopping or errands, and to connect with public transit (NABSA, 2020; NACTO, 2020). Several studies suggested that e-scooters were more heavily used in the afternoon and early evening, although a slight rise in usage was often observed in the morning peak hours (Mathew et al., 2019; McKenzie, 2019; Zou et al., 2020). Also, weekends saw increased e-scooter trip-making over weekdays. Finally, e-scooter trip origins and destinations were usually concentrated, clustering around downtown areas, university campuses, and tourist attractions (Bai and Jiao, 2020; Caspi et al., 2020; Zou et al., 2020).

2.2. Comparison of spatiotemporal patterns of E-Scooter and Bikeshare Trips

Up until 2018 before e-scooters gained widespread popularity, bikeshare (mainly station-based bikeshare) trips have grown steadily in recent years (NACTO, 2020). Meanwhile, while dockless bikes proliferated around the world, especially in Asia, they experienced limited growth in the US. Given this context, the discussion here focuses on comparing e-scooter sharing with station-based bikeshae only. E-scooter sharing differs from bikeshare in two notable ways. First, unlike bikeshare that requires users to pick up and drop off vehicles at fixed stations, e-scooters can be placed at anywhere and so offer a more flexible

[1] The 2021 Lyft Multimodal Report suggests that the share of Black and Hispanic e-scooter users is slightly higher than the share of Blacks and Hispanics in the generate population.

and convenient service. Second, bikeshare programs are mostly government funded in North America, whereas e-scooters are completely operated by private firms so far. While e-scooters and bikeshare may attract travelers with similar demographics, survey results suggested that a very small percentage (usually less than 5%) of e-scooter trips replaced bikeshare trips (NABSA, 2020; NACTO, 2020).

To understand the similarities and differences between e-scooter sharing and bikeshare services, some studies have compared their spatiotemporal usage patterns (McKenzie, 2019; Younes et al., 2020; Zhu et al., 2020). The McKenzie study revealed some degree of similarities but significant differences between e-scooter trips and bikeshare trips both in the temporal and spatial dimensions. Notably, bikeshare trips taken by nonmembers and e-scooter trips had a similar spatial distribution, but they differed substantially in their temporal patterns. Bikeshare usage by members differed from scooter usage significantly both spatially and temporally. These results suggested that e-scooters replaced some bikeshare trips but the two types of services were often used for different purposes (McKenzie, 2019). Also analyzing the Washington DC data, Younes et al. (2020) confirmed some of the McKenzie study findings; they further showed that weather is less of a disutility for e-scooter users than bikeshare users. In Singapore, Zhu et al. (2020) found that e-scooter trips was more spatially concentrated than bikeshare trips. They also suggested that e-scooters had a higher utilization rate but faced a rebalancing challenge due to the need for battery charging.

2.3. The Relationship Between E-Scooters and Transit

Like other new forms of shared mobility such as ridesourcing and bikeshare, e-scooters can be both an enabler and disruptor to public transit. A major deterrent to transit use is the "first-mile/last-mile problem," which refers to the inability of some travelers to reach transit stops that are too far way (Boarnet et al., 2017). By providing a faster and convenient alternative to walking, e-scooters can address this problem and hence augment transit use. Evaluations of e-scooter pilot programs showed that many travelers indeed used e-scooters to connect to transit. For instance, 34% of survey respondents in San Francisco and 18% of e-scooter riders in Arlington, Virginia, respectively reported using e-scooters to get to or from public transit (Mobility Lab, 2019; SFMTA, 2019). Moreover, e-scooters can be deployed in large volumes and widely distributed across space, hence providing access to places that are unserved or underserved by transit. To achieve this goal, some cities have required or incentivized e-scooter companies to place a required amount of vehicles in designated equity zones.[2] On the other hand, e-scooters may replace some transit trips. Survey results from U.S. cities suggested that had e-scooters not been available for the last scooter trip, between 5%–11% of respondents would have taken public transit (Mobility Lab, 2019; PBOT, 2019; SFMTA, 2019). Survey research done in Germany and Greece showed that about a third of e-scooter trips replaced transit transit, indicates a stronger substituting effect of e-scooters on transit use in those study contexts (Kopplin et al., 2021; Nikiforiadis et al., 2021).

Existing research suggests that e-scooters have both complementary and substitution effects on public transit. This finding is consistent with results of previous studies that examined the impact of bikeshare systems on transit (Campbell and Brakewood, 2017; Ma et al., 2015; Martens, 2004; Martin and Shaheen, 2014). Bikeshare studies produced two additional insights that are likely to be applicable for e-scooter services. First, travelers are much more likely to integrate a bikeshare trip with rail than with bus (Martens, 2004). This is likely a main explanation for studies to find that bikeshare has a complementary effect on Metrorail but a substitutionary effect on bus services (Campbell and Brakewood, 2017; Ma et al., 2015). Second, how exactly the complementary and substitutionary effects of bikeshare on public transit play out largely depends on the urban context. Martin and Shaheen showed that bikeshare serves prominently as a first-mile/last-mile facilitator in areas with less intensive transit network but replaces many short transit trips in high-density,

[2]For instance, the Portland Bureau of Transportation required each e-scooter company to locate at least 100 scooters in East Portland communities each day (Portland Bureau of Transportation (PBOT), 2019).

transit-rich areas (Martin and Shaheen, 2014).

In sum, existing research has produced much knowledge on whether and to what extent shared e-scooters substitute or complement transit and bikeshare services. However, two important knowledge gaps remain. First, little is known regarding how the supply of e-scooter services interact with that of public transit and bikeshare. Second, compared to the substitution effects, the complementary relationships between e-scooters and the other two modes are not well quantified (Kong et al., 2020). We addresses these inadequacies by conducting a spatiotemporal analysis of e-scooters' relationships with public transit and bikeshare in Washington DC based on several open big datasets. Our analytical approaches (see details in Section 4) are adapted from some previous studies that infer the substituting or complementary relationship between bikesharing and public transit based on spatial relationships and distance thresholds (e.g., Chen et al., 2021; Kong et al., 2020; Luo et al., 2021).[3] Like these studies, our work complements existing survey research by offering additional insights from spatial and temporal perspectives.

3. Data

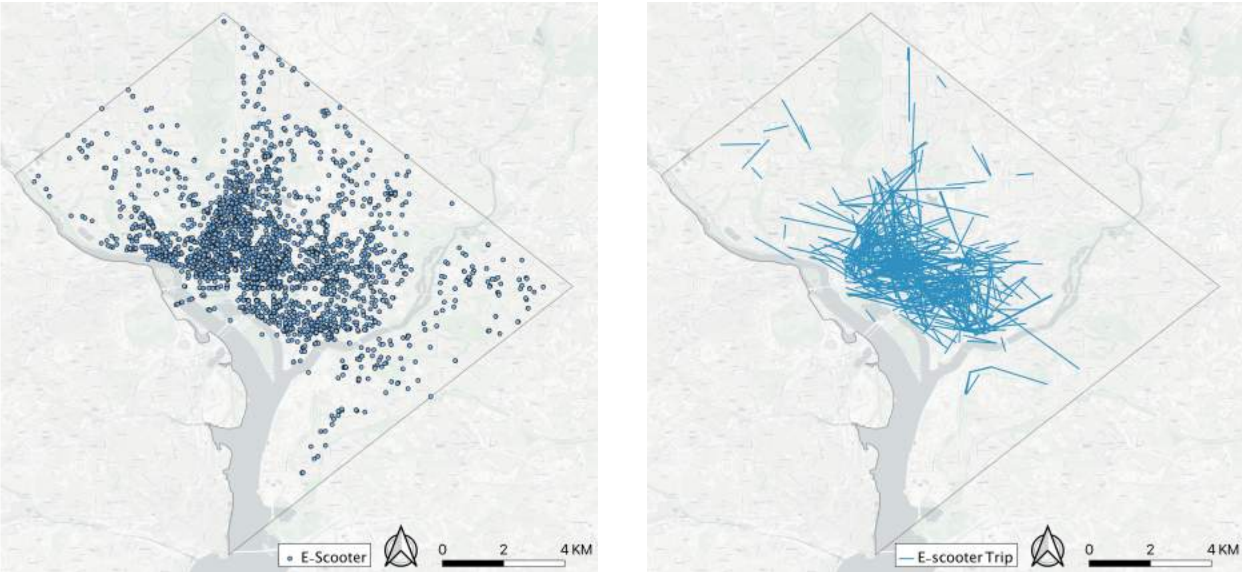
Washington DC is one of the pioneer cities that brought shared e-scooters onto the streets, and it permitted seven vendors (Bird, Jump, Lime, Lyft, Razor, Skip, and Spin) to operate during our study period. The District Department of Transportation (DDOT) has established the terms and conditions for e-scooter operations, and it requires each vendor to provide an Application Programming Interface (API) to share data with the public. The APIs provide data in the General Bikeshare Feed Specification (GBFS) format, an open data

[3] For instance, Kong et al. (2020) determined if a bikeshare trip substitutes or complements public transit by considering three factors: 1) the distance of the bikeshare trip's origin and destination to their closest transit stops; 2) if a transfer is needed if both ends of the bikeshare trip are within the transit coverage area; 3) if a bikeshare trip is classified as a last-mile feeder trip to transit, whether its distance is longer than 2 miles. Chen et al. (2021) assumed a bikeshare trip to be a last-mile feeder trip to transit if its origin or destination are within 50 meter of a rail station entrance.

standard for bikeshare system availability. The GBFS data attributes include vehicle (bike or e-scooter) ID, latitude and longitude of vehicle location, whether the vehicles is reserved or disabled, battery level, etc. We developed a Python program to scrape the GBFS data at a one-minute time interval (vendors update their APIs at a different time intervals, ranging from one minute to 10 min). The raw GBFS data scrapped from the APIs indicate the supply of e-scooters in the city at a given time point; and by examining how the "bike ID" field and the vehicle location change over time, one may also infer trips from the GBFS data.

Since the types of "bike ID" reported by each e-scooter vendor can differ, the trip information to be extracted differs across vendors (Xu et al., 2020). For vendors (including Jump, Skip, and Spin) that assign a consistent ID for the same scooter over time, one can infer trip origin-destination pairs; for vendors (including Bird, Lime, Lyft, and Razor) that assign a dynamic ID for the same e-scooter, one can only infer unlinked trip origins and destinations. Xu et al. (2020) provides a detailed description of the trip inference algorithms adopted in this study. Given the nature of the data, we used data from all vendors when examining the supply of e-scooters (**RQ1**) and data from vendors that assign consistent IDs to scooters when examining e-scooter trips (**RQ2** and **RQ3**). Omitting some vendors' trips for which we were not able to link their origins and destinations is not likely to bias the results, as we expect e-scooters services operated by different vendors to have similar substituting or complementary effects on transit or bikeshare. Figure 1 illustrates the e-scooter availability and e-scooter trip data used in this study.

The transit system in Washington DC consists of Metrorail and Metrobus services. Metrorail includes six lines and 91 stations, and Metrobus has about 270 routes and over 11,000 stations. Metrorail has a distance-based fare system that ranges from \$2.25 to \$6 in peak hours (from opening to 9:30 am and between 3 pm to 7 pm during weekdays) and from \$2 to \$3.85 in off-peak hours; the regular fare for a one-way bus trip is \$2. The Wash-



(a) Available e-scooters at 7:00 am on 6/19/2020

(b) E-scooter trips happening from 7 to 8 am on 6/19/2020

Figure 1: An illustration of the GBFS data

ington DC region has the second largest station-based bikesharing system (named Capital Bikeshare) in the United States, which serves the District of Columbia and several suburban counties and cities. A total of 293 bikeshare stations are located within the district. In this study, we collect data on public transit and bikeshare from two publicly available sources, including the General Transit Feed Specification (GTFS) data published by the Washington Metropolitan Area Transit Authority and the real-time system data published by Capital Bikeshare. The GTFS data provide information on transit routes, stops, and schedules. The real-time bikeshare system data contain the geographic information of bikeshare stations and the number of shared bikes available at each station at a given time point.

To compare the results before and during COVID-19, we pick a typical week from each period for the subsequent analyses. Specifically, we analyze the week of July 15-21, 2019 for the pre-COVID period and the week of June 15-21, 2020 for the COVID-19 period.[4] During

[4]These two weeks were picked qualitatively. We explored data for other weeks of July 2019 and June 2020 and observed minor differences in weekly trip patterns. We chose to analyze data for a week rather than for a month because of missing data. Although we started to collect the GBFS data since January 2019, we can rarely collect a full month of complete data for several reasons such as e-scooter companies

the COVID-19 week, transit services were reduced as ridership fell.[5] The main changes included reducing service frequency and operating hours for both Metrorail and Metrobus services and closing 19 rail stations; and no route changes were not made. The bikeshare system did not experience major service disruptions during COVID, but the operator may have adjusted bike placement and rebalancing efforts due to changed trip patterns.

Table 1 shows some descriptive statistics for e-scooter trips happened in the study period. For the pre-COVID week, the number of available scooters (owned by seven operators) at a given time ranged from 3,766 to 4,034. A total of 16,196 e-scooter trips (served by three operators including Jump, Spin, and Skip) were identified in this period. The median duration was 10 min, and the inferred median trip distance was 0.74 miles. In the COVID week, the available scooters (owned by five operators including Bird, Lime, Lyft, Skip, and Spin) at a given time ranged from 2,646 to 2,916. Two e-scooter operators (Jump and Razor) either ceased operation or deactivated its public API in this period. We identified a total of 6,518 trips provided by Spin and Skip. The median duration was 14 min, and the inferred median trip distance was 0.95 miles. Note that some trips may be falsely identified due to GPS error or vehicle recharging. Thus, following Zou et al. (2020), we have excluded trips that are shorter than 0.02 mile or longer than ten miles, are shorter than five min or longer than 90 min, or have an average travel speed above 20 miles per hour. The next section presents a detailed analysis of the e-scooter availability and trip data to further shed light on e-scooter's relationship with transit and bikeshare services.

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changing the public API URLs.

[5]The estimated transit ridership in Washington DC declined for over 60 percent in the during-COVID week compared to pre-pandemic levels. See estimates by the Transit app at https://transitapp.com/coronavirus.

Table 1: Characteristics of e-scooter trips and their fastest transit alternatives

	June 2019	June 2020	Two-sample t-test[a]
Number of e-scooter trips	16,196	6,518	
Median e-scooter trip length	0.74 mile	0.95 mile	t=-7.66, p-value=0.00
Median e-scooter trip duration	10 min	14 min	t=-21.65, p-value=0.00
Estimated median e-scooter trip cost	\$3.70	\$6.00	t=-47.65, p-value=0.00
% Trips made in morning peak (6 to 9 am)	8.6%	4.8%	
Estimated travel time for transit alternative[b]	14.7 min	16.5 min	t=-2.62, p-value=0.01
(Travel time difference)	(4.7 min)	(2.5 min)	

Notes: a. A two-sample t-test to examine if the means of a given trip attribute in the before-COVID week and in during-COVID week differ significantly. b. We have only estimated this for Trip Type 1 and Trip Type 2 as discussed below in Section 4.2.1.

4. Analysis and Results

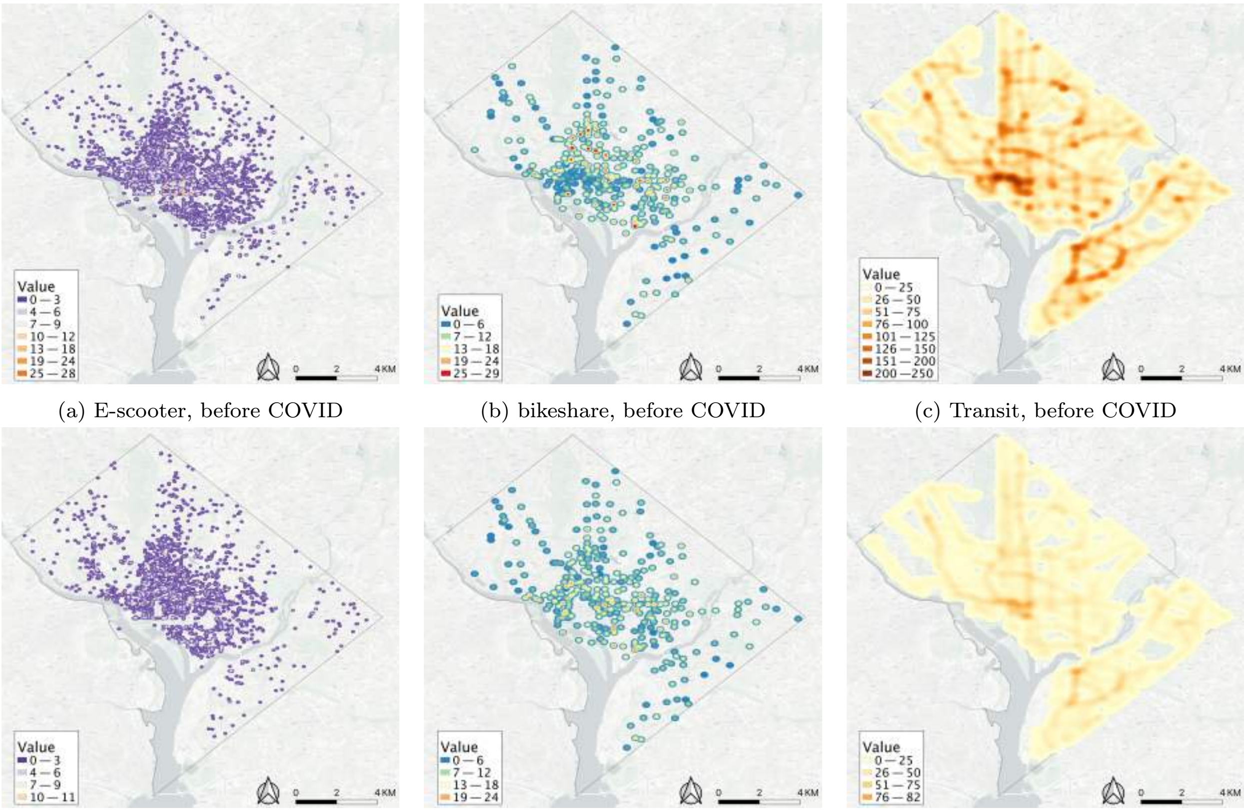
4.1. Supply of E-scooters versus Transit and Station-based Bikeshare

An analysis of the supply side is fundamental to understand how e-scooters interact with bikeshare and public transit. If e-scooters extend mobility services to neighborhoods with low access to the bikeshare and transit systems, e-scooters would be complementing existing travel modes. If these services are offered in the same geographic regions, they might be competing for the same customer base; a special case is when e-scooters are placed at transit stops, which may indicate a complementary relationship as people use e-scooters as a first-/last-mile feeder mode to transit. Therefore, the relationship in question eludes a dichotomous classification. To get more nuanced knowledge on e-scooters' relationship with bikeshare and public transit, a meaningful path of inquiry is to examine the intensity of these mobility services available at different locations (**RQ1**). Since the service supply varies throughout the day, one should also consider the temporal variations. In this study, we compare the supply of the three mobility options at four different points in time: 7:00 am (morning peak hour), 12:00 pm (midday), 5:00 pm (afternoon peak), and 8:00 pm (early evening). We measure the supply intensity of e-scooters and bikeshare with the number of available vehicles across space. The (daily) temporal changes in the supply of e-scooter and bikeshare services arise from two sources: one is imbalanced trip flows, as destinations of e-scooter and bikeshare trips gain available vehicles whereas the trip origins lose supply; and the other is rebalancing efforts from operators of e-scooters and Capital Bikeshare, which counter the imbalanced trip flows. We measure the supply of transit services at each transit stop by counting the number of vehicles passing by in the following hour (e.g., 7:00 am to 8:00 am).

We use kernel density to measure the intensity of mobility-service supply across the city, a commonly applied approach to measure accessibility to spatially distributed attractions or resources such as hospitals and parks (Wang, 2012; Zhang et al., 2011). The "resources" considered here are transit stops, bikeshare stations, and e-scooters. The kernel density approach assumes that the level of accessibility to a given feature (e.g., e-scooter) decreases as the distance to it increases, and the value of accessibility reaches zero at a presumed threshold distance. This threshold distance is usually specified as the service radius of the feature being examined. Here we set this value as a quarter mile for transit stops, one sixth of a mile for bikeshare stations, and one eighth of a mile for e-scooters. These values are assumed to be the comfortable walking distances for DC residents to ride public transit, use a shared bike, and to find an e-scooter.[6] In addition, a population field can be specified to weight some features more heavily than others. We set the population field as the number of vehicles (a rail train is counted as five vehicles) passing by in an hour for transit stops, the number of available bikes for bikeshare stations, and one for e-scooters.

Figure 2 shows the kernel density outputs for the before- and during-COVID week at

[6] To our knowledge, there is little research on the distance that people is willingness to walk to bikeshare stations and to e-scooters. Given that a quarter mile is a commonly used threshold to measure transit service coverage and that people is probably willing to walk less to access a bikeshare station and even less to access a free-floating e-scooter, we set one sixth of a mile as the service radius for bikeshare and one eighth of a mile for e-scooter. We conducted a sensitivity analysis by specifying alternative bandwidth values for bikeshare and e-scooter (i.e., one sixth of a mile or one eighth of a mile for both options), and we found that the results barely changed.



(a) E-scooter, before COVID (b) bikeshare, before COVID (c) Transit, before COVID

(d) E-scooter, during COVID (e) bikeshare, during COVID (f) Transit, during COVID

Figure 2: Kernel density estimation of e-scooter, bikeshare, and transit supply before and during COVID

7:00 am, respectively.[7] The spatial patterns are similar at other time points (i.e., 12:00 pm, 5:00 pm, and 8:00 pm), and so we do not present the results. These maps generate some useful insights. First of all, the spatial distribution of e-scooter supply is similar to that of station-based bikeshare except for two noticeable differences. One is that e-scooters are more spatially concentrated around the Downtown and Capitol areas (locations with the darkest colors in Figure 2(c)), where more trips are likely to be generated. The other is that e-scooters are accessible to a wider geographic area than bikeshare. This illustrates a key advantage of e-scooters: their free-floating nature allow them to be deployed everywhere, providing a great potential to fill the services gaps left out by station-based systems. On

[7]For each week that we studied before and during COVID-19, we computed seven kernel density values (one for each day) and used the median value here.

the other hand, e-scooter services do not appear to expand the service area of public transit. This is because Washington DC has widespread transit coverage in the first place. Moreover, the supply intensity of transit services is more evenly distributed than that of e-scooters and bikeshare, which reflects the fact that the operation of transit services is less market-driven than the other two modes. Finally, the spatial patterns are largely similar for the pre-COVID week and the during-COVID week. Noticeably, the kernel density values for transit supply in the COVID week are much lower than those in the pre-COVID week, which indicate a significant service cut.

We further apply a statistical approach to complement the visual inspections. Specially, we use correlation analysis to evaluate the similarity of the spatial distributions of mobility-service supply intensity. We first develop a quarter-mile by quarter-mile fishnet for the city of Washington DC, based on which we then use zonal statistics to get the mean kernel density value at each cell. The obtained value indicates the supply intensity for a given mode at each cell. Finally, we compute the correlation coefficients between the supply-intensity values of the three modes at different hours (7:00 am, 12:00 pm, 5:00 pm, and 8:00 pm). A correlation coefficient closer to zero, which indicates little overlap in service areas, would suggest a strong complementary relationship. By contrast, a correlation coefficient closer to one generally indicates a stronger competing relationship (especially for travel options that are close substitutes such as shared e-scooters and bikes); however, it can also signal a strong complementary relationship if the co-location mainly results in combined use of two modes (e.g., micromobility options as a last-mile feeder to transit). Considering that combined micromobility and transit trips are probably less common than single-mode micromobility trips even when micromobility vehicles are placed close to transit stops, however, we interpret larger correlation coefficients as indicating stronger competing relationships.

The results are presented in Table 2. At any point in time, the degree of competition is the strongest between bikeshare and e-scooters, whose correlation ranges from 0.60 to

0.73. Moderate level of competition exists between e-scooter services and public transit, as the correlation coefficients are in the range of 0.45 to 0.61. Finally, the correlation is the weakest (coefficient value ranges from 0.37 to 0.53) between bikeshare and public transit, which indicates some level of coordination between the two systems. This is likely because DDOT has prioritized integrating bikeshare into the existing transit system as a major objective in development plans of Capital Bikeshare.[8] Before COVID-19, the competition between different travel modes appear to be more intense in the afternoon and in the evening. By examining the origins and destinations of e-scooter trips and destinations (results not presented), we find that this is largely due to imbalanced trip flows. That is, more e-scooter and bikeshare trips end at central locations (e.g., the downtown and Capitol areas) than they start from these locations, which shifts the supply of e-scooters and share bikes to be more concentrated. This indicates the need for greater rebalancing efforts throughout the day to ensure a more even distribution of e-scooter and bikeshare services. By contrast, the trip flows between different zones of the city are quite balanced for the during-COVID week, and so the correlation coefficients do not vary much by time of day in this week. Finally, the correlation coefficients in the COVID week are generally smaller than those in the pre-COVID week, indicating more complementarity between modes during COVID-19 when transit services are significantly reduced.

4.2. Analysis of E-scooter Trip Origins and Destinations

To address **RQ2**, we conduct a spatiotemporal analysis of e-scooter trip origins and destinations, focusing on their relationships with transit and bikeshare stations. The analysis has two separate parts. First, we classify e-scooter trips into different types by examining whether their origins and destinations fall into the service area of transit or bikeshare sta-

[8]See the recent District of Columbia Capital Bikeshare Development Plan at `https://ddot.dc.gov/sites/default/files/dc/sites/ddot/page_content/attachments/Draft%20DDOT%20Bikeshare%20Development%20FINAL%20reduced.pdf`.

Table 2: Kernel Density Correlation Coefficients

Hour	Before COVID			During COVID		
	Bikeshare & E-scooter	Transit & E-scooter	Bikeshare & Transit	Bikeshare & E-scooter	Transit & E-scooter	Bikeshare & Transit
7:00 AM	0.66	0.48	0.37	0.62	0.45	0.38
12:00 PM	0.72	0.58	0.50	0.60	0.46	0.41
5:00 PM	0.73	0.61	0.53	0.61	0.47	0.40
8:00 PM	0.69	0.54	0.46	0.63	0.45	0.41

Note: All correlation coefficients are significant at the level of 0.01.

tions. Second, we identify likely combined e-scooter and transit trips by examining if an e-scooter trip starts from or ends at a transit stop.

4.2.1. Classifying E-scooter Trips

In this paper, we develop a new typology of e-scooter trips regarding their level of competition/complementarity with transit, as shown in Figure 3. The key distinguishing factor is whether the e-scooter trip ends locate within or outside the transit coverage area. Here, we define the service radius of a transit stop as a quarter mile (a 5-minute walk), a commonly used threshold by transit analysts (Walker, 2012). We use ArcGIS's Network Analyst to generate the service area (a 5-minute walking shed) for each transit stop. For the first two trip types, both the e-scooter trip origins and destinations fall into the transit service area; however, the two transit stops are connected with a direct transit line for Trip Type 1 but not for Trip Type 2. In other words, the transit alternative to an e-scooter trip classified as Type 2 involves at least one transfer. For both trip types, the e-scooter user could have made the trip by transit; but one should not automatically interpret them (especially Trip Type 2) as a substitute for transit use because the traveler may not make the trip by transit anyway (the e-scooter trip is a new trip or it replaces modes other than transit). Moreover, it should be noted that some transit-connecting e-scooter trips are likely classified as Trip Type 1 or Trip Type 2; that is, some travelers have ridden an e-scooter to access a transit stop even if they could have used public transit as the access mode (e.g., someone chooses e-scooter over bus to access a rail station). For Trip Type 3, one trip end locates within the transit service area and the other locates outside of it. E-scooter trips in this category are likely to either serve as a last-mile feeder to transit or fill a spatial gap of transit coverage. Finally, Trip Type 4 fills a spatial gap in the transit network as both trip ends locate outside of the existing service area. Therefore, both Trip Type 3 and Type 4 are clearly a complement to transit.

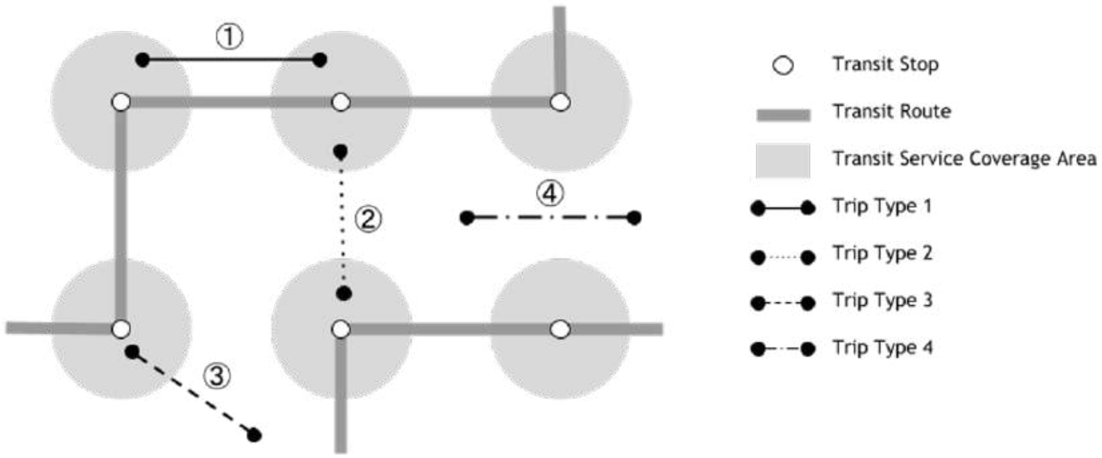


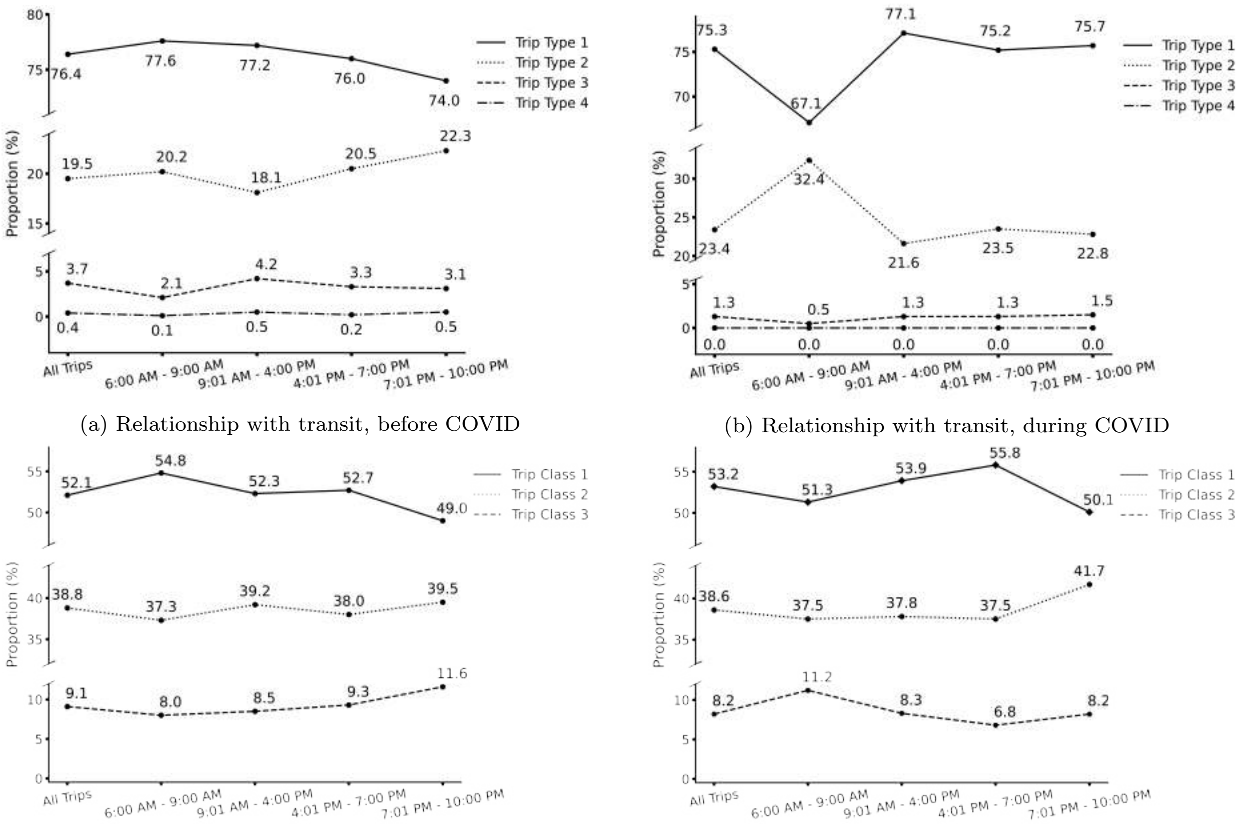
Figure 3: Trip Classification

Likewise, e-scooter trips can be classified into several types to indicate their degree of competition/complementarity with bikeshare. The classification differs from that with respect to e-scooter's relationship with transit in two key aspects. First, we set the service radius of a bikeshare station as one sixth of a mile. Second, only three trip types are identified (the first two trip types should be merged), as bikeshare does not involve transfers. To distinguish the results from those concerning e-scooter's relationship with transit, We name them Trip Class 1, Trip Class 2, and Trip Class 3.

Figure 4 presents the classification results regarding e-scooter's relationship with transit. Over 70% of e-scooter trips are classified into Type 1 and about 20% of trips into Type

2. Less than 5% of e-scooter trips have one of their trip ends fall outside of the transit service area, and very few trips (close to a zero percent of all trips) have both ends fall outside of the transit service area. Considering that the transit network has covered the vast majority of the city's territory, these results are sensible. We conclude from these results that a large majority of e-scooter trips could have been made by transit. We further caution the reader not to conclude that e-scooters are strong substitutes to public transit. As discussed above, the observed e-scooter trips classified as Trip Type 1 or Trip Type 2 are likely substitutes to non-transit modes (e.g., walking) or newly generated trips. Moreover, some transit-connecting e-scooter trips may have been classified as Trip Type 1 or Trip Type 2. To verify the extent to which e-scooters have substituted public transit in Washington DC requires further research (e.g., a survey) into the behavioral motivations behind the observed e-scooter trips.

The distribution of e-scooter trips across the four trip types differs slightly throughout the day, and the patterns have differences between the before-COVID week and the during-COVID week. Before COVID-19, a slightly higher proportion of trips are classified as Trip Type 1 or Trip Type 2 during the morning peak hours (6:00 am to 9:00 am), which is likely because many people use e-scooters for commuting to transit-rich destinations. By contrast, during COVID-19, a much lower proportion of e-scooter trips happening in the morning peak are classified as Trip Type 1. A plausible reason is the significant reduction of activities in central areas and especially the decreases in commuting trips to the downtown. Another significant difference between the before- and during-COVID periods is the decreases in the proportion of e-scooter trips being classified as Trip Type 3 or Trip Type 4; in other words, a higher proportion of e-scooter trips happened during COVID-19 fall within the transit service areas. Together with the observation that e-scooter trips were longer in distance and duration during COVID (which signals that e-scooters may have replaced some short transit trips), we interpret these results as suggesting that e-scooters played an important role in



(a) Relationship with transit, before COVID

(b) Relationship with transit, during COVID

(c) Relationship with bikeshare, before COVID

(d) Relationship with bikeshare, during COVID

Figure 4: E-scooter Trip Classification Results

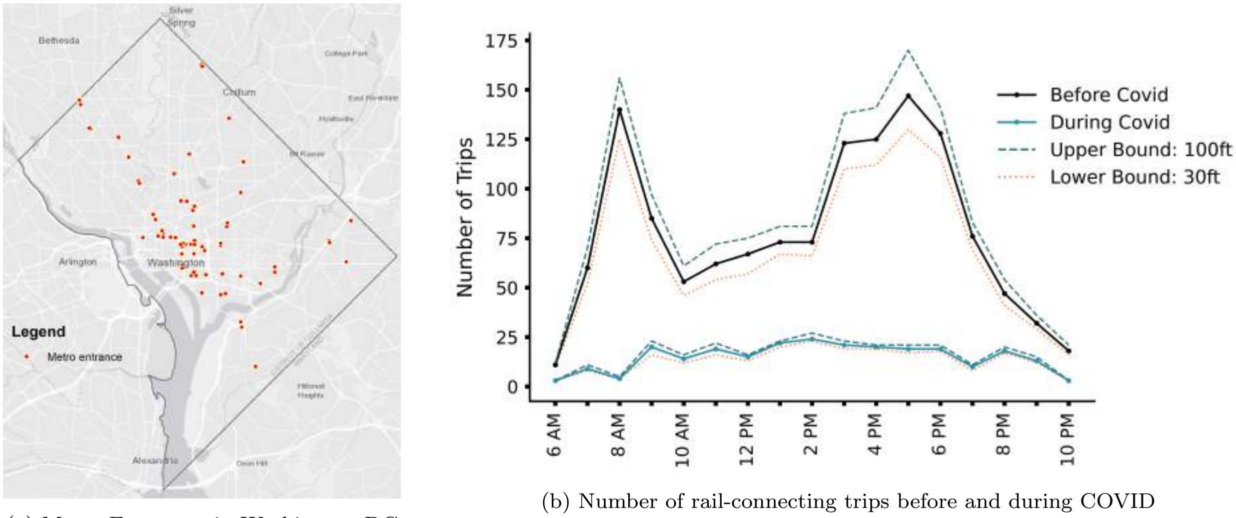
facilitating individual access during a pandemic crisis when virus-wary travelers stay away from public transit.

Regarding e-scooter's relationship with bikeshare, we observe minor differences between the pre-COVID week and the during-COVID week and little variation in trip type distribution throughout the day. Most e-scooter trips (55%-60%) happen at locations where bikeshare services are available, suggesting a spatially competitive relationship. We further hypothesize that e-scooters mainly compete with non-membership bikeshare use rather than membership bikeshare use. This is because previous research has shown that e-scooter trips are similar to bikeshare trips taken by non-members in terms of their temporal distributions but differ from bikeshare trips taken by members both spatially and temporally (McKenzie, 2019).

4.2.2. Identifying Rail-connecting E-scooter Trips

A special case for e-scooters to complement public transit is when they serve as a last-mile connection to transit. If an e-scooter trip starts or ends at a location next to a transit stop, it is likely a leg of a combined scooter-and-transit trip. Since previous studies on bikeshare find that travelers often use shared bikes to connect with rail services but not bus services, we focus on rail entrances only (Martens, 2004; Martin and Shaheen, 2014). We assume e-scooter trips that happen within a distance threshold of a rail entrance as potential integrated e-scooter-and-rail trips. Regardless of the distance threshold chosen here, some e-scooter trips will be falsely labelled and the bias can go both directions. A upward bias happens when trips falling within the distance threshold are not a leg of an assumed "e-scooter plus transit" trip, and a downward bias happens when transit riders park the e-scooter at a distance beyond the chosen threshold. Given these uncertainties, we use 30 feet as the threshold to get a lower bound estimate and use 100 feet to get a higher bound estimate.

In the pre-COVID week, we estimate that between 1174 and 1489 e-scooter trips are potentially connecting to Metrorail, 8% to 12% of all trips. As people stay away public transit during COVID-19, however, both the number and proportion of transit-connecting e-scooter trips declined significantly. In this week, the estimated number of rail-connecting trips is between 6% to 7% of all trips. We further present the number of estimated rail-connecting trips by time of day in Figure 5. The graph shows that more combined scooter-and-transit trips happen during the peak hours, which indicate the use of e-scooters to facilitate commute trips by transit. Notably, in the pre-COVID week, about 20% of e-scooter trips made in the morning peak hour are identified as rail-connecting trips. Therefore, as more and more cities embrace shared e-scooters services, commuting trips should be the main focus for transportation officials to promote e-scooters as a last-mile enhancement to public transit.



(a) Metro Entrances in Washington DC

(b) Number of rail-connecting trips before and during COVID

Figure 5: Identifying first-/last-mile e-scooter trips

4.3. Travel Time Differences between E-Scooter Trips and The Transit Alternative

In this section, we address **RQ3** by examining the travel-time differences between e-scooter trips that are classified as Trip Type 1 and Trip Type 2 and their fastest transit alternative. This analysis helps determine the degree to which observed e-scooter trips competes with transit from a traveler's perspective, which can shed light on *why* people may have chosen e-scooters over transit. In this analysis, We exclude likely leisure e-scooter trips (i.e., taking e-scooters just for fun), which include the following: trips with an estimated travel speed lower than eight miles per hour, trips with a distance under a quarter mile, and trips happening at tourist sites such as the National Mall area.

We generate the fastest transit alternative for each e-scooter trip using the ArcGIS Pro Network Analyst tool. The network is built based on the GTFS data. The before- and during-COVID weeks have different service schedules and hence different GTFS versions. We thus construct two separate networks for each week. Transit travel time includes the following components: walking time to and from transit stops, waiting time, boarding/alighting time (set as half of a min), in-vehicle travel time, and any time required for transfers if necessarily. The ArcGIS Pro Network Analyst tool outputs the total transit travel time by accounting for all of these time components. It does so for a user-specified date and departure time based on the transit schedules specified in the GTFS data. For each e-scooter trip, the departure time of its transit alternative should be approximate to the start time of the e-scooter trip. Here, we estimate and get the median of the transit travel times for every minute of the 10 minutes before and after the start time of the e-scooter trip. This accounts for the possibility that individuals may slightly adjust their schedule to minimize wait time, that is, they do not depart for transit exactly at the time they begin the e-scooter trip.

Table 1 presents the characteristics of e-scooter trips and their fastest transit alternatives in the before- and during-COVID weeks. As discussed above, e-scooters happening in the COVID-19 period are generally longer in distance and duration. While the median trip length is 0.74 miles and the median trip duration is 10 min for the before-COVID week, the median trip length is 0.95 miles and the median trip duration is 14 min for the during-COVID week. We find that the estimated travel times by transit are in generally greater than the e-scooter trip time for both periods. On average, an e-scooter trip's fastest transit alternative would take about 4.7 min longer than the e-scooter trip before COVID, but this travel-time difference decreases to 2.5 min during COVID even though transit service frequency is lower in this period. The decrease in travel-time difference between an e-scooter trip and its fastest transit alternative during the COVID period is likely attributable to reduced congestion levels.

A comparison of the estimated travel-cost differences between e-scooters and public transit sheds further light on travelers' choice behavior. The estimated median cost of e-scooter trips happening in the before-COVID week and the during-COVID week is \$3.7 and \$6.0, respectively.[9] By contrast, the cost of a transit alternative is either \$2 (bus) or \$2.25 (rail) for both time periods. These numbers suggest that before COVID, e-scooter users often

[9]The per-minute charge of e-scooter use has increased from 15 cents per minute in July 2019 to about 25 cents per minute in June 2020.

pay a price premium (about \$1.5) to save a few minutes of travel time. During COVID-19 when e-scooters become more expensive to use, however, e-scooter users pay a much higher price premium (about \$4) for choosing e-scooters over transit but they saved very little time. These results indicate a significant role played by the COVID-19 virus: e-scooters have a stronger substitution effect on transit use during COVID when virus-wary travelers stay away from taking public transit.

5. Discussion

Overall, the results presented above indicate that e-scooters both compete and complement bikeshare and public transit. Evidence from both the supply-side and the demand-side analyses supports this statement. On the supply side, we find that e-scooters compete with station-based bikeshare at many locations, but they also extend micromobility access to neighborhoods where bikeshare is unavailable. Since Washington DC has a widespread transit coverage, e-scooters barely extend the service areas of public transit. Nevertheless, during COVID-19 when transit services are significantly reduced, the supply of e-scooters has a more complementary spatial relationship with public transit.

The trip classification results are largely consistent with the findings from the supply-side analysis. We find that a majority of e-scooter trips could have been made by bikeshare or public transit. Before COVID-19, e-scooter riders, on average, pay a slightly higher price and save some travel time compared to transit users. However, we also find some evidence of a complementary effect, as travelers use e-scooters to reach places inaccessible by bikeshare and transit (Trip Type 3, Trip Type 4, Trip Class 2, and Trip Class 3) and to serve as a last-mile feeder to rail entrances. Notably, e-scooters appear to serve some essential trips, albeit at a higher price, during COVID-19 as virus-wary travelers stay away from buses and trains. This finding suggests that as transit agencies seek to recover from the COVID-19 pandemic crisis, focusing on easing traveler's public health concerns can be more effective than offering fare discounts. In addition, we have estimated that about 10% of e-scooter trips are taken to connect with the rail stations, which indicates the potential for e-scooters to address the last-mile problem of public transit.

These findings have major implications for transportation planning and policymaking. First of all, as e-scooters grow in popularity, cities are expected to see some disruptive impacts on the existing public transportation options. At present, the volume of e-scooter trips is relatively small compared to the volumes of bikeshare and transit trips (the latter are dozens and hundreds of times larger in scale according to our estimates), which may explain why e-scooter trips was found not to affect bikeshare ridership in a Phase 1 Evaluation study conducted in late 2018. However, if e-scooters services keep growing, they can attract away some bikeshare and transit customers; in a city like Washington DC that has robust transit and bikeshare systems, we have shown that the three mobility options are supplied in similar geographic areas. Previous studies showed that younger adults are more likely to switch from station-based bikeshare to dockless bikeshare and that more substitution happens for short-duration trips (Li et al., 2019a,b). Therefore, as city officials develop plans for bikeshare and transit systems, a careful market analysis should be conducted to assess the influences of e-scooters. Moreover, our study has shown some potential for e-scooters to be used as a last-mile connection to public transit. Policymakers may explore strategies such as integrated payment options that can promote this use.

Moreover, results from the spatiotemporal analysis of service availability and use inform policy guidelines on e-scooter deployment and operations. To ensure accessible and equitable mobility services to all travelers, cities should incentivize e-scooter companies to place vehicles at neighborhoods unserved or underserved by existing mobility options. Some cities have already been doing so by requiring permit holders to place a certain number or proportion of vehicles in predefined priority zones or equity zones at the start of the day (National Association of City Transportation Officials (NACTO), 2019). Our study suggests that this requirement can be strengthened in two key aspects. First, besides the commonly considered equity criteria, the definition of the priority or equity zones should incorporate a consideration of the availability of existing mobility options. The kernel density approach adopted here is a plausible way to quantify the supply intensity of different mobility options. In conjunction with an analysis for service demand, this approach allows cities to identify service gaps at a high spatial resolution. The size of the priority or equity zones should not be too large, otherwise e-scooter companies may cluster e-scooters at some locations while leaving other parts of the zone unserved. Second, rebalancing efforts are required to ensure equitable distribution of service availability throughout the day. We finds that e-scooters become less complementary to bikeshare and transit in later hours of day due to imbalanced trip flows.

In addition, e-scooter services can contribute to the resiliency of public transportation systems. COVID-19 has caused transit ridership to plummet as virus-wary travelers stay away from public transit (Liu et al., 2020). As this effect lingers and if public agencies cut transit services due to a declining ridership, cities need to promote other sustainable and affordable mobility options the prevent the foregone transit trips from converting into driving trips. E-scooters, as a personalized and relatively affordable travel option (especially if a low-income program is offered) compared to driving options, are demonstrated here a valuable addition to public mobility systems. The availability of e-scooter services has allowed some to freely get around, and e-scooters may have kept some people from switching to driving during COVID-19. While the long-term implications of shared e-scooters await further research, the preliminary findings from this study suggest that shared e-scooters can strengthen the resiliency of public transportation systems in a pandemic.

6. Conclusion

This paper examines the spatiotemporal patterns of e-scooter service availability and use in Washington DC, focusing on analyzing if e-scooters complement or substitute public transit and station-based bikeshare. The open data scrapped from publicly available APIs allow us to investigate this issue from both the supply and demand side. Existing research has rarely examined if and how much the supply of e-scooter services overlap with that of other modes. We find that e-scooters have both substituting and complementary effects on bikeshare and public transit. E-scooters have mostly been placed at locations where transit and bikeshare services are also available. A further analysis of trip origins and destinations further suggests that most e-scooter trips could have been made by transit or bikeshare. We further show that a majority of e-scooter trips take a shorter time than their fastest transit alternatives. On the other hand, e-scooters complement existing public mobility options by expand accessing to neighborhoods without bikeshare services. Moreover, many travelers have used e-scooters for last-mile connection to public transit.

We should note that our analysis focuses on Washington DC, a city with one of the best public transit and bikeshare systems in the country. The maturity of these systems leaves little room for a new mobility option to supplement the existing services or to fill their service gaps. Therefore, we expect one to find greater complementary effects of e-scooter services on public transit and bikeshare in most other U.S. cities. In other words, we expect the findings of this study to be more transferable to cities with robust transit and bikeshare systems.

The analysis of "big data" scrapped from public APIs generates valuable insights into how e-scooters fit into the existing transportation system. The GBFS data do not have the sample bias issues commonly found in survey studies, but they have other limitations. Notably, the e-scooter trips inferred from the GBFS data are not associated with any demographic and socioeconomic information; that is, we have no knowledge of the people who have made these e-scooter trips. This prevents us from examining how the use of e-scooter services differs across population groups. Moreover, the analysis of traveler's preferences and behaviors is largely absent in this study. Behavioral questions such as how people's use of different travel modes change after adopting e-scooters and under what conditions are people more likely to use e-scooters to connect with public transit are unexplored. The traditional "small data" approaches such as surveys, interviews, and focus groups are more suitable to address these questions. Future research should consider integrate big-data and small-data approaches to generate more accurate and more comprehensive knowledge on how e-scooter services interact with public transit and bikeshare.

Acknowledgement

This research was supported by the U.S. Department of Transportation through the Southeastern Transportation Research, Innovation, Development and Education (STRIDE) Region 4 University Transportation Center (Grant No. 69A3551747104).

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