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Comparing the Temporal Determinants of Dockless Scooter-share and Station-based Bike-share in Washington, D.C.

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A R T I C L E I N F O

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A B S T R A C T

Dockless, or free-floating mobility has gained unprecedented popularity in the last year, from being virtually non-existent in 2017 to facilitating over 38.5 million trips in 2018. Hitherto, few studies have analyzed dockless micromobility, and scooter-share particularly using big data. This paper analyzes and compares the determinants of dockless scooters-share (DSS) and of station-based bike-share (SBBS) rides in D.C. It made use of API data from dockless vendors and historical trip data from Capital Bikeshare from December 2018 to June 2019. Two variables were estimated: hourly number of trips and hourly median duration of trips. A negative-binomial regression model was performed at the hourly scale controlling for environmental and economic variables including weather-related data, gasoline prices, local events or disturbances, day of week, and time of day. Four groups were analyzed: all of micromobility combined and weighed, SBBS members, SBBS non-members, and DSS. Three important findings emerged: (1) Temporal use differences between the three user groups were found, but DSS users behave most similarly to SBBS non-members. (2) Weather is less of a disutility for DSS users than for SBBS users. We attribute this to the physical ease of using a scooter and to the convenience of ending a trip at the actual destination rather than a nearby docking station. (3) All micromobility user types are sensitive to changing gas prices, although DSS users appear slightly more sensitive both in terms of trip count and duration. Additionally, an analysis of the interaction between modes found a possible competition between DSS and SBBS non-members and a complementary relationship between DSS and SBBS members. We conclude that significant differences exist between the two modes, and combined with its sudden and rising popularity, micromobility and DSS in particular could have a major role in promoting a shift towards low-carbon mobility.

1. Introduction

Dockless micromobility, and in particular e-scooter-share (DSS) has emerged as an attractive mode of transportation in recent months. Bike-sharing systems have been an important part of the sharing economy for the last decade and until recently, were station-

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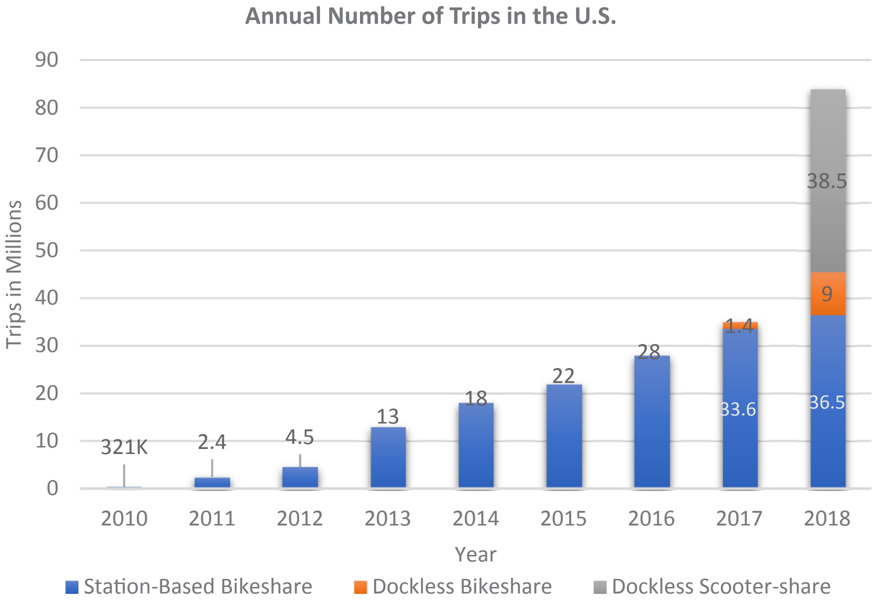

Fig. 1. Recent trends in Micromobility in the U.S. Data source: NACTO (2019).

based. Dockless, or free-floating bicycles arose in 2016 and gained some popularity due to their flexibility and convenience (NACTO, 2019). It wasn't until 2018 that e-scooters and e-bikes became prominent in many U.S. cities, overtaking pedal bikes as the preferred micromobility vehicle (NACTO, 2019). That same year, dockless scooters made up 38.5 million scooter trips, dockless bikes 9 million, and station-based bikes 36.5 million. Fig. 1 displays the recent trend in shared micromobility in the U.S. since 2010. Micromobility has been experiencing a steady increase in trips. In 2018, however, the number of trips more than doubled from the previous year, with most of the added growth coming from dockless scooters (NACTO, 2019). By the end of 2018, there were over 85,000 e-scooters available for public use in the U.S. Dockless e-scooters are a more attractive option compared to conventional bikes in that they require considerably less physical effort and are more convenient to ride than docked bicycles.

The quick growth in dockless micromobility systems has important implications for policy and urban planning decisions relating to transportation and mode choice. However, very few studies have been published on dockless bike- and scooter-share systems (McKenzie, 2019). Given how scooters have disrupted shared micromobility, there is interest in investigating how people use these vehicles differently from station-based bikeshare vehicles. This study aims to fill a gap in the literature by empirically examining the determinants of dockless e-scooters using data from bikeshare systems in Washington, D.C.

The contribution of this study is three-fold: (1) to identify the determinants of dockless scooter-share use, (2) to compare the determinants of both systems to understand whether the effects are different, and (3) to analyze if and how the modes interact together. Based on the results of this analysis, we make several policy and planning recommendations to encourage dockless e-scooters as a sustainable, convenient mode of travel and a complement to the existing city-operated SBBS program. The remainder of this paper is as follow: the next section reviews recent advances in both dockless and station-based micromobility; then, we describe the data used in this analysis; followed by the regression methods employed; and a discussion of the results. We outline limitations with our study and finally, provide conclusions, policy implications and future research directions.

2. Literature review

Dockless bike-share (DBS) and e-scooter-share (DSS) research was virtually non-existent until 2016. Most of the recent literature on DBS uses small scale survey data. This paper is one of the first to use large scale API data, spanning 6 months of trips. To the best of the authors' knowledge, no study has compared the temporal determinants between DSS and SBBS. Also, because of gaps in the previous literature, it is not clear whether the factors that impact temporal travel behavior vary between these two modes of micromobility.

2.1. Dockless micromobility research

Recent research on dockless and free-floating bike-sharing typically uses survey data and has focused in Chinese cities. Li et al. (2019) investigated the social factors influencing choice of bicycle among private bike, station-based bike-sharing and dockless bike-sharing in Kunming, China (Li et al., 2019). They found that DBS is most desirable in connecting other travel modes, is an attractive option for young, low-income and student groups, and is desirable for temporary travel demand. Two separate studies analyzed commuting and non-commuting behaviors in Shanghai, China using questionnaires and found that DBS promotes both commuting and non-commuting trips (Jia and Fu, 2019; Xin et al., 2018).

Luo et al. (2018) analyzed DBS and ride-hailing in New York City and found that multimodal connections between the two modes reduce passenger trip times and decrease road congestion (Luo et al., 2018). Ai et al. (2019) sought to measure traveler's tolerance for walking and DBS using GPS data. They found that passengers who transfer from public transit by walking are more sensitive to distance while DBS users are more concerned with time cost of finding an available bike (Ai et al., 2019). Mooney et al. (2019) explored equity of spatial access to DBS in Seattle. They found inequity in access DBS along sociodemographic lines, similar to other studies of station-based bikeshare systems. However, they also found that no neighborhood was consistently excluded from access (Mooney et al., 2019). Shen et al (2018) investigated the impact of dockless bike fleet size on the usage of bikes in Singapore. They performed a regression on the bike fleet size and controlled for transportation infrastructure, the built environment, and weather. While weather was not the main focus of their analysis, they included two variables: precipitation and extreme temperatures. They found that precipitation appears to have a statistically significant negative impact on the number of rides while extreme temperatures (> 87.8 °F) was not significant at the 0.05 level once accounting for spatial dependencies (Shen et al., 2018).

Luo et al. (2019) conducted a comparative life cycle assessment (LCA) of station-based and dockless bike-sharing systems in the U.S. Their results showed that excluding rebalancing, station-based bikeshare and DBS have a greenhouse gas (GHG) emission factor of 0.148 lb. CO_2/mi and 0.113 lb. CO_2/mi, respectively. However, including rebalancing causes the GHG emission factors to jump to 0.23 lb. CO_2/mi and 0.419 lb. CO_2/mi, respectively, making DBS comparable to conventional bus transit. They conclude that a focus on addressing the rebalancing problem is paramount in reducing GHG emissions (Luo et al., 2019). While these estimates provide a good starting point for comparing emissions between modes, they are dependent on specific assumptions on a single system and therefore, will have to be adjusted for different regions, behaviors, and modes.

McKenzie (2019) used a similar data processing approach to ours to compare DSS and SBBS systems by scraping API data for Lime Scooters every 5 min from June to October 2018. Despite the relatively large scraping interval, the author finds several interesting results. The author identifies spatial and temporal differences and similarities between dockless e-scooters and existing bike-sharing services in Washington, D.C. His findings are that non-member bikeshare ridership is temporally similar but varies substantially in spatial distribution from dockless scooters. Member bikeshare ridership was both temporally and spatially dissimilar from dockless scooters (McKenzie, 2019). This study differs from McKenzie's in that McKenzie addresses distributional differences between the two modes while this one analyzes factors that impact their usage.

2.2. Station-based micromobility research

Research on station-based bikeshare is more abundant than its dockless counterpart. Many studies have looked at the determinants of bikeshare usage using historical trip data (Noland et al., 2016; Shaheen et al., 2010; An et al., 2019; El-Assi et al., 2015; Gebhart and Noland, 2014; Caulfield et al., 2017). Weather factors are some of the vital determinants of bikeshare usage. Unlike car or transit users, bike users are more significantly affected by weather conditions. El-Assi et al. (2015) found that weather conditions in addition to demographic and built environment characteristics have a large influence on the demand of station based bike-sharing trips in Toronto, Canada (El-Assi et al., 2015). Corcoran et al. (2014) reported that wind and rainfall reduce the number of trips while the temperature effect is limited (Corcoran et al., 2014). Gebhart & Noland (2014) analyzed the impacts of weather on station-based bikeshare activity in Washington, D.C. They used a negative binomial model and controlled for temperature, precipitation, wind, weekend and holidays, peak travel times and darkness, and the number of stations in the system (Gebhart and Noland, 2014). They found that weather variables had the expected signs and significance on travel behavior. An et al. (2019) found that weather impacts bike-sharing ridership more than topography, infrastructure, land use mix, calendar events, and peak hours (An et al., 2019).

Several studies have analyzed the relationship between bikeshare and other modes (Ma et al., 2015; Younes et al., 2019; Fishman, 2016; Fishman et al., 2015; Gu et al., 2019). This present study places special attention on modal shifts away from gasoline-based auto travel towards more sustainable modes of transportation. Studies related to auto and bikeshare have focused on traffic congestion (Hamilton and Wichman, 2018; Wang and Zhou, 2017), mode substitution rates (Fishman et al., 2014) and gasoline prices (He et al., 2019). He et al. (2019) analyzed 5-year temporal bikeshare data at the daily scale for three major U.S. cities and found that the price of gasoline had a positive and significant impact on bikeshare ridership and duration (He et al., 2019).

Special events and disturbances with other modes can also impact bikeshare. Bridge closures, strikes, and transit disruptions have all been shown to impact bikeshare ridership (Younes et al., 2019; Fuller et al., 2012; Saberi et al., 2018; Kaviti et al., 2018). During the 6-month period covered in this paper, however; there were no major transit closure affecting other modes of transportation. Nevertheless, because of the importance of such disturbances on mobility, we did include two special month-long disturbances that likely impacted mobility in D.C.: The government shutdown in January 2019 and the Cherry Blossom Festival in March 2019. The Washington Metropolitan Area Transit Authority (WMATA)'s metro reported estimated daily losses of around $400,000 due to a decrease in daily rail and bus ridership during the government shutdown and subsequent closure of Smithsonian Museums and National Parks Services (Siddiqui, 2019). The impact that the shutdown had on micromobility has not been studied. Cherry Blossom Festival, on the other hand, is the annual event in D.C. that attracts an influx of visitors from all over the country and worldwide. We expect to observe a significant increase of micromobility usage during the festival.

The availability of large-scale real time data has made it possible to conduct a temporal regression analysis comparing several important factors that have been empirically proven to be significant on station-based bikeshare, such as wind speed and precipitation. The purpose of this study is to compare these determinants between two modes of micromobility: dockless scooter-share and station-based bikeshare.

3. Data

The authors collected DSS data by accessing each of the six vendors' (Bird, Lime, Skip, Spin, Jump, and Lyft) API in real time every 30 s to 5 min depending on the vendor from December 22nd, 2018 to June 21st, 2019. Because vendors can choose how often to update their API, updates vary from being instantaneous (in real time) to refreshing every 5 min. Several scraping intervals were tested for real-time API data, and we found that limiting scraping to a minimum of 60 s provided an accurate snapshot of trips. Between 0 and 8% of vehicles had a turnover rate of one minute or less, depending on time of the day. The highest vehicle turnover rate was observed during the Cherry Blossom festival, ergo a time that data were scrapped at 30-s intervals. Attribute information includes the vehicle ID, time stamp, and geographic coordinates for all available vehicles. Once vehicles are reserved, they are absent from the API until they are available again. We process the data by assuming that a bike or scooter that is "unavailable" or absent from the API for longer than 2 min designates a trip. We subsequently filter the data by Euclidean Origin-Destination (OD) distance (0.2–10 mi), maximum duration (2–90 min), and speed (< 15 mph based on Euclidean distance) to limit the number of false starts and rebalanced vehicles. Station based bikeshare data are retrieved from Capital Bikeshare (CaBi) Historical data and is similarly processed to include trips longer than 2 min, thereby excluding false starts (Capital Bikeshare, 2018).

Out of the six vendors, two of them had data that was complete and continuous for the entire 6-month period and the other four were only complete and/or continuous for a smaller timeframe. Based on the few weeks that we were able to reconstruct complete data and based on our conversation with the District Department of Transportation (DDOT), we estimate that the data from the two vendors comprise around 50% of the total number of dockless trips in Washington, D.C. This is simply an estimate and is likely to vary, with the proportion of trips changing slightly by vendor from month to month. Moreover, this estimate is in line with the NACTO report that showed that in 2018, trips from dockless navigation had surpassed station-based navigation (NACTO, 2019). The purpose of weighing the data is to provide a broader picture of how micromobility is affected by various temporal variables in D.C. overall.

Data were collected from December 22nd, 2018 to June 21st, 2019, covering a 6-month period. Data for the bike sharing systems are aggregated by hour. Each start of trip time is floored to the nearest hour and combined with hourly weather data from the Ronald Reagan Washington National Airport Weather Station (NOAA, 2019) and weekly gasoline price data (U.S. Energy Information Administration, 2019).

While vehicle type (bicycle versus scooter) and the micromobility infrastructure (dockless versus station-based) are important factors in travel behavior, the pricing scheme of such systems is one that cannot be ignored (Kaviti et al., 2019). DSS throughout the U.S. generally have the same pricing scheme of $1 to unlock the vehicle and an additional $0.15 per minute of ride. Station-based bikeshare typically have a membership service in addition to their single ride fare. A single ride for Capital bikeshare costs $2 for the first 30 min. Membership costs $85 for an annual pass and $28 for a monthly pass and allows for unlimited 30-min rides. Dockless vendors in D.C. do not yet offer a membership service, and thus the data were separated in three distinct populations: DSS users, non-member (referred to as "casual") SBBS users, and member SBBS users.

The descriptive statistics from the 6-month period show us that trip duration is similar for both DSS and SBBS. However, casual riders have much longer trips considering that they pay a single fee for a 30-min time frame. Members have unlimited 30-min rides included so the trip duration is less important to them. DSS users pay to unlock the ride and then per minute of usage, which explains why the median trip duration is about half that of a casual rider. Given the current pricing scheme, the median DSS trip costs $2.80 (Table 1).

Fig. 2 shows the hourly number of Capital Bikeshare trips (separated by member and non-member) and of DSS trips. The most noticeable aspect of this graph is the clear peak hour activity for station-based trips made by members. Weekday DSS trips tend to be more active in the afternoon than in the morning. Both weekend DSS trips and weekend station-based non-member trips are higher than their weekday counterpart. Within weekday variation is apparent for Monday versus other days, where activity is lower per hour. Within weekends, Saturday activity appears higher than Sunday. Additionally, night activity appears to be higher for Friday and Saturday than for other nights.

Fig. 3 displays the relative change in daily trips from the first week that data were collected. Beyond the expected seasonal

Table 1
Summary statistics for the dependent variables.

Vendor		Median OD Distance Miles	Median Duration Minutes	Average Speed MPH	Average hourly number of trips	# Trips (Dec–June)
Dockless[1]		0.63	11.5	3.63	179.7	727,055
CaBi[2]	**All**	0.95	11.48	5.58	329.8	1,394,289 (40,614 loops)
	Members	0.95	10.43	5.95	281.7	1,209,049 (1.7% are loops)
	Casual	0.96	23.45	3.17	48.1	185,240 (10.6% are loops)
TOTAL (ESTIMATED)					705.4	2*727,055 + 1,394,289 = ***2,848,399***[3]

[1] Based on API data from two vendors (approximately 50% of the trips).
[2] Start or end inside Washington, D.C. boundaries.
[3] This figure is the estimated number of micromobility trips during the 6-month period (processed by the length, duration and speed specified in the data processing section of this paper).

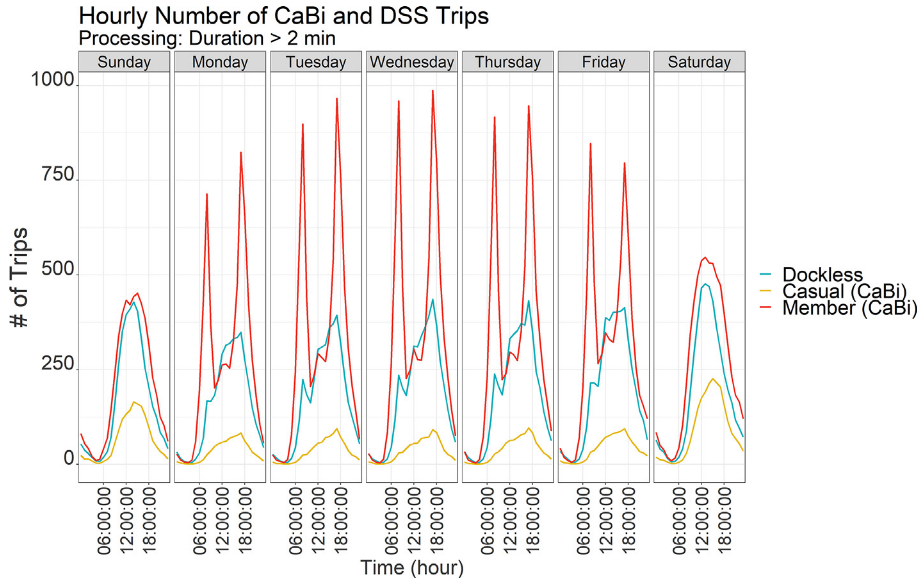

Fig. 2. Trip distribution by time of day and day of week based on available unweighted data.

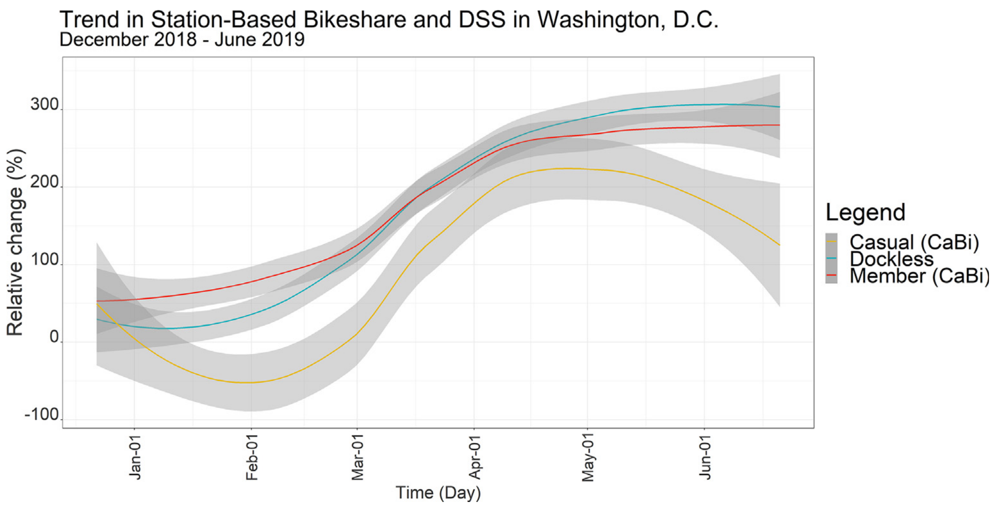

Fig. 3. Relative percentage change in daily micro-mobility ridership in D.C. (December 2018-June 2019). The trend line is based on the relative percentage change in daily ridership from the first week average (December 22nd–29th 2018). It is calculated using the Loess regression method (0.95 confidence interval).

patterns, we find that both DSS trips and member SBBS trips increase at a faster rate than casual SBBS trips; with a final relative change of around 300% from the December baseline compared to 100–200% for casual bikeshare riders.

4. Methods

The purpose of this study is to analyze and compare the temporal determinants between DSS and SBBS. To achieve this objective, we perform models on two dependent variables on three different user groups. The two dependent variables are the hourly number of trips and median hourly trip duration and the three populations are DSS users, non-member SBBS users, and member SBBS users.

Hourly median duration of trip is statistically significantly positively skewed for all three user groups using the D'Agostino test for skewness (D'Agostino, 1970), thus, it is log-transformed in an Ordinary Least Squares (OLS) model that controls for the variables described in Table 2. Hourly trip data requires a count time series model (Younes et al., 2019; Fokianos et al., 2012) and an OLS regression is not appropriate for that variable. A negative-binomial model is deemed more appropriate than a general Poisson model because of statistically significant overdispersion of our data (Gebhart and Noland, 2014; Washington et al., 2010). The negative-binomial model is log-linked, meaning that instead of log-transforming the dependent variable, the linear predictors are exponentiated (allowing for hours with no trips). The model is specified as Eq. (1):

Table 2
Descriptive Statistics of Independent Variables.

Continuous	Average	Standard Deviation	Minimum	Maximum
Temperature (°F)	53.12	17.06	10	92
Precipitation (in)	0.0053	0.0293	0	0.62
Humidity (%)	49.66	19.72	1	86
Visibility (mi)	9.40	1.84	0.1	10
Wind Speed (mph)	8.99	5.23	0	34
Gas Price ($/gallon)	2.622	0.202	2.37	2.932

Discrete	Number of independent variables	Reference variable	Time period/Frequency
Day of week	6	Sunday	Weekly
Time of day in 3-h increments	7	3pm–6pm	Daily
Government Shutdown (weekdays)	1	No shutdown or weekend	Weekdays during December 21st, 2018-January 25th 2019
Cherry Blossom Festival	1	No Cherry Blossom Festival	March 20th – April 13th 2019
Holiday	1	Not a major holiday	Six during 6-month period

$$E_{x_{ik}}^{\lambda_i} = \beta_k x_{ik} = EXP(\boldsymbol{\beta} X_i + \varepsilon_i) \tag{1}$$

where λ is the Poisson parameter (the expected number of events per period) and **β** is the vector of estimable parameters (Washington et al., 2010).

Our model builds on previous bikeshare and weather models (Gebhart and Noland, 2014) with the following modifications: (1) we consider temperature to be a continuous variable; (2) we use time dummy variables as opposed to darkness and peak hour variables to fully understand the role of midday, evening and night hours on micromobility activity; (3) we use a day of week dummy variable instead of a weekend/weekday dummy because we believe that sufficient variance exists between each day; and (4) we add special events (Cherry blossom festival, Government Shutdown) dummy variables and (5) weekly gas prices.

The dependent variable is the number of trips per hour. We performed the model on four populations: (1) all trips combined and weighed, (2) member SBBS trips (i.e. monthly or annual Capital Bikeshare subscribers), (3) casual (i.e. non-members) SBBS trips and (4) DSS trips. Therefore, we assigned a weight of 2 to the dockless trips in the regression. The total estimated number of trips is therefore equal to the sum of dockless trips (from the two vendors) multiplied by two and of all station-based bikeshare trips: approximately 3 million trips over the 6-month (Table 1). This estimation is in line with the only report currently available on micromobility ridership in the U.S., which showed that in 2018, the number of dockless trips was slightly higher than that of station-based trips (NACTO, 2019).

Table 2 displays the descriptive statistics of the model determinants. The 6-month period spanned the entire winter and spring seasons in Washington, D.C., allowing for a wide temporal variation in weather variables. Price of gasoline remained within a 56-cent range throughout the duration of the data collection period. Two local disturbances occurred, lasting between three and five weeks in length.

5. Results

5.1. Analysis of hourly trip counts

Two dependent variables were analyzed: hourly number of trips and median hourly duration of trips. Five models were fitted on four different groups for the number of trips per hour. The first model encompasses all trips coming from micromobility in D.C. The results of this model can be interpreted as the impacts of different variables on all of micromobility in D.C. The second, third and fourth models are for station-based member users, station-based non-member users (i.e. “casual” users) and DSS users. The fifth model is added to show the interaction of SBBS with DSS. The comparison between user types (i.e. pricing scheme, vehicle type, and station structure type) is made between models 2, 3 and 4. The results are presented in Table 3.

5.1.1. Weather

Warmer temperatures and better visibility are associated with higher instances of trips per hour. Conversely, humidity, wind speed and precipitation have a negative impact on number of trips per hour. Casual SBBS users appear to be more sensitive to changing weather conditions as their coefficient is well above that of either DSS or member SBBS users. A likely reason for this difference with scooters is the ease of using free-floating scooters both in terms of physical effort and in convenience of being able to leave the scooter in any permitted area. Members of bikeshare tend to be the least sensitive to changing weather conditions most likely due to the habitual travel behavior of members, the less expensive pricing structure, or not having an alternative mode of transportation. Additionally, we find that DSS users are not statistically sensitive to precipitation at the 0.05 level. We suspect that the ease and convenience of DSS is again a likely reason for this.

Table 3
Negative-Binomial Regression Results for micromobility models.

Dependent variable: Hourly Number of Trips					
	All Trips (weighed)	Member (CaBi)	Casual (CaBi)	Dockless Scooters	
	(1)	(2)	(3)	(4)	(5)
Weather Variables					
Temperature (°F)	0.022^{***}	0.019^{***}	0.038^{***}	0.021^{***}	0.015^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Visibility (1–10 mi)	0.033^{***}	0.022^{***}	0.053^{***}	0.041^{***}	0.044^{***}
	(0.006)	(0.006)	(0.008)	(0.007)	(0.006)
Humidity (%)	-0.007^{***}	-0.008^{***}	-0.012^{***}	-0.006^{***}	-0.003^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Wind Speed (mph)	-0.014^{***}	-0.014^{***}	-0.025^{***}	-0.013^{***}	-0.009^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Precipitation (inch) (lagged 1 h)	-1.138^{***}	-1.461^{***}	-2.278^{***}	−0.733*	−0.313
	(0.348)	(0.360)	(0.414)	(0.378)	(0.334)
Time of day (Reference is 3 pm–6 pm)					
t0_3	-2.677^{***}	-2.747^{***}	-2.546^{***}	-2.643^{***}	-1.976^{***}
	(0.042)	(0.043)	(0.047)	(0.046)	(0.048)
t3_6	-3.132^{***}	-2.797^{***}	-3.476^{***}	-3.559^{***}	-2.897^{***}
	(0.044)	(0.043)	(0.054)	(0.050)	(0.051)
t6_9	-0.529^{***}	−0.048	-1.397^{***}	-1.059^{***}	-1.374^{***}
	(0.042)	(0.042)	(0.045)	(0.045)	(0.043)
t9_12	-0.351^{***}	-0.350^{***}	-0.333^{***}	-0.354^{***}	-0.115^{***}
	(0.042)	(0.042)	(0.043)	(0.045)	(0.041)
t12_15	-0.129^{***}	-0.401^{***}	−0.020	0.037	0.333^{***}
	(0.040)	(0.041)	(0.041)	(0.043)	(0.039)
t18_21	-0.441^{***}	-0.270^{***}	-0.625^{***}	-0.549^{***}	-0.492^{***}
	(0.040)	(0.040)	(0.041)	(0.043)	(0.039)
t21_24	-1.443^{***}	-1.334^{***}	-1.434^{***}	-1.508^{***}	-0.969^{***}
	(0.041)	(0.041)	(0.043)	(0.044)	(0.044)
Day of week (Reference is Sunday)					
Monday	−0.076*	0.042	-0.755^{***}	-0.140^{***}	-0.278^{***}
	(0.039)	(0.039)	(0.042)	(0.043)	(0.039)
Tuesday	0.032	0.150^{***}	-0.721^{***}	−0.039	-0.228^{***}
	(0.039)	(0.039)	(0.042)	(0.042)	(0.039)
Wednesday	0.039	0.161^{***}	-0.716^{***}	−0.030	-0.238^{***}
	(0.039)	(0.039)	(0.042)	(0.042)	(0.039)
Thursday	0.060	0.169^{***}	-0.626^{***}	0.013	-0.167^{***}
	(0.039)	(0.039)	(0.042)	(0.042)	(0.039)
Friday	0.128^{***}	0.180^{***}	-0.441^{***}	0.121^{***}	−0.020
	(0.039)	(0.038)	(0.041)	(0.042)	(0.038)
Saturday	0.118^{***}	0.136^{***}	0.169^{***}	0.099^{**}	0.102^{***}
	(0.038)	(0.038)	(0.040)	(0.042)	(0.037)
Special Events					
Holidays	−0.059	-0.170^{***}	0.511^{***}	−0.032	0.152^{**}
	(0.061)	(0.065)	(0.071)	(0.067)	(0.060)
Shutdown (Weekdays)	-0.124^{***}	0.048	0.063	-0.351^{***}	-0.334^{***}
	(0.037)	(0.039)	(0.046)	(0.041)	(0.037)
Cherry Blossom Festival	0.185^{***}	0.156^{***}	0.371^{***}	0.195^{***}	0.158^{***}
	(0.029)	(0.031)	(0.033)	(0.032)	(0.028)
Weekly Gas Prices ($)	0.780^{***}	0.347^{***}	1.021^{***}	1.192^{***}	1.111^{***}
	(0.090)	(0.087)	(0.095)	(0.098)	(0.087)
# Casual Trips (CaBi)					-0.002^{***}
					(0.0002)
# Member Trips (CaBi)					0.002^{***}
					(0.0001)
Constant	3.978^{***}	4.373^{***}	0.098	1.534^{***}	1.204^{***}
	(0.203)	(0.199)	(0.219)	(0.222)	(0.197)
Observations	3801	4361	4361	3808	3808
Log Likelihood	−25,824	−26,219	−17,159	−20,714	−20,274
McFadden Pseudo R2	0.1477	0.1435	0.2097	0.1635	0.1813
theta	2.629^{***} (0.059)	2.296^{***} (0.049)	2.310^{***} (0.061)	2.300^{***} (0.056)	2.992^{***} (0.077)
Akaike Inf. Crit.	51,694.8	52,483.9	34,365.4	41,474.5	40,598.1

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

5.1.2. Time of day

The times were grouped in 3-h increments and the reference is afternoon peak (3 pm–6 pm). For all three dependent variables, afternoon peak is either the highest or second highest time where trip activity occurs. For DSS trips, the midday (12 pm–3 pm) time is the only time that has a positive coefficient, indicating an association with more trips than 3 pm–6 pm. For casual and member station-based trips, midday and 6am–9am were respectively not significantly different from the afternoon peak time.

5.1.3. Day of week

Because sufficient variations exist between days, we chose to include all days with Sunday as the reference. DSS and casual SBBS users' peak activity occurred on Saturday, followed by Sunday. For DSS, Friday activity was not statistically significantly different from Sunday. All other days have less trip activity. Members show the opposite effect, with all other days having a significant positive coefficient (except for Monday which is not significant), indicating that trip activity is higher during the week.

5.1.4. Special events or disturbances and holidays

Holidays exert a positive effect on casual SBBS and DSS trips and are associated with fewer member trips. The government shutdown, which lasted from December 21st to January 25th exerted a negative effect on DSS trips but had no significant impact on station-based trips. As expected, the Cherry Blossom Festival, occurring for several weeks in March and April had a significant and positive impact on all types of bikeshare trip activity.

5.1.5. Gasoline prices

Gas prices have a significant and positive effect on micromobility. Increasing gas prices are associated with higher instances of trips (controlling for all other factors). Member trips appear to be the least sensitive to such changes (with a coefficient about 1/3rd that of casual SBBS trips and DSS trips) which is expected considering that members have already committed to using bike as a mode of transportation.

5.1.6. Interaction between dockless and station-based micromobility

Based on the initial trend in Fig. 3 in the previous section, we attempted to measure the impact of increasing casual user trips and member user trips on DSS trips. We found an interesting association: casual users have a negative and significant coefficient while member users have a positive and significant coefficient. We speculate that the relationship between casual users and DSS users comes from the fact that the targeted population (demand) is similar: both users opt to pay a single trip fare for the vehicle. However, station-based systems have a restricted supply due to bike capacity infrastructure. In times of high demand for bikes, bikes may not be readily available at popular docking stations. As a result, we assert that users resort to using an alternate mode of transportation such as dockless vehicle instead. The tandem increase in DSS activity and member trip activity is likely due to outside forces, such as the increasing popularity in micromobility overall. The regression results confirm the initial visual trend seen in Fig. 3.

5.1.7. Interpretation of coefficients

Elasticities for continuous variables are calculated by Eq. (2):

$$E_{x_{ik}}^{\lambda_i} = \beta_k x_{ik} \tag{2}$$

The pseudoelasticity for indicator variables is calculated by the following Eq. (3):

$$E_{x_{ik}}^{\lambda_i} = \frac{EXP(\beta_k) - 1}{EXP(\beta_k)} \tag{3}$$

where in both cases, β_k is the estimated parameter for the kth independent variable. The pseudoelasticity gives the incremental change in frequency caused by changes in the indicator variable (Washington et al., 2010). The results are displayed in Table 4.

A 1% increase in each variable is associated with the corresponding percentage change in the number of trips. For instance, a 1% increase in mean temperatures is associated with a 1.05% increase in member SBBS user trips, a 2.13% increase in casual SBBS user trips and a 1.12% increase in DSS ridership. An important difference between casual SBBS users and DSS users is that, despite their similar temporal behavior, DSS users are much less sensitive to weather factors than casual SBBS users. We contend that the physical ease and the dockless convenience of using scooters is likely responsible for this difference.

Beyond the weather variables, gas price sensitivity shows that a 1% increase in mean gas prices is associated with a 0.92% increase in member bikeshare usage, 2.70% in casual bikeshare usage and 3.13% in DSS usage. Assuming the average of \$2.63, an increase of \$0.026 would correspond to 1.3 added casual SBBS trips, 2.7 member SBBS trips and 5.8 DSS trips per hour on average. Using the combined all trips weighed regression, this equates to around 14.4 added trips per hour, or 345.6 added trips per day when controlling for all other factors.

The effect of the local disturbances was statistically significant, although of small magnitude. A change in about 1 trip per hour is estimated due to these events. The average number of trips was 0.13% lower during the shutdown. Conversely, the average number of hourly trips was 0.17% higher during the Cherry Blossom festival. While their effects are small in magnitude, such events are important to consider, especially when they last for several weeks.

Finally, the mean elasticity for the station-based bikeshare coefficients in the fifth model were of 0.543 and −0.098 for member and casual user trip frequency, respectively. The mean elasticity of casual bike trips implies that a 1% increase at the mean frequency

Table 4
Elasticity of coefficients for the negative-binomial model on trip counts.

Continuous variables (Mean Elasticity) (%)	All (1)	Member (2)	Casual (3)	Dockless (4)
Temperature	1.147	1.053	2.131	1.118
Visibility	0.309	0.206	0.503	0.387
Humidity	−0.357	−0.411	−0.617	−0.303
Wind speed	−0.130	−0.128	−0.226	−0.121
Precipitation	−0.006	−0.008	−0.012	−0.004
Gas Prices	2.046	0.917	2.696	3.126
Indicator Variables (Pseudo Elasticity) (%)	**All**	**Member**	**Casual**	**Dockless**
Holidays	−0.061	−0.185	0.400	−0.032
t0_3TRUE	−13.53	−14.60	−11.75	−13.06
t3_6TRUE	−21.93	−15.39	−31.32	−34.14
t6_9TRUE	−0.698	−0.049	−3.04	−1.89
t9_12TRUE	−0.420	−0.419	−0.395	−0.425
t12_15TRUE	−0.138	−0.493	−0.021	0.036
t18_21TRUE	−0.555	−0.310	−0.868	−0.731
t21_24TRUE	−3.24	−2.80	−3.20	−3.52
Shutdown (Weekday)	−0.132	0.047	0.061	−0.421
Cherry Blossom	0.169	0.145	0.310	0.177
Monday	−0.079	0.041	−1.128	−0.151
Tuesday	0.032	0.139	−1.056	−0.040
Wednesday	0.038	0.149	−1.047	−0.031
Thursday	0.059	0.155	−0.871	0.013
Friday	0.120	0.165	−0.554	0.114
Saturday	0.111	0.127	0.155	0.095

of casual bike trips (mean = 48 hourly trips) results in a 0.1% reduction in DSS trip frequency or an average reduction in just 0.2 DSS trips per hour. This negative association could indicate a possible substitution between the two modes.

5.2. Analysis of median hourly trip duration

A second analysis is conducted to detect whether the temporal determinants outlined in part one of this study have an impact on the median hourly duration of trips for which at least one trip was observed in the hour. This time, three models are fitted on member and non-member SBBS and DSS. Because of the pricing structure of DSS users, who have to pay per minute of ride, we expect this group to be the most sensitive to changing conditions. The regression results are outlined in Table 5 below.

Temperature appears to have a positive impact on trip duration, humidity and wind speed have a negative influence on trip duration while visibility (i.e. fog) and precipitation have no significant impact on trip duration. Nighttime and early morning is associated with shorter trips, relative to the 3 pm–6 pm reference. For casual SBBS users and DSS users, the only time associated with longer trips is from 12 to 3 pm. For member SBBS users, 3 pm–6 pm is the time period associated with the longest trips. Weekdays are associated with shorter trips for all user groups. Saturday trips are longer for member and DSS users but not statistically significantly longer for casual users of bikeshare. Holidays and the Cherry Blossom Festival were both generally associated with longer trips for all user groups; although the coefficient was higher for casual and DSS users. The government shutdown appeared to be associated with longer trips for DSS users; the possible reason for which may be a reduction in work trips and an increase in longer leisure trips.

Finally, increasing gas prices had a statistically significant and positive impact on trip duration for member SBBS (12% increase in trip duration for a $1 change in gas prices) and DSS users (15% increase in trip duration for a $1 change in gas prices). This is an interesting finding for members since the previous analysis showed that members were not as sensitive to changing gas prices as other groups in terms of number of trips taken. This indicates that the additional trips and the current trips could be longer due to changing gas prices. Conversely, casual users have additional trips, but the length is not statistically significantly longer. Given that the average casual user trip is already twice the length of a member user trip, this finding makes sense. DSS users have added trips and longer trips that are of statistical and practical significance due to changes in gas prices. The cost of using DSS becomes more expensive than SBBS after just 7 min. Thus, the pricing scheme alone does not explain this difference in gas price sensitivity. A likely reason is the more convenient solution of being dockless, which allows for more efficient first-mile, last-mile travel.

6. Discussion

This study sought to compare the determinants of dockless scooter-share and station-based bikeshare using multiple large temporal and spatially detailed datasets on micromobility trips. Because of the differences in pricing schemes (and hence, travel habits) within station-based bikeshare, bikeshare was separated into “members” and “non-members” (i.e. “casual”) users. Several important findings emerged from this analysis.

First, this study confirms that DSS users are more temporally similar to casual SBBS users than to member SBBS users. Intra weekday and weekend variations were evident. Saturday trip counts were statistically higher than Sunday trip counts. Friday

Table 5
OLS Regression results for Hourly Median Duration from SBBS and DSS.

	Dependent variable:Hourly Median Duration (log-transformed)		
	Member (1)	Casual (2)	Dockless (3)
Weather Variables			
Temperature (°F)	0.005***	0.007***	0.008***
	(0.0003)	(0.001)	(0.001)
Visibility (1–10 mi)	−0.002	0.005	0.001
	(0.002)	(0.004)	(0.003)
Humidity (%)	−0.001***	−0.002***	−0.002***
	(0.0002)	(0.0004)	(0.0003)
Wind Speed (mph)	−0.004***	−0.007***	−0.005***
	(0.001)	(0.001)	(0.001)
Precipitation (in.) (lagged 1 h)	−0.163	−0.269	−0.293*
	(0.111)	(0.225)	(0.157)
Time of day (Reference is 3 pm–6 pm)			
t0_3	−0.088***	−0.120***	−0.004
	(0.013)	(0.027)	(0.019)
t3_6	−0.029**	−0.317***	−0.255***
	(0.013)	(0.028)	(0.020)
t6_9	−0.058***	−0.311***	−0.329***
	(0.013)	(0.025)	(0.019)
t9_12	−0.033**	−0.019	−0.070***
	(0.013)	(0.025)	(0.019)
t12_15	−0.050***	0.046*	0.036*
	(0.013)	(0.024)	(0.018)
t18_21	−0.075***	−0.133***	−0.178***
	(0.013)	(0.024)	(0.018)
t21_24	−0.113***	−0.137***	−0.107***
	(0.013)	(0.024)	(0.018)
Day of week (Reference is Sunday)			
Monday	−0.026**	−0.069***	−0.204***
	(0.012)	(0.024)	(0.018)
Tuesday	−0.017	−0.080***	−0.211***
	(0.012)	(0.023)	(0.018)
Wednesday	−0.016	−0.128***	−0.201***
	(0.012)	(0.024)	(0.018)
Thursday	−0.050***	−0.098***	−0.207***
	(0.012)	(0.023)	(0.018)
Friday	−0.037***	−0.095***	−0.139***
	(0.012)	(0.023)	(0.018)
Saturday	0.028**	−0.024	0.071***
	(0.012)	(0.023)	(0.017)
Special Events			
Holidays	0.023	0.149***	0.219***
	(0.020)	(0.040)	(0.028)
Shutdown (Weekdays)	0.008	−0.003	0.089***
	(0.012)	(0.025)	(0.017)
Cherry Blossom	0.039***	0.071***	0.062***
	(0.010)	(0.019)	(0.013)
Weekly Gas Prices ($)	0.114***	−0.063	0.140***
	(0.027)	(0.053)	(0.041)
Constant	1.841***	3.065***	5.940***
	(0.062)	(0.122)	(0.093)
Observations	4351	3940	3707
R^2	0.250	0.173	0.390
Adjusted R^2	0.246	0.168	0.387
Residual Std. Error	0.207 (df = 4328)	0.388 (df = 3917)	0.279 (df = 3684)
F Statistic	65.616*** (df = 22; 4328)	37.193*** (df = 22; 3917)	107.268*** (df = 22; 3684)

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

appeared to be statistically different from other weekdays. We divided time in 3-h chunks to analyze any time effects beyond the usual peak/non-peak times. We found that midday (12 pm–3 pm) was not statistically different from the 3 pm–6 pm peak time for the casual and DSS users. AM and PM peaks were not statistically different from each other for member dockless usage and both represented the highest trip activity for that user group.

Second, despite their temporal similarity, DSS users were much less sensitive to weather factors than casual users were. The weather elasticities were typically half that of casual users. We attribute this difference to the ease of using scooters, which requires minimal physical effort, and to the convenience of being able to drop the vehicle off very close to a destination. DSS users and member SBBS users actually had very similar weather sensitivities. It is interesting since they are completely different user groups with different spatio-temporal behavior. Unlike the ease of usage of dockless, we attribute the smaller sensitivity of member station-based trips to the pricing structure of the system. For $85 per year (or $28 per month), users receive unlimited 30-min rides. Moreover, members are typically committed to bikeshare as their mode of transportation and are habitual users who are less likely to be affected by adverse weather conditions.

Third, local disturbances or special events effects were found to be non-negligible in this analysis. The authors recommend that city planners consider these effects in travel demand management. Additionally, this information is of practical importance for planning for the number of vehicles deployed during planned special events or disturbances. Examples would be to rebalance or increase the number of vehicles around the National Mall during the Cherry Blossom festival (or other large events or parades), or to exemplify a more global issue in cities, to increase the number of vehicles around temporarily closed fixed transit stations during a disturbance (Younes et al., 2019). For unplanned disturbances that impact the economy, in this case the shutdown of the government, and of major touristic activities such as the Smithsonian Museums and the National Parks Services, in Washington, D.C. for five winter weeks, we calculated that the average overall micromobility ridership was 0.13% less than when the government was open. Although small in magnitude, the reduction in trips appeared to come in majority from DSS activity. Moreover, the impact would have likely been stronger had the shutdown happened during peak season for visitors.

Fourth, we found that all three groups were sensitive to weekly gasoline price changes. Increasing average gas prices by just 1% is associated with an increase of approximately 2% in hourly trips, or 345 daily trips. DSS trips were the most sensitive to increases in gas prices, followed by casual SBBS users. As expected, members were the least sensitive to gas prices. This group of users has already committed to using bikeshare as a major mode of transportation; they are likely not car users or seldom use cars and hence, the price of gas is not as important of an indicator of their behavior as it is for casual or DSS users who pay per ride. Moreover, the price of gas appears to influence trip duration the most for DSS users. This finding has important implications for non-member riders, which now comprise the majority of micromobility trips in the U.S. Cars produce 2–3 times more greenhouse gas (GHG) emissions per passenger kilometer than dockless and station-based micromobility (when accounting for entire lifecycle emissions) (Luo et al., 2019). The possible shift from cars to cleaner modes due to gasoline pricing is important to consider for policy makers in reducing emissions and in promoting sustainable shared mobility.

Finally, a fifth model specification was fitted to understand interactions between different micromobility modes. Our findings broadly showed that some interaction exists, namely that casual bikeshare trip activity has a negative relationship with dockless trip activity while that of member bikeshare trip activity with dockless trip activity was positive. With respect to dockless trip activity, this indicates a possible competition with casual station-based activity (i.e. single trip fares) and a complement with member station-based activity (i.e. annual or monthly members). Since dockless vendors do not yet have the option to have a member-based subscription, it is not clear whether dockless micromobility would have an adverse impact on station-based bikeshare as a whole and vice versa. Moreover, the magnitude of the coefficient is relatively small, and further research is needed to confirm this interaction.

7. Data limitations

This study has several limitations. First, the authors used only two of the six dockless vendor data which provides somewhat of an incomplete picture of dockless activity. While dockless activity is unlikely to vary greatly between vendors (the temporal trip count correlation between the two usable vendors was 0.77), it would still be useful to have complete dockless data. Second, the usable data comprised only scooter data usage, despite the existence of e-bikes in Washington, D.C. Dockless and station-based e-bikes were not analyzed in this study. Analyzing the same vehicle (with a similar pricing scheme) would isolate the effect of being station-based versus free-floating. Third, the API data were updated by one of the vendors at 5-min intervals. When using real time API data (updated in real-time) by another vendor, we found that depending on the time of the day, between 0 and 8% of bikes had a turnover rate of 1 min or less. This means that potential trip ends and starts were missed, resulting in an underestimation of DSS trips from one of the two vendors, particularly during high demand times. Additionally, even at very small scraping intervals (30 s), there is always a possibility of missing a trip end and start of a new trip that occurred within that interval. Lastly, spatial variations were not analyzed in this study. We suspect that the two major variations are with gas prices and with trip distribution due to disturbances.

8. Conclusions

DSS users are less sensitive to weather changes than their SBBS user counterparts, while concurrently being more sensitive to changes in gasoline prices. Weather factors have been shown to impact SBBS rates more than other built-environment, calendar events, and time of day factors (An et al., 2019). The implications of DSS users being less sensitive to weather factors are positive in the respect that it makes DSS more competitive with car and public transportation modes (which are generally less affected by weather factors than bicycles). Indeed, DSS could cut costs in inclement weather-related infrastructure typically associated with biking while also being more environmentally friendly than auto-travel and public transit. Moreover, DSS users appear to be more sensitive to changes in gas prices, which provides a more promising opportunity to analyze modal shifts towards low-carbon shared mobility. The sudden popularity in micromobility could have a significant and positive impact on reducing the effects of climate change (Luo et al., 2019).

Unlike municipal-owned SBBS systems, DSS programs take advantage of a private-public partnership that can minimize the out-of-pocket cost for the city government to expand its efforts in promoting green transportation. From a policy perspective, complementing SBBS with DSS may be the most cost-effective approach to help meet transportation related climate change targets. Moreover, it is important that city transportation agencies focus on having different pricing structures to accommodate differences in user preference in order to maximize the number of trips. In addition, city planners should coordinate with dockless vendors on how to best use resources during special events. Finally, while DSS is convenient, it also causes controversies that should be addressed through better transportation planning and policymaking, such as clutters of vehicles on sidewalks, risky riding behavior (i.e. riding on auto lanes and riding on pedestrian paths), and vandalism. Supervision from the city together with a close partnership with DSS vendors are key to a successful city-wide micromobility operation. In recent years, travel mode distribution has seen the emergence of new travel modes, most notably shared mobility (i.e. ride share, car share, bike share) but also cleaner modes of car travel such as electric vehicles, and more efficient cars due to automated technology. This shows a potential major shift in the way we travel.

Future research directions include analyzing the spatial differences in dockless and station-based micromobility to complement this temporal analysis. Additionally, we propose analyzing the determinants in other cities with different characteristics (e.g. weather, population density, street network design, built environment, presence of fixed transit) to investigate the spatial determinants of micromobility. Finally, future research could focus on complementing large scale API data analysis with survey data to fully understand attitudinal preferences towards modal shifts to emerging mobility.

CRediT authorship contribution statement

Hannah Younes: Conceptualization, Methodology, Investigation, Data curation, Validation, Visualization. **Zhenpeng Zou:** Methodology, Data curation, Writing - review & editing. **Jiahui Wu:** Software, Data curation. **Giovanni Baiocchi:** Methodology, Writing - review & editing, Supervision.

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