Scoot over: Determinants of shared electric scooter use in Washington D.C.

Leila Hawa
Department of Civil Engineering
McGill University, Montreal, Quebec, H3A 0C3
Email: leila.hawa@mail.mcgill.ca

Boer Cui
Department of Civil Engineering
McGill University, Montreal, Quebec, H3A 0C3
Email: boer.cui@mail.mcgill.ca

Lijun Sun
Department of Civil Engineering
McGill University, Montreal, Quebec, H3A 0C3
Email: lijun.sun@mcgill.ca

Ahmed El-Geneidy
School of Urban Planning
McGill University, Montreal, Quebec, H3A 0C3
Email: ahmed.elgeneidy@mcgill.ca

Word Count: 6,718 words

Submitted November 4, 2019

For Citation Please use: Hawa, L., Cui, B., Sun, L., & El-Geneidy, A. (2020). *Scoot over: Determinants of shared electric scooter use in Washington D.C.* Paper to be presented at the Transportation Research Board 99th Annual Meeting, Washington DC, USA.

ABSTRACT

Micromobility, including the use of shared electric scooters (e-scooters), has emerged rapidly in North America and is marketed as a method to decrease car reliance, especially for short distance travel in urban settings. Our study aims to contribute to our understanding of how shared e-scooters are used by examining the factors that determine the presence of e-scooters, as well as those that cause variation in e-scooter presence between each consecutive hour and throughout the day. Data on the location of e-scooters in the Washington D.C. area over six full days was collected. Then, multi-level mixed effects linear regression models were generated to investigate the impact of time, land use characteristics, and the built environment while controlling for weather conditions. We found that temporal effects were present as weekends and late nights were associated with fewer e-scooters and less variation in hourly e-scooter presence. Higher population density, density of places of interest, and activities were generally associated with more e-scooters and contributed to more change in the hour-to-hour numbers of e-scooters but less variation throughout the day. Bikeshare stations and bicycle lanes positively impacted presence and change in e-scooters but it is unclear whether e-scooters were used as first-mile last-mile solutions for public transport. These findings can help policy-makers make appropriate decisions in recognizing e-scooters as an urban mobility solution and where to expect them to emerge in different parts of the city.

Keywords: shared electric e-scooter, land USE, TRANSPORTATION INFRASTRUCTURE, MICROMOBILITY

1. INTRODUCTION AND LITERATURE REVIEW

Concerns about climate change and the negative impacts associated with an increase in personal vehicle use such as emissions and the promotion of a sedentary lifestyle are growing. Active, more sustainable modes of transport have gained attention as a way to decrease personal vehicle use and improve quality of life (Shaheen, Guzman et al. 2010). As a response to sprawl, which is associated with personal vehicle use, cities are moving towards new urbanism and transit-oriented developments, which focus on mixed-use neighborhoods and increasing active and public transport. Additionally, traditional motor companies as well as emerging technology companies have embraced micromobility as an opportunity to grow and expand their businesses (Timo Möller 2018). This shift in urban planning ideology combined with the drive for business opportunity and technological innovation by the private sector, set the stage for the growth of non-personal vehicle mobility solutions, such as shared dockless electric scooters (e-scooters). In addition to environmental benefits, active transport is associated with higher levels of traveler satisfaction than other modes of transport (St-Louis, Manaugh et al. 2014) and is noted for its positive impacts on quality of life by contributing to physical and mental well-being (by facilitating social interaction) (Richard J. Lee 2016). In an effort to decrease personal vehicle use and increase quality of life, cities in North America are striving to encourage active transport such as cycling, walking and public transit. This intention is evidenced by the recent growth of bikeshare systems and the expansion of bicycle infrastructure in cities such as New York (Dill and Carr 2003, 2019). In fact, the growth of shared micromobility in the U.S.A. since 2017 has been epic and speedy: shared micromobility use in the form of shared e-scooters and bicycles has grown nearly 2.5-fold in 2018 compared to 2017, reaching 84 million trips per year (2019). The shared e-scooter has experienced standout success. E-scooter companies are now functioning in approximately 100 cities in the U.S. and shared e-scooter use topped 38.5 million trips in 2018, which accounts for nearly 20% of all of the e-scooter trips taken since 2010 in the U.S.(2019).

Since shared e-scooters are a new mode of transportation, there is uncertainty about the impacts of the growth of micromobility on transportation systems and land use. However, there could be benefits associated with the success of e-scooters in cities. Shared e-scooters can increase the number of trips where active transport modes are competitive to the automobile (Smith and Schwieterman 2018). They could increase accessibility to jobs by increasing the catchment areas around public transport stations (Smith and Schwieterman 2018). Additionally, shared e-scooter users reported a decrease in taxi, ride hailing services, and personal car use (Chowdhury, Hicks et al. 2019). Trips via e-scooters were shown to directly replace driving and ride hailing trips (2018). However, they were shown to replace walking trips as well (2018). Additionally, e-scooters are used by a variety of travelers, including both commuters and visitors (2018). This could partially align shared e-scooter systems with city transport goals to increase active transport mode share.

Despite the concerns about e-scooters cluttering sidewalks when parked, a 2018 study of e-scooter parking in San Jose, California has shown that most e-scooters are well parked in ways that comply with bicycle parking rules and do not infringe on sidewalk use (Fang, Agrawal et al. 2018). A Portland, Oregon report on e-scooter use in the city also found that e-scooter parking was typically appropriate, yet reported concerns from residents about precarious parking in addition to illegal sidewalk use (2018). Thus, city officials have an important role to play in ensuring that e-scooters are parked and used properly to avoid negative effects of e-scooter use. Providing appropriate parking and guidelines for use requires a knowledge of the different factors that impact the presence of an e-scooter in an area and how that presence changes over the course of a day, and between weekdays and weekends.

Shared e-scooter systems share some fundamental characteristics with bikeshare systems. They both allow users to access and pay for devices on an as-needed basis and the companies take care of maintenance, storage and security aspects of bicycle and e-scooter ownership(Stephen D. Parker 2013). Differences between bikeshare and shared e-scooter systems include the fact that bikeshare systems exist in both docked and dockless forms while shared e-scooter systems only exist in dockless forms in North America (2019). In fact, station-based bikeshare systems have existed in North America since 2009, when BIXI launched in Montreal (Ahmadreza Imani 2014). Additionally, shared e-scooters are electric while bikeshare programs exist with both electric assist bicycles and fully manual bicycles (2019). Further, the role that public sectors has played in each respective system is different, as publicly owned and privately operated in addition to for-profit vendor operated models existed for bikeshare systems in North America, while shared e-scooter systems have not experienced that same publicly owned and privately operated model (Stephen D. Parker 2013, Moore 2019). Thus, in order to better understand the potential impacts of e-scooters on cities, the impacts of bikeshare systems, which are more established and share some similarities with shared e-scooter systems can be reviewed.

Shaheen et al. conducted a review of bikesharing and found that bikeshare systems have positive environmental and social effects (Susan A. Shaheen 2010). In 2009, 16% of the bikeshare users in Washington D.C. would have made personal vehicle trips otherwise, thus causing a greenhouse gas reduction for those trips (Susan A. Shaheen 2010). Further, Shaheen et al. found that bikeshare programs helped grow the public perception that bicycles are a convenitent form of transportation, since almost 79% of Washington D.C. bikeshare users considered bikeshare to be a more convenient or faster mode of transportation than other modes (Susan A. Shaheen 2010). In 2018, Hamilton and Wichman investigated the impact of Capital Bikeshare on congestion in Washington D.C. (Timothy L. Hamilton 2018). They found a causal link between the presence of bikeshare stations and a reduction in congestion (Timothy L. Hamilton 2018). In fact, among areas in Washington D.C. that have a Capital Bikeshare station, the researchers found a 4% reduction in traffic congestion, which is associated with social and economic benefits (Timothy L. Hamilton 2018). Hamilton and Wichman estimate that a 4% reduction in traffic congestion across Washington D.C. would result in $182 million in annual travel time savings and a reduction of wasted fuel, in addition to $1.82 million from reductions in carbon dioxide emissions (Timothy L. Hamilton 2018). McKenzie investigated the difference in use patterns between specifically Lime shared e-scooters and Capital Bikeshare bicycles in Washington D.C. (McKenzie 2019). McKenzie suggested that Capital Bikeshare trips were more commuter oriented and Lime e-scooter trips were more leisure oriented, although theorized that this might be because Capital Bikeshare is more established in the city than Lime e-scooters are (McKenzie 2019). Thus, bikeshare systems in Washington D.C. have demonstrated positive impacts on the city, and which calls for more research into the use and impact that shared e-scooters have there as well.

Imani et al., investigated how land use, temporal, weather and transport infrastructure attributes impact bicycle flows in station-based bikesharing systems (Ahmadreza Imani 2014). They found that usage was higher during the week compared to the weekend, closer to the central business district (CBD), in more densely populated areas, and in the evening compared to other times of day(Ahmadreza Imani 2014). They also found that bikeshare use was connected to station density in an area(Ahmadreza Imani 2014). It will be interesting to compare these findings to our study, which can highlight differences or similarities between docked and dockless shared vehicle use and shared vehicle type. Shared dockless bicycle systems, which entered the American market in 2017, have existed there for a slightly longer time than shared dockless e-scooters, which emerged in 2018 (2019). Shen et al. studied dockless bicycle sharing in Singapore and found a connection between built environment, fleet size, and weather on dockless bicycle use (Shen, Zhang et al. 2018). Although there can be parallels drawn between bikeshare systems and dockless e-scooter systems, our study is unique as it addresses the relationship between land use, transport infrastructure, temporal, and weather variables and e-scooter use in a North American context.

2. METHODS AND DATA

Presence of E-scooters

Washington D.C. was selected for this study because it has a relatively mature shared e-scooter network compared with other North American cities (Teale 2019). Additionally, Washington D.C.'s District Department of Transportation (DDOT) provides real time access to shared e-scooter data as well as an expanse of publicly available descriptive information. DDOT requires companies that have permits to operate dockless vehicles in Washington D.C. to provide public access to the current location of their vehicles that are not in use through an application programming interface (API) (2018). The data for each of the six companies that operate dockless transport services in Washington D.C.: Bird, Jump, Lime, Lyft, Skip and Spin, is available through APIs on the DDOT website . The APIs were leveraged to collect the location data of e-scooters for this study. It is important to note that the details regarding the e-scooter location did vary between each company as some reported lat/long only while others reported e-scooter unique identification numbers. In total 240,624 locations of e-scooters in Washington D.C. were collected over the course of the six days in 2019: Sunday May 12th, Monday May 13th, Tuesday May 14th, Thursday May16th, Saturday June 1st, and Friday June 14th. Data collection was conducted over the course of three weeks between May and June 2019. Unfortunately due to technical difficulties with the collection, such as the APIs pausing the data collection, only six full uninterrupted days of data were achieved. In order to prepare the data for the model, Washington D.C. was divided into 1,671 geographic grid cells areas, referred to as fishnets, which were 0.07 miles^2 (0.19 km^2) squares. Grid cells were selected as the unit of analysis instead of zones because they are a reliable representation of a space and are more computationally efficient than zones (Eric J Miller 2004). The fishnets were sized as such so that they were small enough that a change in the concentration of e-scooters could be seen from hour to hour and to avoid aggregation bias (Eric J Miller 2004). As e-scooter location information was available every five minutes, the number of e-scooters present in each fishnet at 5-minute intervals was determined by spatially summarizing the e-scooters distributed around the Washington D.C. region to the fishnets. As we are interested in an analyses at a more aggregated level, the number of e-scooters counted every five minutes is summed to the hour for each fishnet, then this cumulative sum of e-scooters was divided by 12 to obtain the average number of e-scooters per hour for each fishnet. **Figure 1** depicts the distribution and concentration of e-scooters in each fishnet in Washington D.C. throughout the day on Thursday, May 16, 2019. We observe that e-scooters were highly concentrated in the central business district and near the subway lines. Additionally, we observe that e-scoters are more highly concentrated later in the day, with the highest concentration in the early afternoon, and lowest concentration during the late night. Further, the concentration of e-scooters was higher in the evening than the morning.

Covariates

The explanatory variables that were used in this study are related to time, land use, transport infrastructure and weather. Collinearity among the explanatory variables was checked and guided our decision making process for which variables to include in the models. The temporal variables were used to analyze the effects of day of the week and time of day on e-scooter use. We divided the 24-hour day into four six-hour categories: 12AM to 6 AM (late night), 6AM to 12 PM (morning), 12PM to 6 PM (afternoon) and 6PM to 12 AM (evening) and these were entered into the models. Another dummy variable was entered to indicate that the data was taken on a weekend or weekday in the models.

The land use and transport infrastructure data was collected from a combination of Washington D.C.'s Open Data initiative . The land use variables include various sociodemographic and land use characteristics. Sociodemographic effects were measured at the census tract and fishnet level and used to depict the populations that are near e-scooters. The variables collected for analysis include number of jobs per fishnet, weighted population density in the census tract that the fishnet is a part of, and weighted median household income of the census tract that the fishnet is a part of. The population density of the census tract and the median income are depicted in **Figure 2**, where there is greater population density surrounding the CBD and on the outskirts of the city boundary. There are higher median income neighborhoods further away from the CBD and lower median income neighborhoods closer to the middle of the city. Additionally, the median income was divided into four categories and treated as a set of dummy variables in the models: low income (less than or equal to $50,000), low-medium income (greater than $50,000 and less than or equal to $100,000), high-medium income (greater than $100,000 and less than or equal to $150,000), and high income (greater than $150,000). Land use variables, which are depicted in **Figure 3**, were used to capture the type of locations people would want to access using e-scooters. The number of museums, marketplaces (grocery stores and healthy corner stores), liquor licenses, and restaurants and cafes per fishnet were collected for the regression analysis. Additionally, whether the fishnet is part of the CBD, a college or university campus, or a national park were included as dummy variables. The number of jobs per fishnet, which was collected from the Census Bureau, was found to be highly correlated to the CBD, so the number of jobs per fishnet was excluded from the models. Models were tested with the number of jobs instead of if the fishnet is a part of the CBD, and they were found to be adequate. However, we decided to keep the CBD variable instead of the number of jobs because we were interested in exploring the relationship between the CBD and e-scooter use. Additionally, the number of restaurants and cafes was found to be highly correlated with the number of liquor licenses in an area. Thus, the locations of restaurants and cafes from DC Open Data were excluded from our analysis. Since bars and restaurants typically have liquor licenses, the locations of liquor licenses is considered to be a representative list of bars and restaurants.

The transport infrastructure characteristics were used to describe the type of infrastructure that is more conducive to e-scooter use, such as the number of bus stops, metro stations, parking meter spaces, and Capital Bikeshare stations per fishnet. Additionally, the presence of a bicycle lane in the fishnet was included in the models as a dummy variable. The number of parking meter spaces was included as an indication of car traffic in the area.

Hourly weather information for Washington D.C. was collected from the Dark Sky API (2019) in order to control for the impact of weather while at the same time, identifying the weather conditions that could be conducive to e-scooter use, particularly to cause variations in e-scooter presence between one hour to the next and throughout the day. We collected hourly temperature, precipitation intensity, humidity, wind speed and cloud cover data for Washington D.C. for the day of e-scooter data collection. We found cloud cover to be correlated with precipitation intensity and was subsequently removed from the modelling process.

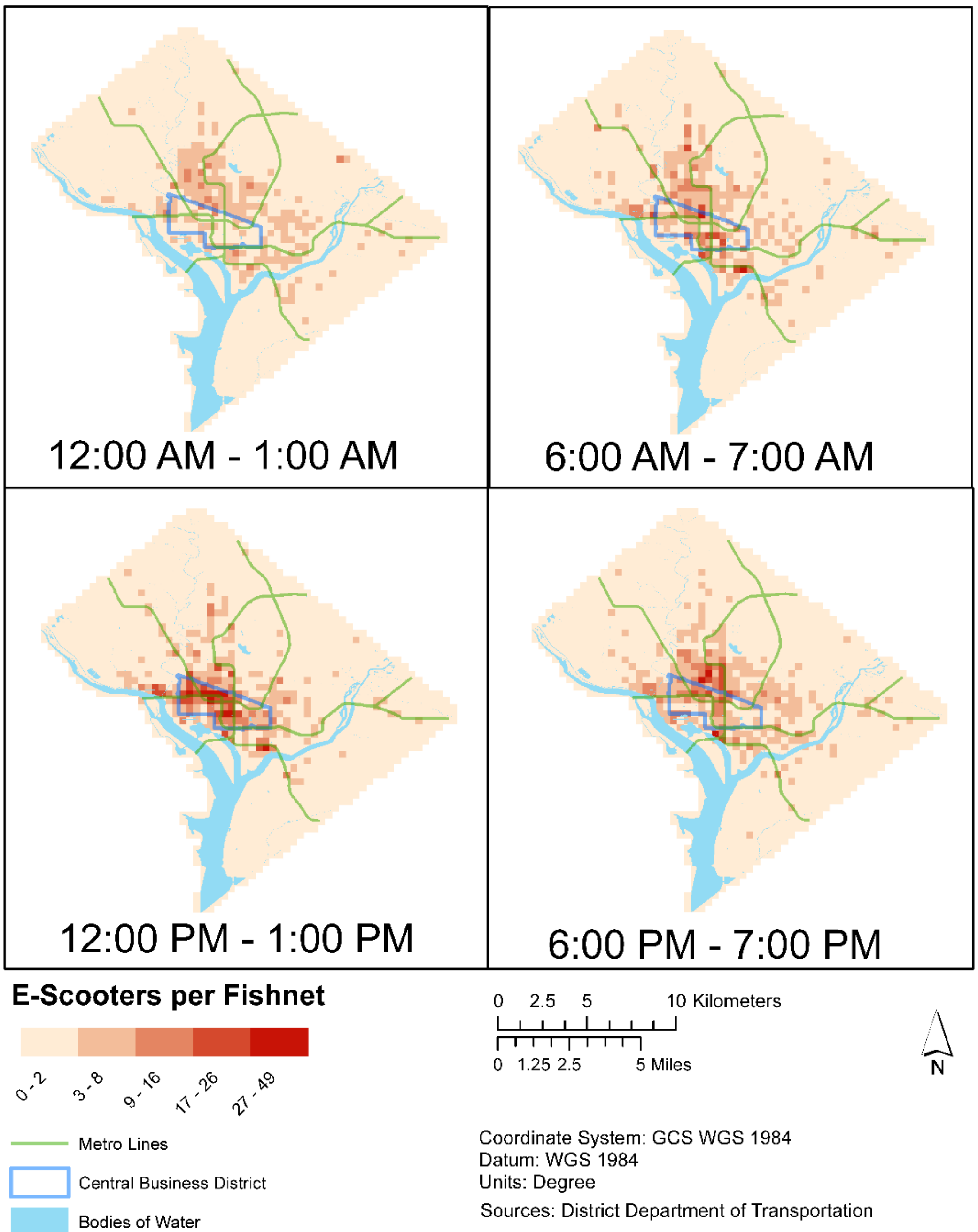

FIGURE 1 Average number of e-scooters during hours throughout the day

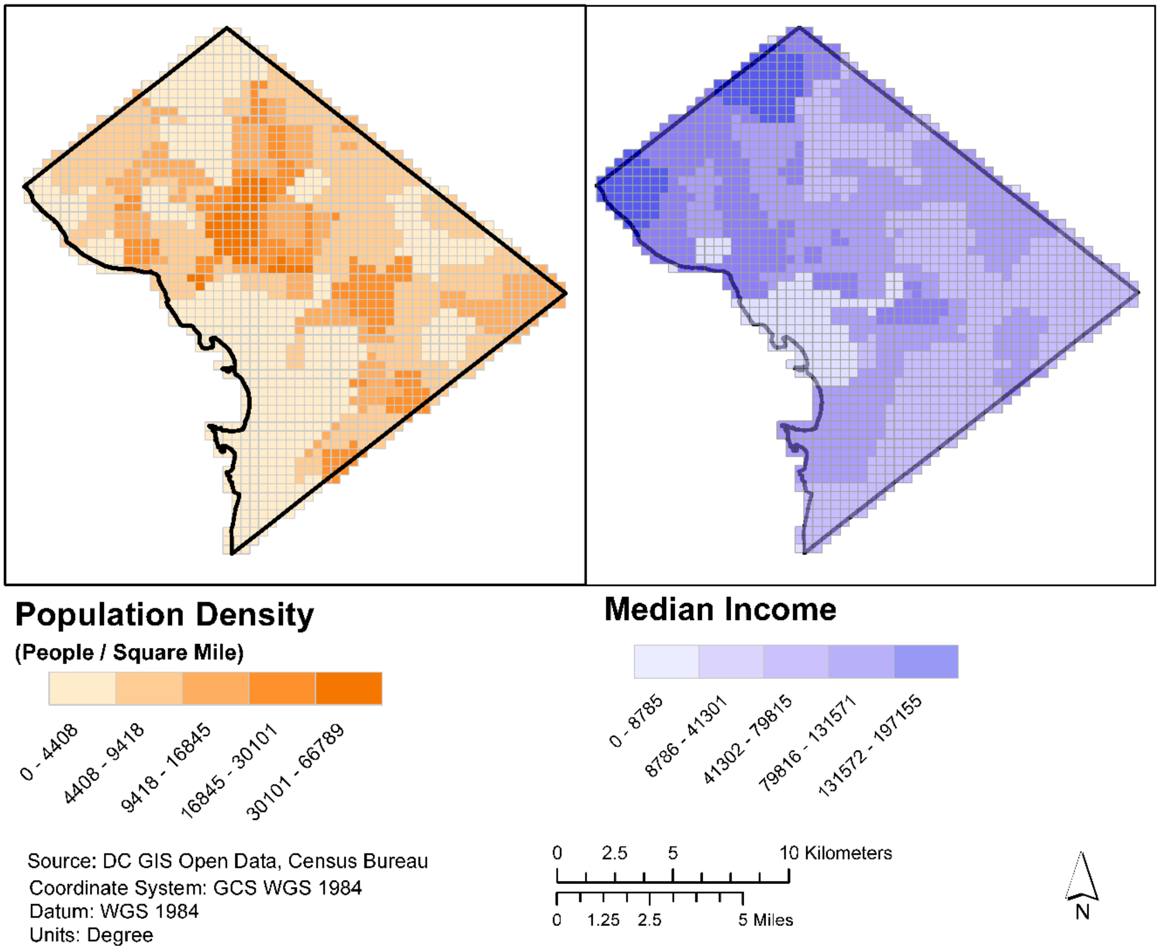

FIGURE 2 Sociodemographic Characteristics of Washington D.C.

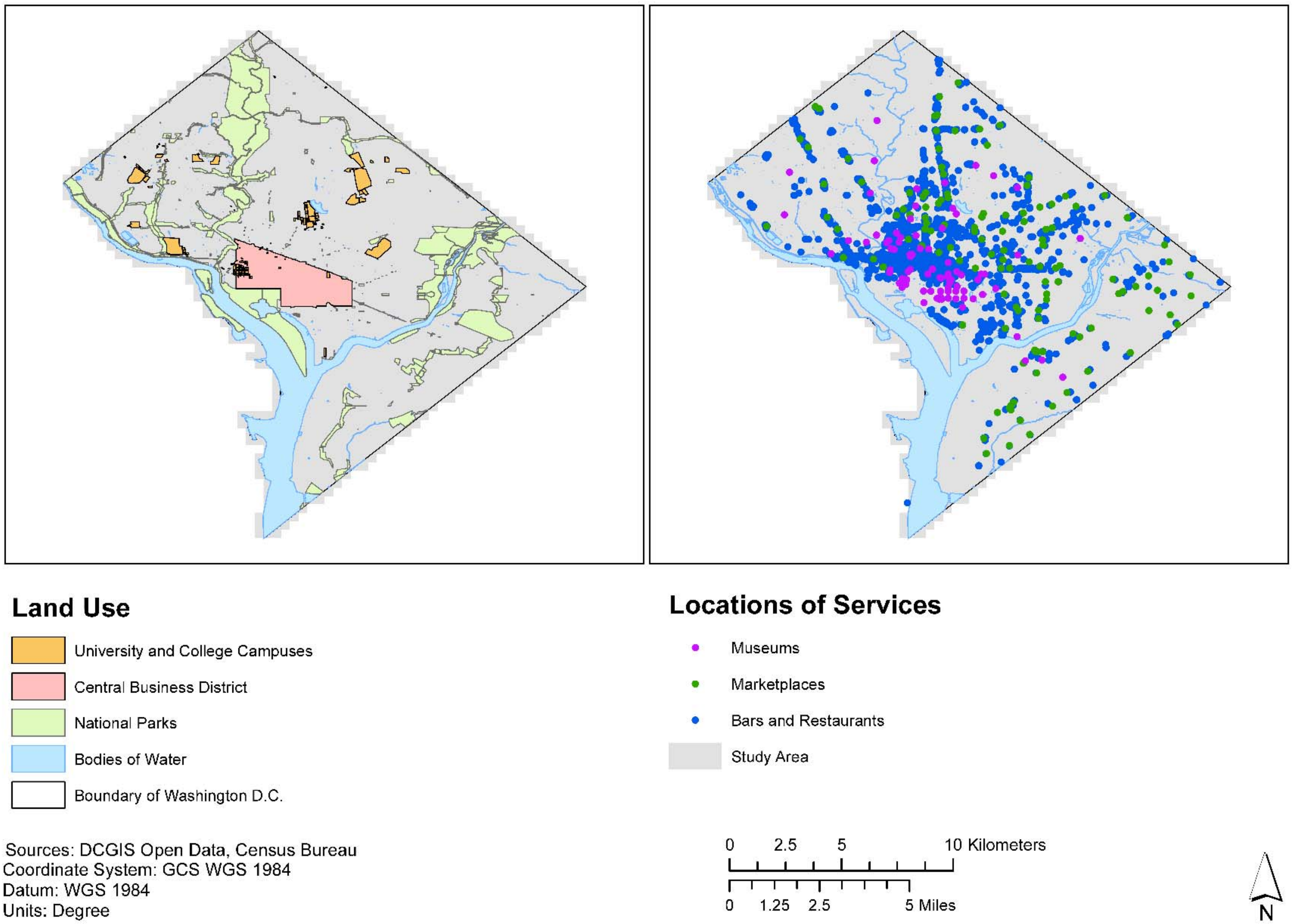

FIGURE 3 Land Use in Washington D.C.

Model Development, Processing and Validation

Prior to modelling, the average number of e-scooters present as well as the collected land use and transport infrastructure information was intersected for each fishnet. This was done for the entire Washington D.C. region. To clarify, the fishnet is used as the spatial unit of analysis, while the hour of data collection is the temporal unit.

The analysis of the impact of covariates on e-scooter utilization patterns is carried out through four regression models. The first model (*Model 1*) aims to understand the impact of the covariates on the likelihood of there being at least one e-scooter present in a fishnet within the hour. The second model (*Model 2*) builds upon the first, and examines, for those observations where at least one e-scooter was observed, the factors that contribute to a higher number of e-scooters present in the fishnet within the hour. The third and fourth models are further extensions of the first two, as they examine the factors that cause a variation in the number of e-scooters present in a fishnet. Specifically, the third (*Model 3*) examines the hour-to-hour variation for observations where a difference in e-scooter numbers was observed between the present and the previous hour. The last model (*Model 4*) examines the factors that influence an overall variation in the presence of e-scooters throughout the day for each fishnet using the coefficient of variation. The coefficient of variation per fishnet was generated by dividing the standard deviation of the number of e-scooters per fishnet per day ($\sigma_{i,j}$) by the average number of e-scooters per fishnet per day ($\mu_{i,j}$):

$$\text{Coefficient of Variation}_{\text{i,j}} = \frac{\sigma_{i,j}}{\mu_{i,j}}$$

Thus, the coefficient of variation indicates how much the average number of e-scooters per fishnet varies throughout the day. The models were selected to examine the degree of e-scooter presence (*Models 1 and 2)* and then to investigate degrees of variation in e-scooter presence (*Models 3 and 4).* Additionally, they were selected to start broad with *Model 1* taking in to account all of the observations and then narrowing down the samples with *Models 2, 3, and 4* based on their objectives.

Multi-level mixed effects regression modelling was used due to the incorporation of longitudinal panel data (every hour for six days) for each fishnet. The temporal levels of the model varied based on the model, from every hour for six days (144 hours) to simply six days. Additionally, the size of the units of analysis on the geographic level was consistently the same (a fishnet), although the number of fishnets included in each model varied. To clarify with an example: the total number of observations available in *Model 1* is 144 hours (24 hours over 6 days), multiplied by 1,671 (the total number of fishnets), equally to 240,624 observations; as such, a two-tiered multi-level model with panel data is called for to analyze the presence of e-scooters in each fishnet for different periods of time (by hour and by day). To validate the models, bootstrapping with replacement was carried out for *Models 1, 2 and 3* to ensure that the statistical significance values and confidence intervals for each covariate are a reliable representation of the entire dataset. As well, the sample size was limited to 10,000 in the bootstrapping process to avoid sample biases due to a large number of observations. Thus, bootstrapping was limited to *Models 1, 2 and 3* because they had sample sizes larger than 10,000 and bootstrapping was not employed for *Model 4* because its sample size is smaller than 10,000. A summary of the four models carried out in the analysis is shown in **Table 1**. It should be noted that the initial data set is zero-inflated, and to account for this, we used a logit model to differentiate between zero and above zero counts (*Model 1*) and then a linear regression model which only included the positive, non-zero observations (*Model 2)*. Ideally, a zero-inflated multi-level linear regression would have been used to combine these two models, however that is technically tedious with Stata, the statistical program that we used, and the combination of *Model 1* and *Model 2* is an appropriate substitute for a zero-inflated model (Rodriguez 2018).

TABLE 1 Model design

	Model 1	Model 2	Model 3	Model 4
Model type	Logit	Linear	Linear	Linear
Dependent variable	Likelihood of at least one e-scooter present	Average number of e-scooters	Change in the average number of e-scooters between current and previous hour	Coefficient of variation*
Omission	None	Observations with no e-scooters present	Observations with change in the average number of e-scooters per hour before and for the hour of observation not equal to zero	Observations with the coefficient of variation, standard deviation and average equal to zero; 12AM – 6AM observations
Temporal unit	Hour (144)	Hour (144)	Hour (138)	Day (6)
Spatial unit	Fishnet (1,671)	Fishnet (1,308)	Fishnet (1,306)	Fishnet (1,297)
No. observations	240,624	78,260	75,044	5,539
Notes			Since the days that the data was collected over were not consecutive, the hour from 12AM – 1AM of each day was omitted	Did not consider 12AM – 6AM for each day because e-scooters are typically charged overnight; the weather variables used in this model were averaged throughout the day

*The coefficient of variation is defined in the description of Model 4 above

3. RESULTS AND DISCUSSION

Summary Statistics

The summary statistics for the variables, both explanatory and dependent are presented in **Table 2** and are distinguished between categorical variables, where the frequencies are summarized and continuous variables, where the mean, minimum and maximum values are presented. Due to the difference in the number of observations included in each model, the tabulations and means of the variables vary slightly between models. Out of the entire sample of observations spanning over 144 hours for 1,671 fishnets, 32.52% (78,620) contained an e-scooter. Of the observations where e-scooters were present, the average number of e-scooters present in each fishnet was 3.33 per hour. For every observation that had a different average number of e-scooters per hour per fishnet than the previous, the average absolute change in the number of e-scooters per hour was 0.82. Lastly, the average coefficient of variation for fishnets that contained e-scooters throughout the study time was 1.54 on a daily basis. Interestingly, the maximum coefficient of variation was 4.24, which indicates that at some point during the day, there may have been over four times as many e-scooters (averaged for the hour) in a specific fishnet than the average number of e-scooters for the day.

TABLE 2 Summary Statistics

	Percent of observations					
Categorical Variables	Model 1	Model 2	Model 3	Model 4		
Weekend Day	33.33	31.20	31.16	32.48		
12AM - 6AM	25.00	23.25	19.96	N/A		
6AM - 12PM	25.00	23.79	24.81	N/A		
12PM - 6PM	25.00	25.89	27.00	N/A		
6PM - 12AM	25.00	27.07	28.23	N/A		
Low Income Area	58.23	55.03	55.02	56.42		
Low-Med. Income Area	24.96	32.10	32.10	28.20		
High-Med. Income Area	12.09	12.36	12.37	14.30		
High Income Area	4.73	0.51	0.51	1.08		
Part of the CBD	5.21	15.09	15.11	9.42		
Part of a College Campus	7.60	12.33	12.36	10.92		
Part of a National Park	45.60	48.39	48.40	46.33		
Contains a Bicycle Lane	23.76	44.21	44.21	36.14		
Dependent variable = presence of e-scooters	32.52	N/A	N/A	N/A		
Continuous Variables	**Mean**				**Min.**	**Max.**
Census Tract Population Density (1000s)	8.44	12.92	12.91	11.10	0.00	66.79
Number of Museums	0.05	0.13	0.13	0.09	0.00	5.00
Number of Marketplaces	0.07	0.15	0.15	0.12	0.00	3.00
Number of Bars & Restaurants	1.24	3.21	3.21	2.16	0.00	40.00
Number of Bus Stops	1.96	3.08	3.08	2.69	0.00	19.00
Number of Metro Stations	0.02	0.06	0.06	0.04	0.00	2.00
Number of Parking Meter Spaces	0.48	1.38	1.37	0.87	0.00	182.00
Number of Capital Bikeshare Stations	0.18	0.43	0.43	0.30	0.00	3.00
Temperature (Celsius)	16.35	16.44	16.52	17.44	8.84	29.34
Precipitation Intensity (mm/hr)	0.07	0.06	0.06	0.06	0.00	2.03
Humidity (0-1)	0.87	0.87	0.87	0.86	0.36	0.97
Wind Speed (km/h)	8.65	8.70	8.82	9.56	0.00	20.86
Dependent variable = average number of e-scooters/hour	N/A	3.33	N/A	N/A	0.08	79.92
Dependent variable = change in number of e-scooters hour to hour	N/A	N/A	0.82	N/A	0.00	39.42
Dependent variable = coefficient of variation in e-scooter presence	N/A	N/A	N/A	1.54	0.02	4.24

Regression Results

The regression results are presented in **Table 3** where they are discussed individually for each model.

Model 1

We found that the likelihood of at least one e-scooter being present in an area for a given hour decreased on a weekend compared to a weekday which may be due to more individuals using e-scooters for their commute. Compared to the evening (6PM to 12AM), the likelihood of e-scooter presence decreased late at night (12AM – 6AM) and during the morning (6AM – 12PM). This finding implies that e-scooters were likely to be used in the evening where not only would they be used for commuting, but for leisure activities. Population density was linked with an increase in the likelihood of e-scooter presence as supply of e-scooters is dependent on the surrounding population. Compared to a high-income area, low-, low-medium, and high-medium income areas were linked to higher likelihoods of e-scooter presence where the likelihood was highest for high-medium income areas. This is related to the geographic locations of the different income groups where the presence of e-scooters shown in **Figure 2** coincides with areas of low- and medium-income areas presented on the right in **Figure 3**. Being close to marketplaces, restaurants and bars as well as being located in the CBD and college campus increased the likelihood of e-scooter presence. This is expected, as attractive destinations prompt more e-scooter use. The presence of bus stops, bikeshare stations, and bicycle lanes increased the likelihood of e-scooter presence, which is consistent with existing research (Shen, Zhang et al. 2018). However, the number of metro stations was not significant in this model despite the highly positive odds ratio. On the other hand, parking meter spaces, as a proxy for the presence of cars, decreased e-scooter presence, indicating that e-scooter use may have been prevalent in more walkable areas.

Model 2

The second model builds upon the results from the previous one to examine the determinants of the number of e-scooters in an area. The number of e-scooters was fewer during weekends than on weekdays. Fewer e-scooters were observed late at night but more in the afternoon compared to the evening. The higher number of e-scooters present in the afternoon could show that a greater concentration of individuals may use e-scooters for commuting compared to individuals who use them for leisure in the evening. Population density was positively correlated with the number of e-scooters present. A low-medium income area was associated with more e-scooters. The presence of museums and restaurants and bars as well as being located in the CBD and national parks were positively associated with the number of e-scooters but the presence of marketplaces had a negative association. Perhaps places with a high density of marketplaces (i.e. commercial centers) are located in more residential areas than the central region where marketplaces are more spread out (see **Figures 2 and 3**). The presence of transport infrastructure was positively associated with e-scooters except for parking meter spaces, where a negative association was observed, and bicycle lanes, which was not significant.

Model 3

The difference in the average number of e-scooters present by the hour implies the movement of e-scooters, which reveals more information about how e-scooters are used throughout the region. Less hourly change in the number of e-scooters (less movement) was observed on weekends, illustrating that the use of e-scooters was not only less frequent, but also more consistent from hour-to-hour on weekends than weekdays. There was also less movement late at night as expected. As density increased, hourly e-scooter movements also increased (but to a small degree). Density of museums and restaurants and bars increased e-scooter movements as these are locations of interest or located in areas where more movements are expected (e.g. areas that are denser like commercial areas). Similar reasoning can be extended to areas in the CBD. Being located in a national park also increased e-scooter movements but this may be attributed to the location of some parks close to the CBD, which prompted more e-scooter use (see **Figure 3**). The density of metro stations per fishnet increased hourly changes in the number of e-scooters. Perhaps evidence of first-mile last-mile trips was observed as more e-scooter movements were observed around metro stations, but this is not completely clear given the negative results from *Model 1*. In addition, the density of bikeshare stations as well as presence of bicycle lanes were associated with more e-scooter movements. More intense precipitation and higher temperature was associated with decreased hourly variation in e-scooter numbers.

Model 4

First off, areas with lower coefficients of variation in the number of e-scooters throughout the day can be areas where e-scooters were used constantly with people arriving and departing, resulting in a standard deviation very close to the average. On the other hand, a lower coefficient can also occur when there is consistently low utilization of e-scooters. To differentiate between these two cases, we need to examine the impact of the covariates on the coefficient of variation with the results of previous models, to discern whether the variable is associated with constantly high utilization or constantly low utilization.

Weekends were associated with less variation in the number of e-scooters throughout the day. This finding summarizes the results from *Model 3* where we observed that the use of e-scooters was more constant throughout the day, but based on the results from *Models 1 and 2*, we can also suggest that the utilization is constantly low throughout the day in these areas. Higher population density was associated with less daily variations in the number of e-scooters. Low- or low-medium income areas, compared to high income, were associated with less variation which can also be attributed to them being centrally located where e-scooter use was more consistent. More access to marketplaces, restaurants and bars was associated with less variation which is expected as these are destinations where individuals may arrive and/or depart using e-scooters frequently throughout all periods of the day. The reasoning is similar to explain the lower degree of variation observed for areas located in the CBD. The presence of transport infrastructure also had an impact on the degree of variation in the number of e-scooters, namely, the number of bus stops, number of Capital Bikeshare stations and presence of a bicycle lane was associated with lower variation. Although the weather variables were averaged for the day in this model, we can still identify the impact of temporal changes in weather conditions within the day because it is likely that higher daily precipitation intensity and wind speed were the results of sudden weather events occurring some point during the day, which could have prompted people to stop using e-scooters, thus increasing the coefficient of variation examined in this model. Interestingly, higher humidity was linked with less variation throughout the day.

TABLE 3 Regression Results

		Model 1				Model 2				Model 3				Model 4			
		O.R		95% CI		Coef.		95% CI		Coef.		95% CI		Coef.		95% CI	
Temporal	Weekend Day	0.79	*	0.64	0.96	-0.26	*	-0.47	-0.05	-0.16	***	-0.23	-0.09	-0.31	**	-0.50	-0.11
	12AM - 6AM	0.58	***	0.47	0.72	-0.82	***	-1.04	-0.61	-0.41	***	-0.49	-0.34	N/A	N/A	N/A	N/A
	6AM - 12PM	0.65	***	0.53	0.80	0.21		-0.04	0.45	-0.03		-0.12	0.05	N/A	N/A	N/A	N/A
	12PM - 6PM	0.88		0.71	1.09	0.68	***	0.48	0.88	0.04		-0.04	0.12	N/A	N/A	N/A	N/A
Land Use	Census Tract Population Density (1000s)	1.13	***	1.11	1.14	0.02	***	0.01	0.03	0.00	**	0.00	0.01	-0.02	***	-0.03	-0.01
	Low Income Area	9.58	***	4.99	18.38	0.27		-0.02	0.55	0.05		-0.05	0.14	-0.39	*	-0.77	-0.01
	Low-Med. Income Area	11.22	***	5.89	21.37	0.35	*	0.06	0.63	0.09		-0.01	0.19	-0.39	*	-0.78	0.00
	High-Med. Income Area	17.33	***	8.89	33.78	0.05		-0.25	0.34	0.04		-0.07	0.14	-0.25		-0.64	0.15
	Number of Museums	1.44		0.69	2.99	0.64	***	0.38	0.90	0.22	***	0.10	0.33	-0.14		-0.31	0.03
	Number of Marketplaces	2.15	***	1.56	2.96	-0.31	***	-0.45	-0.16	-0.07	**	-0.12	-0.02	-0.16	*	-0.33	0.00
	Number of Bars & Resturaunts	1.16	***	1.07	1.25	0.23	***	0.20	0.25	0.05	***	0.04	0.06	-0.03	***	-0.05	-0.02
	Part of the CBD	25.36	***	9.73	66.09	3.57	***	3.25	3.89	1.00	***	0.87	1.13	-0.63	***	-0.87	-0.40
	Part of a College Campus	2.28	***	1.67	3.12	-0.13		-0.35	0.08	-0.01		-0.09	0.07	-0.10		-0.27	0.08
	Part of a National Park	1.12		0.96	1.30	0.14	**	0.05	0.24	0.06	**	0.02	0.09	0.06		-0.04	0.17
Transport Infrastructure	Number of Bus Stops	1.26	***	1.22	1.31	0.06	***	0.03	0.09	0.00		-0.01	0.02	-0.02	*	-0.05	0.00
	Number of Metro Stations	1.94		0.83	4.58	2.01	***	1.46	2.56	0.51	***	0.31	0.71	-0.20		-0.49	0.09
	Number of Parking Meter Spaces	0.96	**	0.93	0.99	-0.02	**	-0.03	-0.01	0.00		-0.01	0.00	0.01		0.00	0.01
	Number of Capital Bikeshare Stations	3.16	***	2.42	4.11	0.83	***	0.64	1.03	0.19	***	0.14	0.25	-0.30	***	-0.42	-0.19
	Fishnet contains a Bicycle Lane	2.73	***	2.30	3.24	0.02		-0.07	0.12	0.08	***	0.04	0.12	-0.21	**	-0.34	-0.09
Weather	Temperature (Celsius)	1.02		1.00	1.04	-0.04	***	-0.07	-0.02	0.01	*	0.00	0.02	0.02	*	0.00	0.03
	Precipitation Intensity (mm/hr)	0.85		0.64	1.13	0.05		-0.28	0.38	-0.14	**	-0.23	-0.04	1.76	***	0.78	2.74
	Humidity (0-1)	2.60	*	1.00	6.73	2.36	***	1.48	3.23	0.18		-0.12	0.47	-1.44	***	-1.98	-0.89
	Wind Speed (km/h)	0.99		0.97	1.01	0.03	**	0.01	0.04	0.01		0.00	0.01	0.03	***	0.02	0.04
	Constant	0.00		0.00	0.00	-1.02		-2.11	0.07	-0.09		-0.45	0.28	3.34		2.77	3.92
	Number of observations	240624				78260				75044				5539			
	Log Likelihood	-72397.3				-209009.5				-125327.300				-8175.5956			
	Interclass correlation	0.6754269				0.1784231				0.0754403				0.4344523			
	Akaike's information criterion	144844.6				418071.1				250706.6				16397.19			
	Bayesian information criterion	145104.3				418312				250946.5				16549.44			

*p<0.05 **p<0.01 ***p<0.001

Discussion

Compared to weekdays, e-scooters experienced less utilization, implied by fewer e-scooters detected and less change in the numbers of e-scooters present, on weekends as well as late at night. Population density of an area had an overall positive impact on e-scooter use which is reasonable because the supply of e-scooters relies on the neighboring population. The impact of income on e-scooter presence can be characterized by the fact that lower income areas were associated with greater e-scooter presence and variation (activity) compared to high income areas. This trend might be influenced by the fact that the high-income neighborhoods are located on the outskirts of Washington D.C. Thus, the impact of income itself was difficult to isolate because of its association with location due to the use of median household income at the neighborhood level, rather than the income of the e-scooter rider. The models showed a significant impact of the CBD on e-scooter presence and movement as increase in accessibility to opportunities in the CBD creates for demand for e-scooters as well as supply from more users in the area. The impact of other notable land uses such as national parks and college campuses on e-scooter use was less clear.

The number of bus stops in an area had a significant impact on e-scooter presence but the variation in e-scooter presence near bus stops was low. This could be because areas with a higher density of bus stops are more likely to be located near or around the CBD where there are more public transport corridors serviced by buses. Metro stations increased the average number of e-scooters in an area and the amount of e-scooter movement to and from the area but was not a significant determinant of whether or not an e-scooter would be presented in an area (refer to *Model 1*). Although there seems to be some sort of connection between public transport and e-scooter presence, it is not totally clear whether e-scooters served as first-mile last-mile solutions in this study. The consistent association between Capital Bikeshare stations and e-scooter presence and movement indicate that e-scooters may have been often available near bikeshare stations. Thus, Capital Bikeshare stations could be an intuitive place for riders to park e-scooters. The positive impact of the presence of a bicycle lane on e-scooter presence and movement, and the fact that there was little variation in the presence of e-scooters near bicycle lanes indicate that there could be an association between bicycle lanes and e-scooters. The models suggest that e-scooters were available near bicycle lanes, which could mean that e-scooter users ride on bicycle lanes and park them at a point between their destination and the bicycle lane.

The models showed an association between temperature and e-scooter movement, which could be because daily temperature is typically highest in the afternoon which coincided with the time of day that was most associated with e-scooter use. Further, rain events were shown to increase the variation in e-scooter supply and decrease e-scooter movement. The models suggest that e-scooters were consistently available in humid weather conditions.

4. CONCLUSIONS

In this study, we investigated the impact of time, land use and transport infrastructure on e-scooter use in Washington D.C. We collected e-scooter location data for six days and generated four multi-level mixed effects regression models to investigate e-scooter presence (likelihood of there being an e-scooter and the number of e-scooters present) as well as the variation in number of e-scooters present between consecutive hours and throughout the day.

The limitations of this study include the fact that it is based on Washington D.C. and thus we should be cautious in applying its findings to all other places where shared e-scooters are being operated. Rather, it is fitting to consider these results applicable to urban settings that have similar transport systems, built environment components and sociodemographic attributes in both scale and character. Additionally, the dataset cannot address whether the e-scooter was placed in a location as part of a rebalancing effort by the company or as the result of a trip by a user. This inability to reliably distinguish if an e-scooter placement was the result of rebalancing or use limits our interpretation of the results, as we could not differentiate between a company's interpretation of where e-scooters are used and where riders actually use them. This study was also limited by the fact that it took place during six days in spring, and thus did not include other weather extremes such as colder temperatures or snow. Additionally, since the sample represented six non-consecutive days of data, there could have been a circumstance that occurred on one of those days which impacted e-scooter presence that is atypical or not always present. It is important to note the information related to e-scooters posted on the DDOT website was not consistent, some companies posted only their name and location of the e-scooters and others added the e-scooter IDs. The absence of the e-scooter IDs made it impossible to generate an origin-destination matrix for the analysis of trips. As a result, we could only study the presence and absence of e-scooters in an area. Entering the full information about each e-scooter, including if it was placed by a rebalancing effort or user, by all companies should be the best practice in the future to allow researchers to study them to assist policy-makers in their decision-making process.

Next steps for future research would include using trip information instead of e-scooter location information. Additionally, the models could be further adjusted by including distance to the CBD (rather than including location in the CBD as a dummy variable), and distance to the nearest metro station. Another next step to refine the models would be to incorporate the road network in order to capture the impact of block length, type of street and intersection on e-scooter use. Further, the Moran statistic or spatially autoregressive models could be used to explore spatial autocorrelation in the data (Clarence Woudsma 2008). Lastly, the level of detail for temporal unit of analysis in *Model 3* could be increased in order to examine movement to and from fishnets at a finer scale.

This study contributes to a more comprehensive understanding of the factors that impact the presence as well as variations in the presence of e-scooters in a given area using data obtained for e-scooters operating in Washington D.C. In doing so, the utilization patterns are revealed implicitly which can contribute to how city planners and officials understand shared electric e-scooter are used and how they interact with existing transportation infrastructure and systems.

ACKNOWLEDGMENTS

We acknowledge the support of the Natural Sciences and Engineering Research Council of Canada (NSERC).

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: L. Hawa, A. El-Geneidy, L. Sun; data collection: L. Hawa; analysis and interpretation of results: L. Hawa, B.Cui, A. El-Geneidy; draft manuscript preparation: L. Hawa, B.Cui, & A. El-Geneidy. All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

. "Dockless Data and Application Programming Interface (API)." from https://ddot.dc.gov/page/dockless-api.

. "Open Data DC." from https://opendata.dc.gov/.

(2018). 2018 E-Scooter Findings Report. Portland, Portland Bureau of Transportation.

(2018) "Dockless Sharing Vehicles Permit Application 2019 Permit Year." District Department of Transportation - Dockless Vehicles in the District.

(2019). "Dark Sky API." from https://darksky.net/dev.

(2019). Shared Micromobility in the U.S.: 2018. New York, NACTO.

Ahmadreza Imani, N. E., Ahmed El-Geneidy, Michael Rabbat, Usama Haq (2014). "How land-use and urban form impact bicycle flows: Evidence from the bicycle-sharing system (BIXI) in Montreal " Transport Geography **41**: 306-314.

Chowdhury, A., J. Hicks, O. James, J. I. Swidersji, A. Wilkerson and R. Buehler (2019). Shared Mobility Devices in Arlington. Arlington, Virginia Tech Urban Affairs and Planning Studio.

Clarence Woudsma, J. F. J., Pavlos Kanaroglou, Hanna Maoh (2008). "Logistics land use and the city: A spatial–temporal modeling approach." Transportation Research Part E: Logistics and Transportation Review **44**(2): 277-297.

Dill, J. and T. Carr (2003). "Bicycle Commuting and Facilities in Major U.S. Cities." Transportation Research Record: 116-123.

Eric J Miller, J. D. H., John E Abraham, Paul A Salvini (2004). "Microsimulating urban systems." Computers, Environment and Urban Systems **28**(1-2): 9-44.

Fang, K., A. W. Agrawal, J. Steele, J. J. Hunter and A. M. Hooper (2018) "Where Do Riders Park Dockless, Shared Electric Scooters? Findings from San Jose, California." Mineta Transportation Institute.

McKenzie, G. (2019). Spatiotemporal comparative analysis of scooter-share and bike-share usage patterns in Washington, D.C. M. University**:** 26.

Moore, O. (2019). The e-scooter invasion is coming to Canada. What will our cities do with them? The Globe and Mail.

Richard J. Lee, I. N. S. (2016). "Transportation planning and quality of life: Where do they intersect?" Transport Policy **48**: 146-155.

Rodriguez, G. (2018). Multilevel Models. 10. Models for Overdispersed Count Data, Princeton University.

Shaheen, S. A., S. Guzman and H. Zhang (2010). "Bikesharing in Europe, the Americas, and Asia Past, Present, and Future." Transportation Research Record: Journal of the Transportation Research Board: 159-167.

Shen, Y., X. Zhang and J. Zhao (2018). "Understanding the usage of dockless bike sharing in Singapore." International Journal of Sustainable Transportation: 686-700.

Smith, C. S. and J. P. Schwieterman (2018) "Chaddick Institute for Metropolitan Development." E-Scooter Scenarios Evaluating the Potential Mobility Benefits of Shared Dockless Scooters in Chicago.

St-Louis, E., K. Manaugh, D. van Lierop and A. El-Geneidy (2014). "The happy commuter: A comparison of commuter satisfaction across modes " Transportation Research Part F: Traffic Psychology and Behaviour: 160-170.

Stephen D. Parker, G. M., Susan A. Shaheen, Adam P. Cohen (2013). "Understanding the diffusion of public bikesharing systems: evidence from Europe and North America." journal of Transport Geography **31**: 97-103.
Susan A. Shaheen, S. G., and Hua Zhang (2010). "Bikesharing in Europe, the Americas, and Asia: Past, Present, and Future." Transportation Research Record: Journal of the Transportation Research Board **2143**(1): 159-167.
Teale, C. (2019). Inside Washington, DC's dockless revolution. Smart Cities Dive.
Timo Möller, A. P., Dickon Pinner, Andreas Tschiesner (2018). "Reserve a seat - the future of mobility is arriving early." https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/reserve-a-seat-the-future-of-mobility-is-arriving-early 2019.
Timothy L. Hamilton, C. J. W. (2018). "Bicycle infrastructure and traffic congestion: Evidence from DC's Capital Bikeshare." Journal of Environmental Economics and Management **87**: 72-93.