

SCOOT OVER: DETERMINANTS OF SHARED ELECTRIC SCOOTER PRESENCE IN WASHINGTON D.C.

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<https://doi.org/10.1016/j.cstp.2021.01.003>

For citation please use: Hawa, L., Cui, B., Sun, L., & El-Geneidy, A. (accepted). Scoot over: Determinants of shared electric scooter use in Washington D.C.. *Case Studies in Transport Policy* 9(2), 418-430.

ABSTRACT

Micromobility, including the use of shared electric scooters (e-scooters), emerged rapidly in North America and is marketed as an alternative to 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. The object of this study is to investigate how temporal, land use, transport infrastructure, and weather attributes impact available e-scooter distribution and variation in e-scooter presence in Washington D.C., to reveal use patterns and develop a framework for studying citywide e-scooter systems. Data on the location of e-scooters in the Washington D.C. area over six full days was collected. Then, multilevel 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. We observed that the average number of e-scooters available per 0.07 mile² on weekends was 0.26 (7.81%) fewer than on weekdays, and 0.82 (24.62%) fewer during the late night than other times of day, all else held constant. 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, they increased the odds of e-scooter presence by 3.16 and 2.73 times respectively and change in the average number of e-scooters nearby. The hourly change in the average numbers of e-scooters near bikeshare stations was 0.19 all else held equal, and it is unclear whether e-scooters were used as first-mile last-mile solutions for public transport. These findings can help policy-makers in cities with comparable climates, land use characteristics, and transport infrastructure. The findings can help city planners and engineers make appropriate decisions in recognizing e-scooters as an urban mobility solution, where to expect them to emerge in different parts of the city, and how e-scooters interact with established transport systems.

Keywords: land use, micromobility, shared electric scooter, transportation infrastructure

INTRODUCTION

E-scooter companies first launched in the United States in 2017 and the vehicles started appearing in cities across the country that fall (Dickey, 2018a; Teale, 2019). In fact, since fall 2017 the growth of e-scooters in the U.S.A. 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 and 1.6-fold in 2019 compared to 2018, reaching 136 million trips per year by the end of 2019 (NACTO, 2020). Shared e-scooter use drove the growth of shared mobility in the U.S., which topped 38.5 million trips in 2018 and grew to 86 million trips in 2019 (NACTO, 2019, 2020). In 2019 e-scooter companies functioned in 109 cities in the U.S., which is 45% more cities than in 2018 (NACTO, 2020). The private nature of the micromobility industry, which has attracted over a billion dollars of investment as a business opportunity, is playing a role in supporting the growth of e-scooters across North America (Möller et al., 2018). However, some American cities such as Portland, Or and Washington D.C. have also started e-scooter pilot programs (DDOT, 2019b; Irfan, 2018; Portland Bureau of Transportation, 2018c). Based on the contents of the pilot programs, it is evident that cities consider e-scooters as a potentially helpful in meeting their transportation goals to shift travel away from private motorized cars (DDOT, 2010, 2020; Portland Bureau of Transportation, 2018a).

Although e-scooters are relatively new, there has been some research into e-scooter use and their environmental impact, which depends on the life cycle of the vehicles and the modes of transport they are replacing. The impact of temporal, land use, transport infrastructure, and weather attributes on dockless bikeshare systems, which are similar to e-scooter systems, is documented in the literature and is useful in understanding for transport planning but has not extensively been

studied for e-scooters. This research aims to help cities with e-scooter pilot programs understand the determinants of shared e-scooter distribution, which they can in turn leverage to help meet their transportation goals through specific parking and distribution policies.

1.1 E-SCOOTER DRIVER AND PARKING BEHAVIOR

Arnello and Fang conducted an observational study about e-scooter driver behavior as it compares to cycling (Arellano & Fang, 2019). They found that in San Jose, California e-scooters tend to cruise at lower speeds and they exhibit lower helmet use than cyclists (Arellano & Fang, 2019). Similar to cyclist behavior, men on e-scooters were found to travel faster than women on e-scooters, although overall e-scooter travel speeds were faster on streets than sidewalks (Arellano & Fang, 2019). Notably, cellphone use was low among e-scooter drivers than any other mode (Arellano & Fang, 2019).

Since shared e-scooters are a new mode of transport, there is uncertainty about the impacts of the growth of shared micromobility on the built environment. Concerns persist about e-scooters cluttering sidewalks when parked. A 2018 study of e-scooter parking in San Jose, California concluded that although 72% of e-scooters were parked on the sidewalk, 90% are well parked in ways that comply with bicycle parking rules and do not infringe on pedestrian traffic (Fang et al., 2018). James et al. further corroborated these findings in their observational study of 606 e-scooters parked in Rosslyn, Virginia (James et al., 2019). They found that only 16% of e-scooters were not parked properly and 6% blocked the pedestrian right-of-way (James et al., 2019). 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 (Portland Bureau of Transportation, 2018a). 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.

1.2 ENVIRONMENTAL IMPACTS – GREENHOUSE GAS EMISSIONS

E-scooter companies market themselves as sustainable transport, namely that they are electric vehicles that can induce mode shift, however understanding the environmental impact, including the greenhouse gas emissions of e-scooter use is complex (Bird, 2020; Hollingsworth et al., 2019; Lime, 2020). The greenhouse gas emissions associated with e-scooter use depends on the lifecycle emissions of the vehicle and mode of the trip they are replacing (i.e. – what mode the traveler would have used if an e-scooter were not available) (Hollingsworth et al., 2019; Moreau et al., 2020). The lifecycle assessments account for the materials and manufacturing of e-scooters, as well as the collection of e-scooters for charging when calculating their greenhouse gas emissions (Hollingsworth et al., 2019; Moreau et al., 2020; OECD/ITF, 2020). For example Hollingsworth et al. analyzed Xiaomi M365 e-scooters, which were representative of the e-scooter that companies such as Bird and Lyft used at least for the fall of 2018 in North America (Dickey, 2018b; Hollingsworth et al., 2019). Although using an e-scooter instead of walking or a non-electric bicycle would consistently be associated with larger relative greenhouse gas emissions, when replacing a personal automobile trip, e-scooter use results in a net decrease of environmental impacts (Hollingsworth et al., 2019; Moreau et al., 2020).

The life cycle analysis of the greenhouse gas emissions per e-scooter is highly dependent on the lifespan of the vehicle (Hollingsworth et al., 2019; Moreau et al., 2020; OECD/ITF, 2020). The literature conducts sensitivity tests by generating lifecycle analyses with a range of different lifespans, such as 0.5 – 2 years, 1 month – 2.5 years, 9.6 months for first generation e-scooters and 1.97 years for newer e-scooters (Hollingsworth et al., 2019; Moreau et al., 2020; OECD/ITF,

2020). With their base case assumptions, including that an e-scooter lifetime is between 0.5-2 years, e-scooters are associated with life cycle greenhouse gas emissions relatively greater than 65% of the transport modes they replace: a bus with high ridership, an electric bicycle and a personal bicycle on a passenger-mile traveled basis (Hollingsworth et al., 2019). Based on an analysis of Bird e-scooters in Louisville, KY, the average lifespan of an e-scooter is 28.8 days, which would imply that e-scooters might have relatively higher greenhouse gas emissions than a larger percentage of other transport modes than Hollingsworth et al. predict (Griswold, 2019; Hollingsworth et al., 2019). Conversely, Moreau et al. found that e-scooters must have a 9.5-month lifespan to have a lower global warming potential than using a combination of public transport, a personal car, bicycling, electric bicycling, motorcycling and walking in Brussels, where their study took place (Moreau et al., 2020). The ITF study confirmed that e-scooter sharing is associated with higher emissions than walking, public transport and cycling, although notes the environmental benefit of multimodal trips including shared e-scooters and public transit (OECD/ITF, 2020). E-scooter sharing companies now use vehicles that are more durable and the lifespans of their vehicles are increasing with innovation, which should decrease the environmental impacts of e-scooters (Hawkins, 2019; Moreau et al., 2020; OECD/ITF, 2020). In fact, e-scooter operators even repaired first generation e-scooters to extend their lifespan to a year from a few weeks or months, and newer models are designed to have two-year lifespans (Möller & Simlett, 2020).

1.3 JOURNEYS REPLACED BY E-SCOOTERS

Shared e-scooters can increase the number of trips where active transport modes are competitive with the automobile (Smith & Schwieterman, 2018). An Arlington, VA survey found that 52% of e-scooter users reported a decrease in taxi and ride hailing service use, and 35% reported a decrease in personal car use (Chowdhury et al., 2019). Chowdhury et al. found that if

e-scooters were not available, 39% of e-scooter users would have taken a taxi or ridehailing service, 33% of those in the survey would have walked, and 7% would have used public transit (Chowdhury et al., 2019). A review of the Portland Bureau of Transportation's (PBOT) first four-month e-scooter pilot program in 2018 included a survey of e-scooter users who participated in the pilot (Portland Bureau of Transportation, 2018a). PBOT found that 17.7% of those who were surveyed would have driven if an e-scooter had not been available, and 19.9% of respondents would have used a taxi or ride hailing service (Portland Bureau of Transportation, 2018b). However, e-scooters were shown to replace walking and public transit trips in Portland as well, where 36.3% of those surveyed would have walked, and 8.7% would have used public transit for their last e-scooter trip if an e-scooter were not available (Portland Bureau of Transportation, 2018b). It should be noted that the percent of e-scooter trips that replace personal vehicle and taxi or ridehailing trips likely vary in different geographic contexts where people exhibit different travel patterns. For example, in Vienna a survey 110 shared e-scooter users found that e-scooter trips mostly replaced walking and public transit trips, while people who used shared e-scooters rarely replace car trips (80-90% responded that they never did) (Laa & Leth, 2020). Similarly, a survey of 380 people who used e-scooters in New Zealand found that 64% of e-scooter trips replaced trips that would have been made by walking, cycling, skateboarding, e-biking, or would not have occurred, and 28% replaced personal or for hire car travel (Fitt & Curl, 2019).

1.4 BIKESHARE AND E-SCOOTERS

E-scooter systems share some fundamental characteristics with bikeshare systems. Since there is little literature about how to measure determinants of e-scooter distribution, we will look to how determinants of bikeshare use are investigated in section 1.5. Before doing so, in this section we compare the characteristics of bikeshare and e-scooter systems to explain why studying

the determinants of e-scooter distribution can be modeled with similar approaches to how the determinants of bikeshare system use have been studied. Both e-scooter and bikeshare systems allow users to access and pay for devices on an as-needed basis and the companies take care of the maintenance, storage and security aspects of bicycle and e-scooter ownership (Parkes et al., 2013). Bikeshare systems exist in both docked and dockless forms while e-scooter systems only exist in dockless forms in North America (NACTO, 2019). In fact, station-based bikeshare systems have existed in North America since 2009, when BIXI launched in Montreal (Imani et al., 2014). Additionally, shared e-scooters are only electric while bikeshare programs exist with both electric assist bicycles and fully manual bicycles (NACTO, 2019). Further, the relationships between the public sector and bikeshare systems and shared e-scooter systems are different. Bikeshare systems in North America operate as publicly owned and privately operated models in addition to for-profit vendor operated models (Parkes et al., 2013). Conversely, e-scooter systems are privately operated and funded through investments (NACTO, 2019). McKenzie investigated the difference in use patterns between 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).

1.5 SHARED MICROMOBILITY AND THE BUILT ENVIRONMENT

There is limited research into the determinants of dockless bikeshare or e-scooter use. Thus, in order to understand how to study the determinants of e-scooter use, the determinants of bikeshare systems, which are more established and share some similarities with shared e-scooter systems (see section 1.4) can be reviewed as well. Shen et al. studied dockless bicycle sharing in Singapore

and found a connection between the built environment, fleet size, and weather on dockless bicycle use (Shen et al., 2018). Shen et al. found that mixed land use, transport infrastructure and cycle infrastructure positively impacted dockless bikeshare use in Singapore, while rainfall negatively impacted it negatively (Shen et al., 2018). Further, a study of the determinants of MoBike's dockless bikeshare program in Shanghai found that bicycle trip density is positively associated with floor area ratio (a measure of urban density), mixed land use, higher percentages of residential, green space, and industrial land uses, and the density of primary and secondary roads (Tu et al., 2019). Although there are parallels 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. Noland investigated the impact of temporal and weather variables on the number of e-scooter trips per day and average daily trip speed and distance (Noland, 2019). The study highlighted that e-scooter trips are geared towards short commute trips and that warmer weather lead to longer and faster trips while precipitation reduces use overall (Noland, 2019). This suggests an opportunity for further research: to investigate the determinants of e-scooter use at a finer temporal scale, the hourly scale, and to consider more determinants of e-scooter use together: temporal, land use, transport infrastructure, and weather attributes.

The use of regression models to study determinants of docked bikeshare flows is established in the literature (Buck & Buehler, 2012; El-Assi et al., 2017; Imani et al., 2014). Imani et al. and El-Assi et al., used multilevel regression models to investigate how land use, temporal, weather, and transport infrastructure attributes impact daily and hourly bicycle flows in station-based bikesharing systems in Canadian cities (El-Assi et al., 2017; Imani et al., 2014). Imani et al. 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 (Imani et al., 2014). Imani et al. and El-Assi et al. also found that bikeshare use was connected to station density and cycle infrastructure in an area (El-Assi et al., 2017; Imani et al., 2014). Buck & Buehler studied the determinants of daily bikeshare use in Washington D.C., and similarly found that bicycle infrastructure, population density and density of bars and restaurants in a location increased bikeshare use (Buck & Buehler, 2012). Comparing these findings to our study can highlight differences or similarities between docked and dockless shared vehicle use and shared vehicle type. Additionally, these studies were able to reveal bikeshare use patterns that policymakers and transport planners could use to plan for bikeshare use. They demonstrate the relevance of using multilevel regression models to study the impact of temporal, land use, transport infrastructure, and weather determinants on bikeshare use, which highlights the knowledge gap since this has not been investigated yet for e-scooter distribution.

MATERIAL AND METHODS

Our approach to studying determinants of e-scooter distribution in Washington D.C. is summarized in **Figure 1**. We started by collecting e-scooter location data and intersecting it with temporal, land use, transport infrastructure, and weather data. Next the data was analyzed with multilevel regression models to quantify the determinants of e-scooter presence as well as hourly and daily variation in e-scooter presence. To achieve this, each model had different dependent variables and dataset parameters.

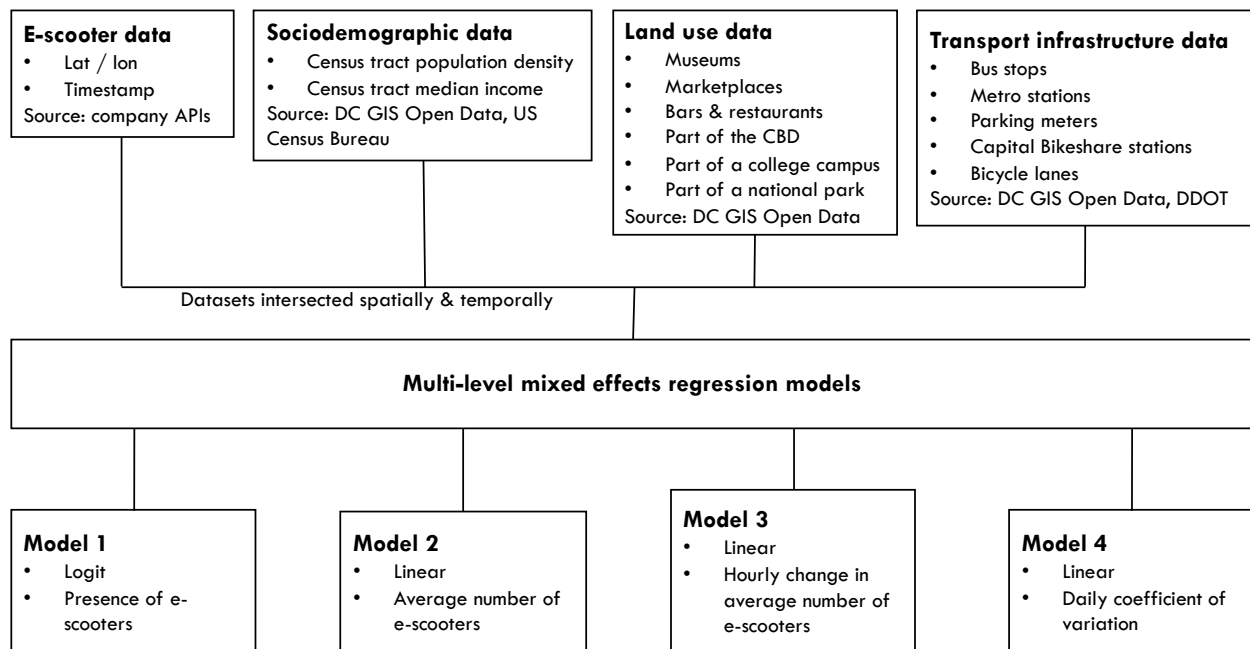


Figure 1 Research process flow chart

2.1 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. E-scooters have been in the city since 2017 (Teale, 2019). Additionally, Washington D.C.'s District Department of Transport (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) (DDOT, 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 (DDOT, 2019a). 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 varied between each company, as some reported lat/long only while others reported e-scooter unique identification numbers.

In total 240,624 observations of e-scooters in Washington D.C. were collected over the course of six days in 2019: Sunday May 12th, Monday May 13th, Tuesday May 14th, Thursday May 16th, 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. Although six days is a short study period, especially compared to some studies on determinants of docked bikeshare use which are four months (Imani et al., 2014) and a yearlong (El-Assi et al., 2017), there is precedent for using study periods that are on the day scale, and not the month scale, such as Shen et al.'s study which included nine days of dockless bicycle data (Shen et al., 2018). Given the precedent of using nine days to establish trends about dockless bicycle data (Shen et al., 2018), six days' worth of e-scooter data is adequate to establish trends. It should also be noted that Sunday May 12, 2019 was Mother's Day, however since that is not a legal holiday, it is not observed with business closures or public transport service changes. It is possible that the short study period introduced uncertainty in the data, for example if the data is unrepresentative. Weather during the study was controlled for in an attempt to remedy this uncertainty.

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 miles² (0.19 km²) squares using ArcMap. 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 (Miller et al., 2004). The fishnets were sized 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 (Miller et al., 2004). **Figure 2** 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-scooters 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.

No-locking zones where e-scooters are not supposed to be parked are apparent on the applications that are used for renting e-scooters, such as Lime. In light of the absence of a centralized database for no-locking zones, they are not outlined in DDOT's terms and conditions for e-scooter companies to operate in Washington D.C., the map of no-locking zones on the Lime application was used to locate fishnets that were completely within no-locking zones (DDOT, 2019c). Twenty-four fishnets were completely in the Washington Monument & Grounds, West Potomac Park, Lincoln Memorial, Vietnam Veterans Memorial, FDR Memorial, East Potomac Park, and Lady Bird Johnson Park national parks, and were considered for removal from the dataset in order to avoid a zero inflated model. However, about a third of the sample of 24 fishnets fully within no-locking zones exhibited e-scooters over the course of the 144 hours. 31.11% of the 3,456 observations that occurred in no-locking zones had e-scooters, which is very close to the overall percent of the 240,624 observations which have e-scooters, 32.52% (see **Table 2**). Thus, we concluded that e-scooter riders may not have respected no-locking zones or different companies had different no-locking zones, and the 24 fishnets that were considered for removal because of being fully in no-locking zones were kept for the analysis since they did not zero-inflate the data.

2.2 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 presence. 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 observation 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 and the U.S. Census Bureau's OnTheMap application (DC.GOV, 2019; U.S. Census Bureau, 2015). The land use variables include various sociodemographic and land use characteristics, to understand how they impact e-scooter distribution and variation in e-scooter distribution. 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 the number of jobs per fishnet, the weighted population density in the census tract that the fishnet is a part of, and the 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 3**, 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 in order to be more clearly interpreted: 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 4**, 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, e-scooter presence and variation in e-scooter presence. 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 list of 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 presence and the variation in presence, 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 ("Dark Sky API," 2019) in order to control for the impact of weather. At the same time, the data was used to identify weather conditions that could be conducive to e-scooter presence and variation in e-scooter presence, particularly that 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.

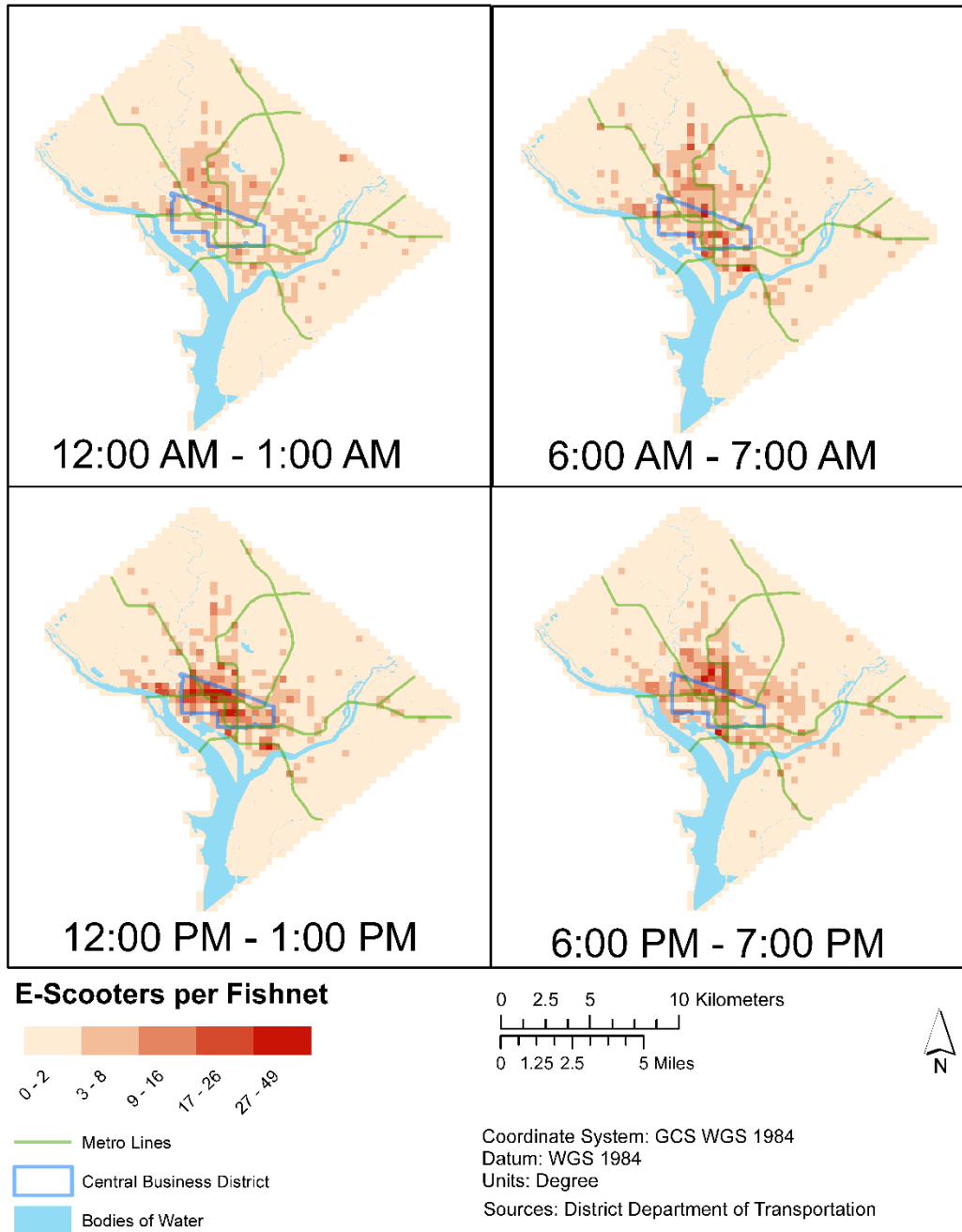


Figure 2 Average number of e-scooters during hours throughout the day

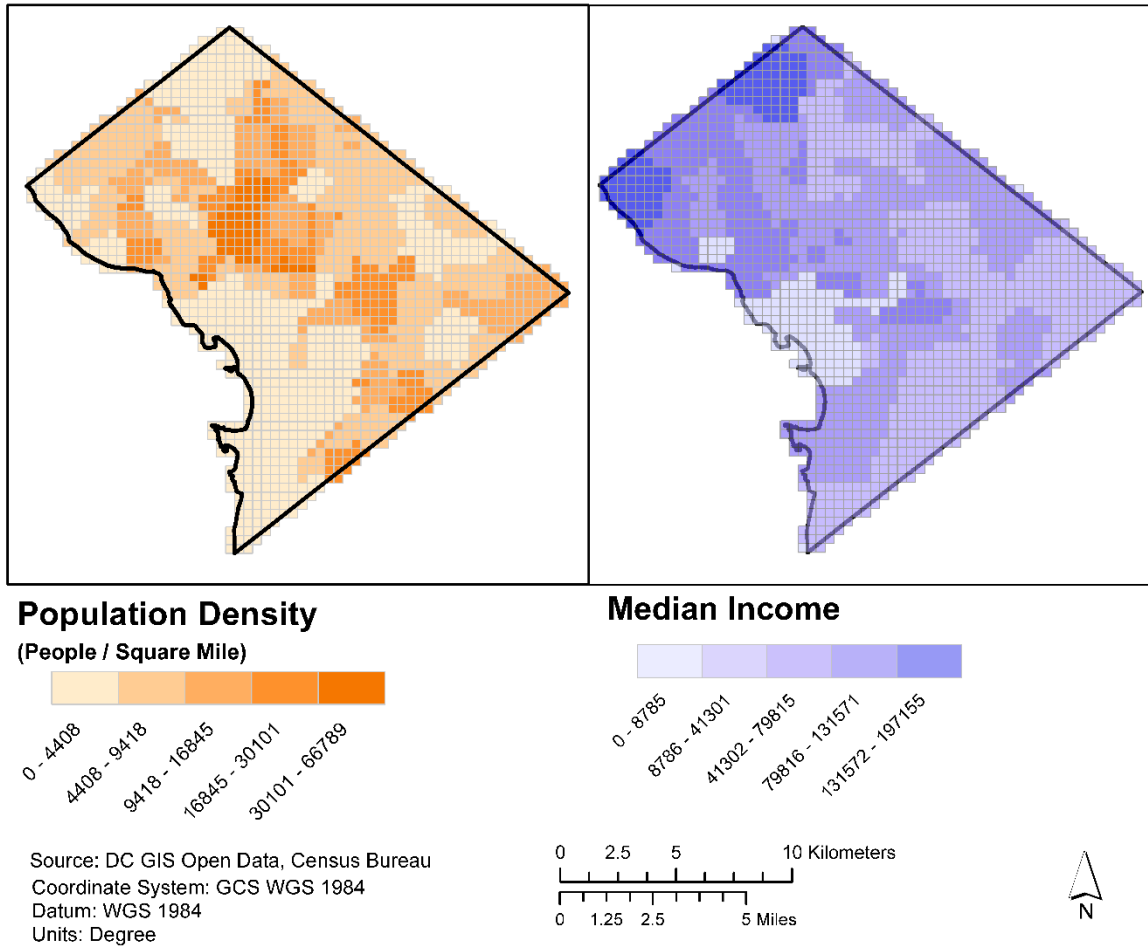
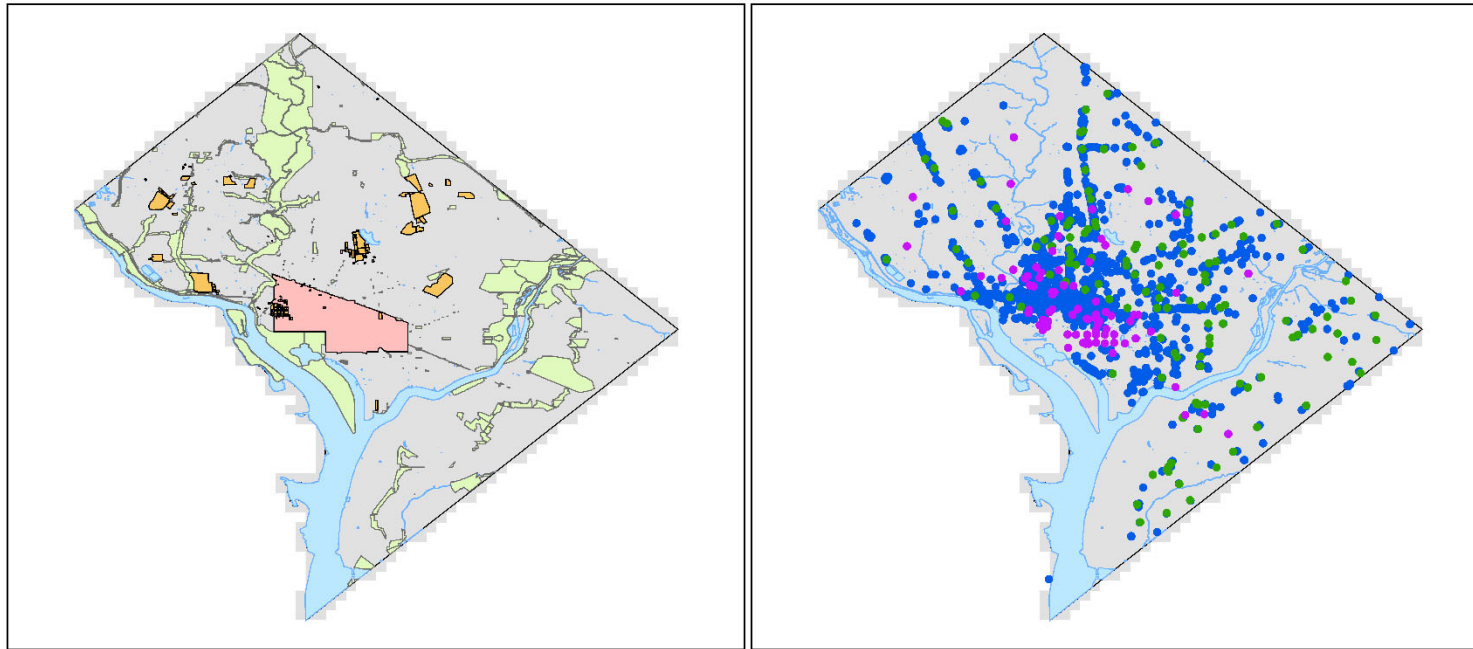


Figure 3 Sociodemographic characteristics of Washington D.C.



Land Use

- University and College Campuses
- Central Business District
- National Parks
- Bodies of Water
- Boundary of Washington D.C.

Sources: DCGIS Open Data, Census Bureau
 Coordinate System: GCS WGS 1984
 Datum: WGS 1984
 Units: Degree

Locations of Services

- Museums
- Marketplaces
- Bars and Restaurants
- Study Area

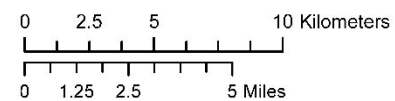


Figure 4 Land use in Washington D.C.

2.3 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 location patterns was carried out through four regression models in Stata. The first model (*Model 1*) aimed 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 examined, for those observations where at least one e-scooter was observed, the factors that contribute to a higher average number of e-scooters present in the fishnet within the hour. The third and fourth models were further extensions of the first two, as they examined the factors that cause a variation in the number of e-scooters present in a fishnet. Specifically, the third (*Model 3*) examined the hour-to-hour variation for observations where a difference in average e-scooter numbers was observed between the present and the previous hour. The last model (*Model 4*) examined the factors that influence an overall variation in the average 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 average number of e-scooters per fishnet per day ($\sigma_{i,j}$) by the average number of e-scooters per fishnet per day ($\mu_{i,j}$):

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

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.

Multilevel mixed effects regression modelling was used due to the incorporation of longitudinal panel data (every hour for six days) for each fishnet (geographic unit of analysis), and as they are documented in the literature for investigating determinants of bikeshare use (El-Assi et al., 2017; Imani et al., 2014). Additionally, multilevel mixed effects models account for similarities within the nested levels that are not accounted for in the covariates in the dataset, which can help account for spatial and temporal auto-correlation. The temporal levels of each model varied, 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. Thus, a two-tiered multilevel 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 were a reliable representation of the entire dataset. 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 necessary for *Model 4* because its sample size was smaller than 10,000. *Model 4* was still included because it provided a measure of the determinants of variation

in e-scooter presence over the course of the day rather than hourly. 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 multilevel 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 (absolute value) 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 equal to zero; 12AM – 1AM observations	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)
Number of observations	240,624	78,260	75,044	5,539
Bootstrapping	Yes	Yes	Yes	No
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

RESULTS AND DISCUSSION

3.1 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 1 Summary statistics

<i>Categorical Variables</i>	Percent of observations					
	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		
<i>Continuous Variables</i>	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

The average hourly difference in the number of e-scooters, averaged for each of the fishnets in the study area is graphed in **Figure 5**. The first hour of the day, 12AM – 1AM is excluded for each day for consistency since not all of the days are consecutive. An increase in the average number of e-scooters per fishnet overall compared to the hour before can be observed before the morning peak, in the early morning of each day. A decrease in the average number of e-scooters per fishnet overall compared to the hour before can be observed in the afternoon and evening.

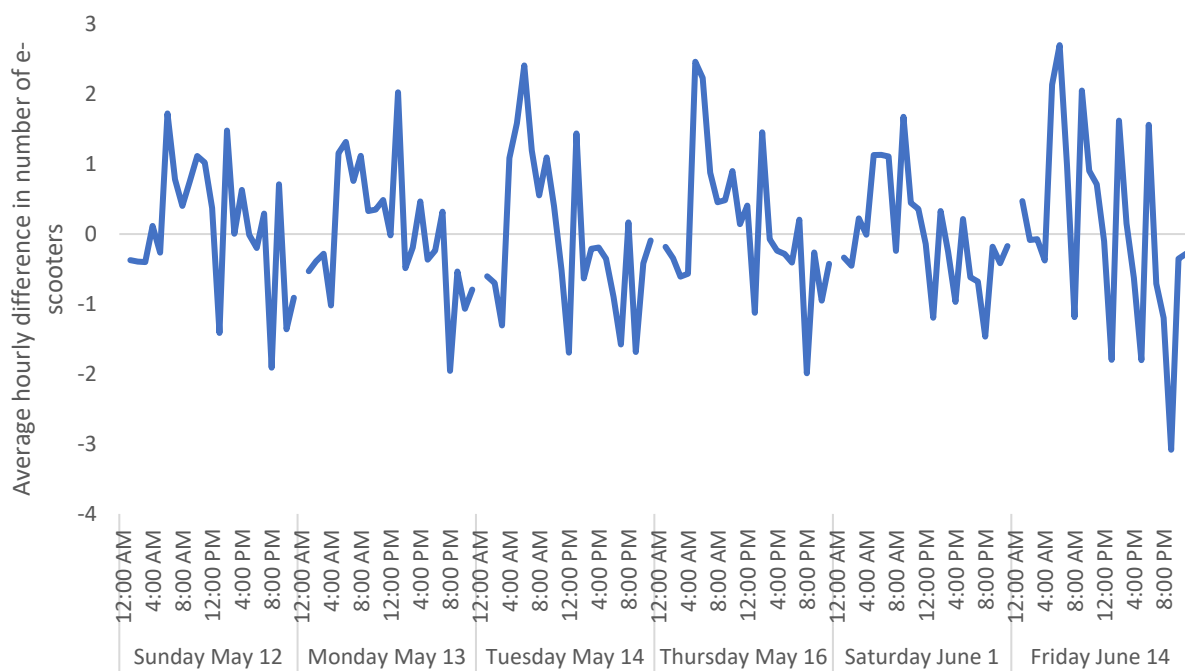


Figure 5 Average hourly difference in number of e-scooters across study area

3.2 REGRESSION RESULTS

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

Model I: Presence of e-scooters

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 could imply that e-scooters were likely to be used in the evening where not only would they be used for commuting, but for leisure activities too. 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 could be 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 near college campuses increased the likelihood of e-scooter presence. This is expected, as attractive destinations prompt a larger e-scooter presence. The presence of bus stops, bikeshare stations, and bicycle lanes in a fishnet increased the likelihood of e-scooter presence, which is consistent with existing research about dockless bikeshare (Shen 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-scooters may have been prevalent in more walkable areas.

Model 2: Average number of e-scooters

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, 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 3 and 4**). 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: Hourly change in average number of e-scooters

The difference in the average number of e-scooters present by the hour implies the movement of e-scooters. Less hourly change in the number of e-scooters (less movement) was observed on weekends, illustrating that the movement of e-scooters was not only less frequent, but also more consistent from hour-to-hour on weekends than weekdays. A decrease in hourly bicycle flows to and from bikeshare stations was similarly observed on the weekends in Imani et al. (Imani et al., 2014). There was also less movement late at night as expected. As population 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. Imani et al. also observed the positive impact of the CBD and density of restaurants on bicycle flows (Imani et al., 2014). 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 4**). The density of metro stations per fishnet increased hourly changes in the number of e-scooters, which Imani et al. similarly found to be the impact of metro stations near bikeshare stations (Imani et al., 2014). 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 movement, which Imani et al. and Shen et al. similarly observed for hourly dockless bicycle flows (Imani et al., 2014; Shen et al., 2018). More intense precipitation and decreased temperature were associated with decreased hourly variation in e-scooter numbers, which Imani et al. and Shen et al. also noticed for bikeshare flows, except Shen et al. observed a decrease in bicycle flows with increased temperature, since their study occurred in Singapore (Imani et al., 2014; Shen et al., 2018).

Model 4: Coefficient of variation

First off, areas with lower coefficients of variation in the number of e-scooters throughout the day can be areas where e-scooters were constantly 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 variation in the number of e-scooters in a fishnet throughout a day. 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 variation in the number of e-scooters in an area or constantly low variation.

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 presence of e-

scooters was more constant throughout a weekend day, but based on the results from *Models 1 and 2*, we can also suggest that the utilization is constantly low throughout weekend days. 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 presence 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, and agrees with Buck & Buehler's analysis of daily Capital Bikeshare trip counts (Buck & Buehler, 2012). 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. The presence of bicycle infrastructure positively impacts the hourly movement of e-scooters (*Model 3*) and negatively impacts the coefficient of variation of the number of e-scooters throughout the day (*Model 4*), potentially because e-scooter use increases near cycle infrastructure, which Buck & Buehler also observed in their study of the determinants of the number of bikeshare trips per day (Buck & Buehler, 2012). 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 2 Regression results

		Model 1				Model 2				Model 3				Model 4			
		O.R	95% CI			Coef.	95% CI			Coef.	95% CI			Coef.	95% CI		
<i>Temporal</i>	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
<i>Land Use</i>	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 & Restaurants	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
<i>Transport Infrastructure</i>	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
<i>Weather</i>	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

3.3 DISCUSSION OF RESULTS

Compared to weekdays, there were fewer e-scooters detected and less change in the numbers of e-scooters present on weekends as well as late at night. The population density of an area had an overall positive impact on e-scooter presence, the number of e-scooters present, and a small increase in the variation in e-scooter presence, as well as a low variability in the number of e-scooters in the area throughout the day, which is reasonable because the supply of e-scooters relies on the neighboring population. 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. This is further supported by the observations that e-scooters, which can cost between \$2.90 and \$4.90 for a ten-minute trip in Washington D.C. and on average cost \$3.50 per trip, are a relatively expensive mode of transport compared to public transport, where a metro trip can cost between \$2.00 and \$6.00 (Lazo, 2019; NACTO, 2019; Washington Metropolitan Area Transit Authority, 2020). 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, potentially because the increase in accessibility to opportunities in the CBD creates 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 presence and variation in presence 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 or for e-scooter companies to place 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 increases in numbers of e-scooters. 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.

CONCLUSIONS

This study investigated the impact of time, land use, and transport infrastructure on e-scooter presence and variation of e-scooter presence in Washington D.C. E-scooter location data was collected for six days, which was used to generate four multilevel 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 its findings should not be applied 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 the 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. Another limitation of this study is the size of the fishnets which were used as the geographic unit of analysis relative to how far people might travel to access an e-scooter or walk after dropping it off to their next destination. 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 including all e-scooter companies. As a result, only the presence and absence of e-scooters in an area could be studied. 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 density on e-scooter distribution. Further, the Moran statistic or spatially autoregressive models could be used to further explore spatial auto-correlation in the data (Woudsma et al., 2008). In the future, models could also be tested with different sized geographic units of analysis than the fishnets used in this study. Future research could also include origin-destination analysis for the data scraped from companies with reliable e-scooter IDs. 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 variation 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 distribution patterns are revealed which can contribute to how city planners and officials understand the ways shared electric e-scooter are used and how they interact with existing transport infrastructure and systems. Namely, since e-scooters were found to be highly utilized near cycle infrastructure and in areas with higher population density, policymakers and engineers can encourage e-scooter use strategically (i.e. – to relieve congestion or public transit) by implementing cycle infrastructure such as bike lanes or cycle tracks where that is needed, and in higher population density areas.

This study also contributes a framework for collecting e-scooter data and studying the determinants of e-scooter distribution.

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