Scooting around town: Determinants of shared electric scooter use in Washington D.C.

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ABSTRACT

Personal vehicle use in North America causes a wide variety of negative externalities, although it is nonetheless still the predominant mode of transport in the region. As a result, North American cities are working to support and encourage active transport, including public transit, cycling, and walking. Privately run shared-electric-scooters (e-scooters) have rapidly grown in popularity in the United States since their launching in 2017. E-scooters are marketed as an environmentally friendly solution for various transport issues. For example, as an alternative to private vehicle short distance trips, and a solution for first-mile and last-mile to reach public transit. Furthermore, some cities in the U.S. view e-scooters as having the potential to support their transport goals, and even create pilot programs for the mode to exist legally in their cities. Yet, they have vague regulations that do not maximize the potential use of e-scooters. This thesis investigates the impact of temporal, weather, sociodemographic, land use, and transport infrastructure on e-scooter presence and variation of e-scooter presence, as well as trip distance and frequency. The research is based on publicly available data, and thus contributes a framework for studying e-scooters in North American cities that engineers, policymakers, and researchers can use to understand determinants of e-scooter use. The findings from the studies indicate that e-scooters are available near bicycle lanes, and that the central business district (CBD) has a significant impact on e-scooter presence. The research suggests that e-scooter trips that start or end near bicycle lanes are longer than the average e-scooter trip, as are e-scooter trips with metro stations near their destination.

RÉSUMÉ

En Amérique du Nord, l'utilisation de véhicules personnels est le mode de transport prédominant malgré de nombreux effets négatifs. C'est pour cela que les villes américaines travaillent sur des stratégies pour encourager le transport actif (not sure here what would be the correct translation), c'est à dire les transports en commun, le vélo et la marche. Les sociétés privées de scooters électriques en libre service ont rapidement gagnées en popularité aux États Unis depuis leur lancement en 2017. Ces e-scooters sont présentés comme une solution écologique à de nombreux problèmes de transports. Par exemple, ils proposent une alternative pour les trajets de courte distance, et une solution pour faire le lien entre le domicile et les lignes de transports en commun, et de la ligne de transport en commun jusqu'à destination. D'autre part, certaines villes aux États Unis considèrent les e-scooters comme une valeur ajoutée contribuant à leur politique de transport citadin, et créent des programmes d'essais pour implémenter légalement leur usage en ville. Cependant, leur régularisation est vague et ne maximise pas leur utilisation. Cette thèse étudie l'impact temporel, climatique, socio-démographique et géographique sur l'utilisation des e-Scooters et les variations d'utilisation en terme de distance et fréquence en fonction de l'infrastructure des transports. La recherche se base sur des données publiques, créant ainsi un cadre d'étude sur les e-scooters dans les villes américaines accessible aux ingénieurs, responsables politiques, et chercheurs pour appréhender leur usage. Les résultats de cette étude indiquent que les e-scooters sont disponibles près de pistes cyclables et que les quartiers d'affaires ont un impact important quand à la présence des scooters. La recherche note aussi que les trajets de e scooters sont plus longs que la moyenne lorsqu'ils commencent ou finissent près d'une piste cyclable ou bien sont proches d'une station de métro.

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CONTRIBUTION OF AUTHORS

Chapters 2, 3, and 4 of this thesis are based on manuscripts, which I am the primary author of, that were submitted to peer reviewed journals or may be in the future. I am also the author of Chapters 1 and 5 of this thesis.

Chapter 2 consists of a manuscript that was presented as a poster at the 99th Meeting of the Transport Research Board in January 2020 and was submitted to Case Studies in Transport Policy. The secondary authors for the manuscript, titled *Scoot over: determinants of shared electric scooter presence in Washington D.C.*, are Boer Cui, a colleague who was also a civil engineering master's student while we were preparing the research, as well as my supervisors Prof. Ahmed El-Geneidy and Prof. Lijun Sun. We 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.

Chapter 3 is made up of a manuscript that will be the basis of a paper submitted for publication, potentially to Transport Research D. Chapter 4 is a manuscript that will not be submitted to for publication.

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CHAPTER 1: INTRODUCTION

The case for decreasing personal vehicle use is well established due to its association with environmental, economic, and societal externalities. Existing transport systems in North America are reliant on personal motor vehicle use, which is a significant cause of greenhouse gas emissions. Notably, nearly a quarter of the world's greenhouse gas emissions come from energy consumption, 75% of which can be attributed to road vehicles (Ribeiro et al., 2007). Further, land transport was the source of over 30% of the North American mortality caused by fine particulate matter (Silva, Adelman, Fry, & West, 2016). In addition to the vast amount of greenhouse gas emissions and pollution caused by personal motor vehicle use, inactivity is associated with the predominant use of personal vehicles. This in turn contributes to growing physical and mental health issues that are caused by a sedentary and isolated lifestyle. Active transport, including the use of public transit, walking, and cycling promotes exercise which combats obesity, heart disease, and diabetes (Wilkinson & Marmot, 2003). In fact, countries with higher rates of active transport have been linked with lower obesity rates at the national level (Bassett, Pucher, Buehler, Thompson, & Crouter, 2008). Compared to personal vehicle use, active modes of transport also promote space for social interactions on the street and a sense of community, both of which contribute to the wellbeing of individuals (Wilkinson & Marmot, 2003). Shared electric scooters (e-scooters) are a relative newcomer to the North American transport world. The privately-run e-scooter operators sell the mode as a sustainable transport option for urban travelers that can be used to decrease reliance on personal vehicles (Bird, 2020b; Lime, 2019). However, more research on the way that e-scooters are used is required to understand if they are helping cities meet their transport goals to decrease personal vehicle use and increase active transport mode share, and how cities can generate policies that encourage e-scooter use.

1.1 COMPARISON WITH BIKESHARING

Although e-scooters are new in North America, the shared economy has existed in the transport field since the 1960s in the form of bikesharing (Parkes, Marsden, Shaheen, & Cohen, 2013). The established transport mode that e-scooter sharing systems are most similar to is bikesharing systems. Thus, is it helpful to understand how bikesharing emerged, its impacts, and how bikeshares compare with e-scooters to understand the wider shared micromobility context and the potential impact of e-scooters.

Bikesharing has evolved in three waves, since the 1960s in Europe, from free bikes, to coin deposit systems, to the systems common around the world today that are characterized by technology (Parkes et al., 2013). Shared bicycle systems, like shared e-scooters, provide mobility and convenience. They both offer access to the respective transport modes on an as needed, flexible basis and take care of vehicle maintenance, as well as storage (Parkes et al., 2013). While both bikesharing and e-scooter systems tend to operate in urban areas and are self-serve, they require varying levels of operator attendance, as bikesharing systems exist in docked and dockless forms, and e-scooter systems only exist in dockless forms to date (NACTO, 2019; Parkes et al., 2013). Bicycle fleets that make up bikesharing systems can be either electric assist or fully manual, or a mixture of the two, while shared e-scooter fleets are made up entirely of e-scooters with electric throttle assist (NACTO, 2019). Interestingly, bikesharing exists as both non-profit (i.e. Capital Bikeshare and Citi Bike) and profit businesses (i.e. Jump), where the public can be involved in ownership or operations (Citi Bike, 2020; Jump, 2020; Parkes et al., 2013). Shared e-scooter systems in North America are operated by private for-profit companies that are supported by venture capital and their business models are not associated with the public sector (NACTO, 2019).

Bikesharing is championed for its environmental and societal benefits, and shared e-scooters are similarly advertised to cause such advantages (Bird, 2020b; Lime, 2019; Shaheen, Guzman, & Zhang, 2010). Although the degree of positive environmental impact of bikesharing is debated, bikeshare trips have been credited with replacing a very small number of auto trips (Bachand-Marleau, Larsen, & El-Geneidy 2011; Shaheen et al., 2010). A 2010 survey found that the presence of successful bikesharing in a city can positively impact the public perception surrounding cycling and lead to decreases in the frequency of personal vehicle use (Shaheen et al., 2010).

Micromobility is widely discussed as a first and last mile solution (Heineke, Kloss, Scurtu, & Weig, 2019; Lime, 2018; Yanocha & Allan, 2019). First and last mile solutions specifically refer to the first leg of a public transit trip from the origin to the station, or the last leg of the trip from the public transit station to the destination. Bikesharing and e-scooter systems are both viewed as having the potential to extend the catchment areas of transit stations by increasing the distance that people can easily travel to reach them, acting as a complement to public transit (Bachand-Marleau et al., 2011; Lime, 2018). In fact, bikeshare can be maximized by placing bikeshare stations in residential areas, and trips are more likely combined with public transit if cycling can be the first mile (Bachand-Marleau et al., 2011; Bachand-Marleau, Lee, & El-Geneidy 2012). Although these findings are for more established bikesharing systems, they are relevant to consider for e-scooters, as they can function analogously in transport systems due to their operational similarities from the user perspective.

1.2 E-SCOOTERS IN NORTH AMERICA

The expansion of e-scooters to cities across North America has been exceptionally fast since they first started appearing in the fall of 2017 (Glambrone, 2019). There were an estimated

38.5 million e-scooter trips in 2018 alone, which accounted for around 45% of the shared micromobility trips in the United States that year (NACTO, 2019). E-scooters became known for precipitously appearing on city streets. However, around 25% of the 100 cities where e-scooters existed in 2018 created pilot programs surrounding them (NACTO, 2019). Since e-scooter companies are privately run and supported by venture capitals, the business opportunity that they represented is partly responsible for their aggressive growth in the U.S., whereby January 2020, e-scooters were available in 175 cities (Heineke et al., 2019; Smart Cities Dive, 2020).

The response to e-scooters by North American cities has been mixed. On the one hand, some North American cities have pilot programs for e-scooters and generated e-scooter centric legislation to govern their pilot programs. The pilot programs signal that some transport planners see a potential for e-scooters to help meet city transport goals and shift travel away from private vehicle use (DDOT, 2020; Portland Bureau of Transportation, 2018b). Even among cities that have e-scooter pilot programs, such as Washington D.C. and Portland, Oregon, the rules governing e-scooter distribution and parking are vague when it comes to actually leveraging the vehicles to meet city transport goals (DDOT, 2019c; Portland Bureau of Transportation, 2018e). In contrast, 32 North American cities have banned e-scooters (including recently Montreal), which signals that some cities have been less hospitable to e-scooters (CBC News, 2020; Smart Cities Dive, 2020).

Although shared e-scooters are a relatively new phenomena in North American cities, there has been some research into their use patterns. Krizek and McGuckin studied “little vehicles” which include vehicles such as bicycles, scooters, skateboards, and segways (Krizek & McGuckin, 2019). Although their analysis was based on the 2017 National Household Travel Survey, which did not contain many e-scooters, it found that modes with similar characteristics are generally used for short to middle range trips that could compete with walking or ridesharing (Krizek &

McGuckin, 2019). They confirmed that little vehicles are predominantly used in urban areas for a variety of trip purposes (although recreation constituted the largest share), and a majority of the people who used them were young men (Krizek & McGuckin, 2019).

Arellano and Fang conducted an observational study of e-scooter riders in San Jose, California between fall 2018 and winter 2019, and noticed that riders' cruising speed is faster on streets and slower on sidewalks and other mixed use paths (Arellano & Fang, 2019). They also found that males tended to ride e-scooters faster than females, and overall e-scooters traveled at slower cruise speeds than cyclists (Arellano & Fang, 2019). Further, helmet use was much lower among the population of e-scooters that they observed, where only 2% of observed e-scooter riders wore helmets, compared with 56% of the cyclists that they observed (Arellano & Fang, 2019). Arellano and Fang observed that headphone use among the e-scooter and cyclist populations were at similar rates, although phone use among the e-scooter population was much lower than any mode of transport, at less than 1%, possibly because e-scooters require two hands to balance (Arellano & Fang, 2019). An earlier observational study in San Jose, CA examined e-scooter parking around the city, and found that most e-scooters were in fact parked in ways that comply with bicycle parking rules which do not infringe on sidewalk use (Fang, Agrawal, Steele, Hunter, & Hooper, 2018).

Organizations such as the Institute for Transport and Development Policy (ITDP) are recognizing the opportunity that e-scooters, and more broadly micromobilty, have to decrease reliance on personal vehicle use in a way that they consider to be environmentally friendly (i.e. with a ridehailing trip) (Yanocha & Allan, 2019). Policy recommendations from organizations, like the ITDP, for cities surrounding e-scooters are characterized by overarching trends (Yanocha & Allan, 2019). The recommendations include making car travel less convenient and increasing exposure to e-scooters, but lack specific strategies for how cities can encourage e-scooter use support public transit and replace cars instead of competing with other forms of active transport (Yanocha & Allan, 2019). Additionally, cities such as Washington D.C., that offer permits for e-scooter companies to operate, formed city-scale regulations about e-scooter distribution and parking (Government of the District of Columbia, 2020). Evidently, there is a need for research that investigates determinants of e-scooter presence and trip length in cities, in order to understand use patterns and generate more specific policy recommendations if cities intend to use e-scooters to meet transport goals.

1.3 DETERMINANTS OF SHARED ACTIVE TRANSPORT

Temporal, weather, sociodemographic, land use, and transport infrastructure determinants have been shown to impact bikeshare use including arrival and departure rates at stations (El-Assi, Mahmoud, & Habib, 2017; Imani, Eluru, El-Geneidy, Rabbat, & Haq, 2014). Imani et al. intersected 2012 hourly arrival and departure rates from BIXI bikeshare stations in Montreal with weather, temporal, land use, and bicycle infrastructure attributes (Imani et al., 2014). Similarly, El-Assi et al. leveraged real time Bike Share Toronto ridership data for 2013 to investigate the influence of weather, sociodemographic, land use, and transport infrastructure on trip generation and attraction (El-Assi et al., 2017). Both studies employed multi-level mixed effects regressions models in order to specify that observations were taken from the same stations repeatedly (El-Assi et al., 2017; Imani et al., 2014). They found that bicycle flows increased with warmer weather, in the afternoon, when there was bicycle infrastructure near stations, closer to the central business district, as well as in areas with higher population and population density, larger numbers of BIXI stations, metro stations, and services nearby (El-Assi et al., 2017; Imani et al., 2014). Although these pieces of research pertained to docked bikeshare and not dockless shared e-scooters, they demonstrate that temporal, weather, sociodemographic, land use, and transport infrastructure impact shared bikeshare use, and that multi-level mixed effects regression models are appropriate to use for datasets that include repeated observations from geographic locations. Thus, the structure of these projects: intersecting vehicle presence data with covariate data, and then using multi-level mixed effects regression modeling to analyze use patterns, influenced how we designed our studies to explore the impact of determinants on e-scooter presence.

1.4 THESIS SCOPE: SCOOT OVER, FURTHER, AND THE FIRST AND LAST MILE

The research presented in this thesis is motivated by a curiosity surrounding e-scooter use. To study e-scooter use patterns, we investigated e-scooter presence, and variation in e-scooter presence, as well as e-scooter trip length and frequency, by scraping e-scooter location data in Washington D.C. Specifically, real time e-scooter location data, which included the location of all shared e-scooters available for rent and not in use, was scraped from the DDOT website at five-minute intervals for six days in the spring of 2019. To explore the determinants of e-scooter use, we collected land use, weather, sociodemographic, and temporal covariate data that describes Washington D.C. during our study time. The covariate data was collected from a combination of the Dark Ski API, Washington D.C.'s Open Data platform, the census bureau and DDOT. Next, analyses were run to interpret the relationship between e-scooter presence, variation in presence, trip length, and trip frequency, and the covariate data through regression models and distance decay curves.

Chapter 2 investigates e-scooter presence, and variation in e-scooter presence, while Chapter 3 and 4 focus on e-scooter trip length. Additionally, Chapter 2 and 3 incorporate regression models into their analyses. Chapter 3 and 4 contain distance decay functions in their analyses. Chapter 2 and 3 include weather, sociodemographic, land use, and transport infrastructure covariate data. Chapter 4 is comprised of temporal and transport infrastructure covariate data only.

Chapter 2 explores the impact of temporal, weather, sociodemographic, land use, and transport infrastructure on e-scooter presence, variation in e-scooter presence between consecutive hours and throughout the day. The research in Chapter 2 was presented as a poster at the 99th Meeting of the Transport Research Board in January 2020 and was subsequentially submitted to Case Studies in Transport Policy for publication. Chapter 3 examines the effect of temporal, weather, sociodemographic, land use, and transport infrastructure on e-scooter trip frequency and length, and will potentially be submitted for publication in Transport Research D. Chapter 4 investigates the relationship between e-scooter trips and first mile and last mile travel.

CHAPTER 2: SCOOT OVER: DETERMINANTS OF SHARED ELECTRIC SCOOTER PRESENCE IN WASHINGTON D.C.

2.1 INTRODUCTION

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 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 (Möller, Padhi, Pinner, & Tschiesner, 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, van Lierop , & El-Geneidy 2014). Active transport is also noted for its positive impacts on quality of life by contributing to physical and mental well-being (by facilitating social interaction) (Lee & Sener, 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 that are associated with city governments and the expansion of bicycle infrastructure in cities such as New York (Dill & Carr, 2003; NACTO, 2019). E-scooter companies first launched in the U.S. in 2017 and the vehicles started appearing in cities across the country that fall (Dickey, 2018a; Teale, 2019). In fact, the growth of e-scooters in the U.S.A. since the fall of 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 (NACTO, 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 in the country since 2010 (NACTO, 2019).

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 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 been studied for e-scooters. The knowledge gap about the determinants of e-scooter use motivated this study and is what this research contributes to understanding.

2.1.1 E-scooter driver behavior 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. Despite the concerns about e-scooters cluttering sidewalks when parked, a 2018 study of e-scooter parking in San Jose, California concluded that most e-scooters are well parked in ways that comply with bicycle parking rules and do not infringe on sidewalk use (Fang 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 (Portland Bureau of Transportation, 2018b). 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.

2.1.2 Environmental impacts

Although e-scooter companies market themselves as sustainable transport, namely that they are electric vehicles that can induce mode shift, the environmental impact of e-scooter use is disputed (Bird, 2020a; Hollingsworth, Copeland, & Johnson, 2019; Lime, 2020). The environmental impact of e-scooter use depends on the 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). Hollingsworth et al. conducted a life cycle assessment of Xiaomi M365 e-scooters, which was 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). They found the materials and manufacturing of e-scooters, as well as the collection of e-scooters for charging contribute greenhouse gas emissions (Hollingsworth et al., 2019). Although using an e-scooter instead of walking would consistently be associated with larger relative greenhouse gas emissions, Hollingsworth et al. found that when replacing a personal automobile trip, e-scooter use results in a net decrease of environmental impacts (Hollingsworth et al., 2019). The life cycle analysis of the greenhouse gas emissions per e-scooter is highly dependent on the life of the vehicle (Hollingsworth et al., 2019). With their base case assumptions which include 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, KT, 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).

2.1.3 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, 2018b). PBOT found that 17.7% of those who 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, 2018c). 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, 2018c). 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. In this investigation, we focus on the North American context, so the percent of trips that e-scooters have been found to replace per mode are drawn from existing North American sources. Additionally, e-scooters are used by a variety of travelers, including both commuters and visitors (Portland Bureau of Transportation, 2018b). This could partially align shared e-scooter systems with city transport goals to increase active transport mode share.

2.1.4 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 that is studied for bikeshare systems. 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). Differences between bikeshare and e-scooter systems include the fact that 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 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).

2.1.5 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 **2.1.4**) can be reviewed. 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, & Zhao, 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). 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. Noland investigated the impact of temporal and weather variables on the number of e-scooter trips per day and average daily trip speeds 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). 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. 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 as it has not been investigated yet for e-scooter use.

2.2 MATERIAL AND METHODS

Our approach to studying determinants of e-scooter distribution in Washington D.C. is summarized in **Figure 2.1.** 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 of e-scooter presence. To achieve this, each model had different dependent variables and dataset parameters.

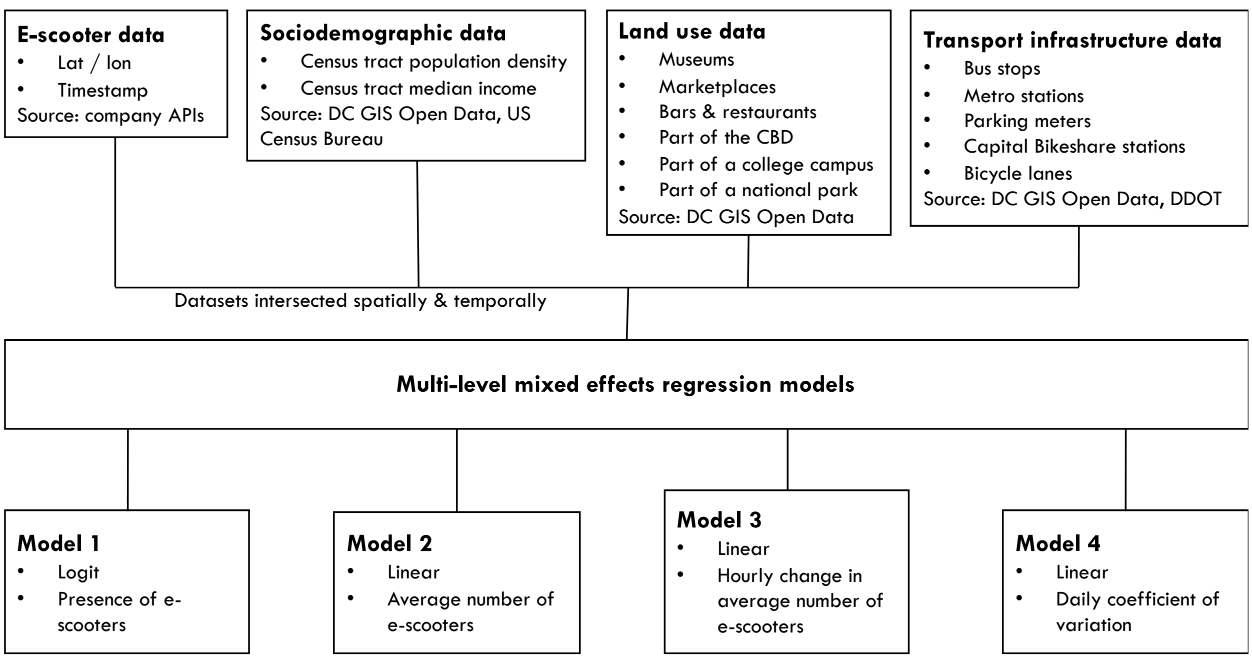


Figure 2.1 Research process flow chart

2.2.1 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, as 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 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. 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 year long (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 miles^2 (0.19 km^2) 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, Hunt, Abraham, & Salvini, 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 (Miller et al., 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 2.2** 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-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.

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 2.2**). 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.

2.2.2 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. 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 2.3**, 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 2.4**, 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 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 while at the same time, identifying the weather conditions that could be conducive to e-scooter presence and variation in e-scooter presence, 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.

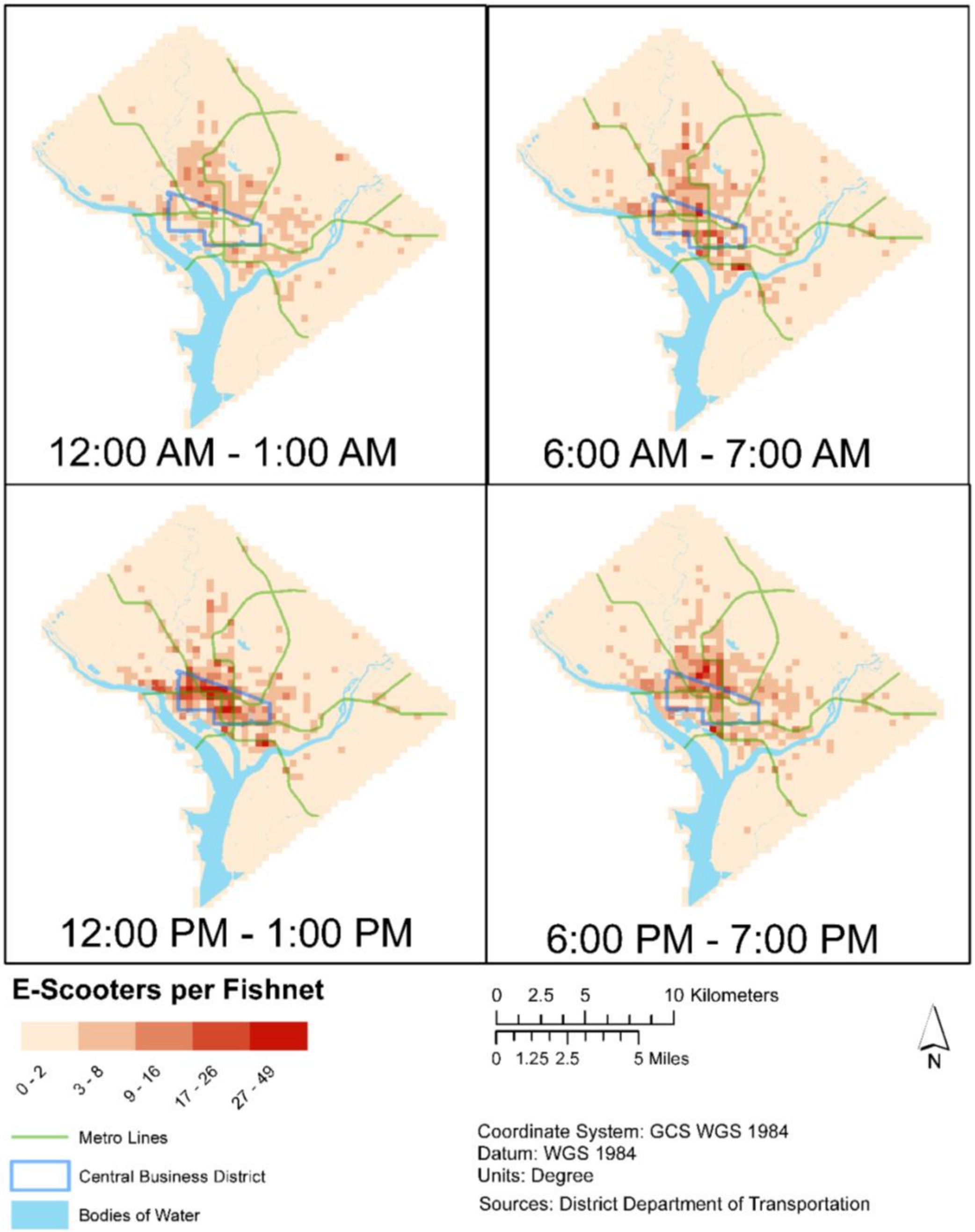


Figure 2.2 Average number of e-scooters during hours throughout the day

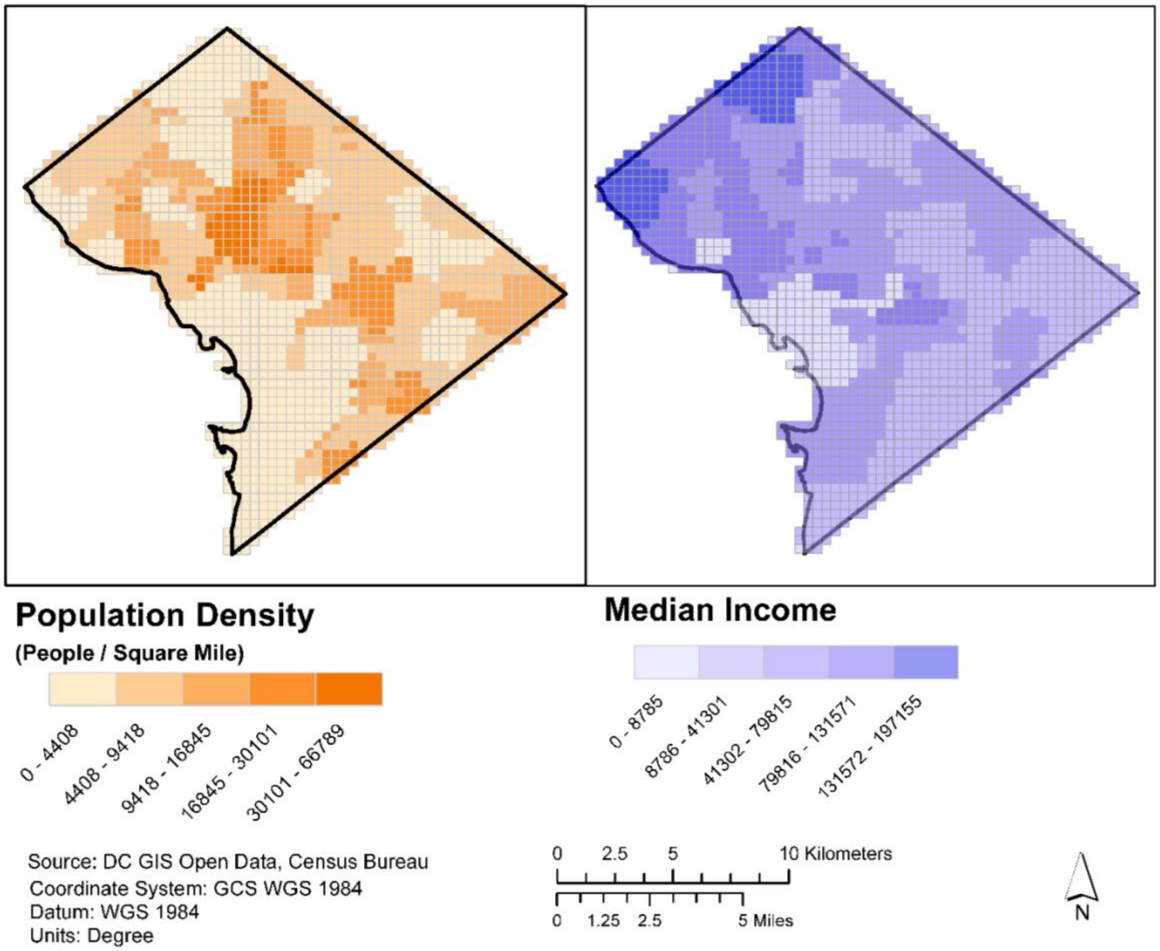


Figure 2.3 Sociodemographic characteristics of Washington D.C.

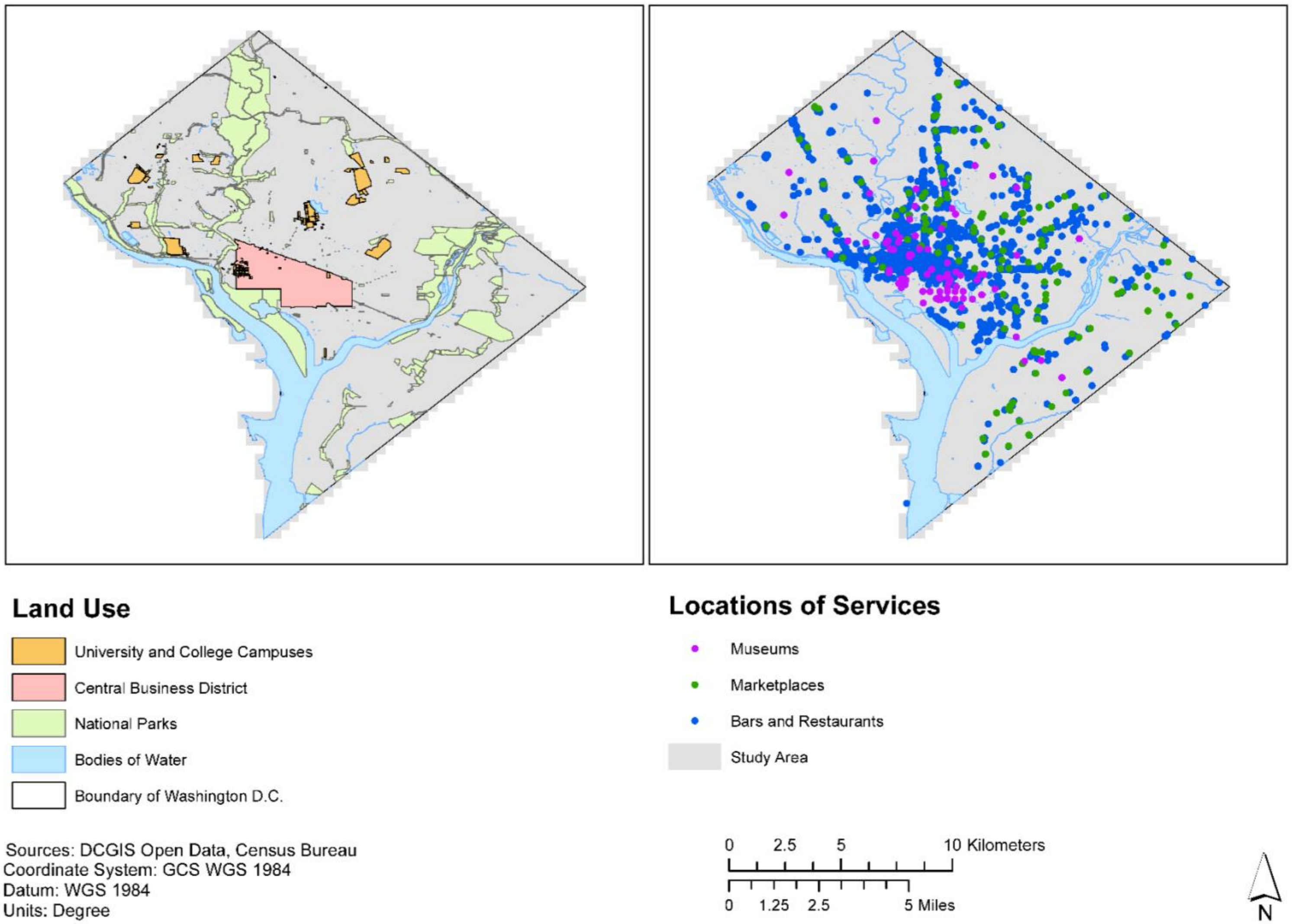


Figure 2.4 Land use in Washington D.C.

2.2.3 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 is carried out through four regression models in Stata. 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 average 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 average 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 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.

Multi-level 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, multi-level 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 auto-correlation. 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 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 2.1**. 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 2.1 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

2.3 RESULTS AND DISCUSSION

2.3.1 Summary statistics

The summary statistics for the variables, both explanatory and dependent are presented in **Table 2.2** 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 2.2 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

Further, the average hourly difference in the number of e-scooter, averaged for each the fishnets in the study area is graphed in **Figure 2.5.** 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.

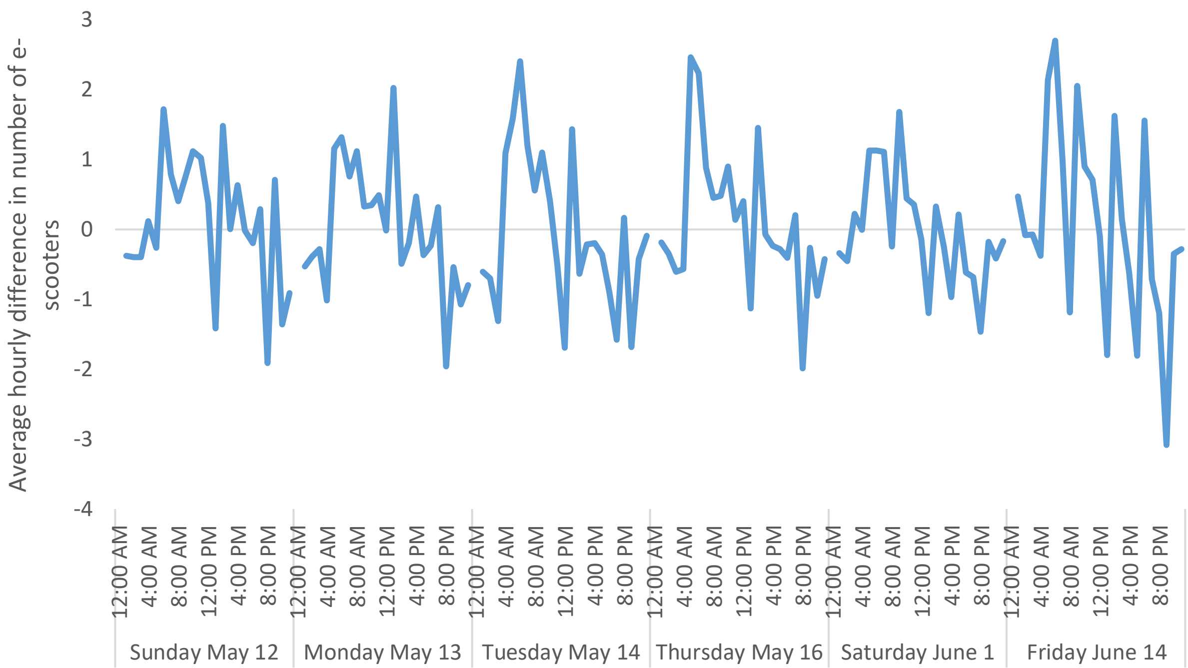


Figure 2.5 Average hourly difference in the number of e-scooters across the study area

2.3.2 Regression results

The regression results are presented in **Table 2.3** where they are discussed individually for each model.

Model l: 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. 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 2.2** coincides with areas of low- and medium-income areas presented on the right in **Figure 2.3**. 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 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 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 2.3 and 2.4**). 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 to 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 2.4**). 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 2.3 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 & 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
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

2.3.3 Discussion of results

Compared to weekdays, e-scooters experienced 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 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. 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. 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.

2.4 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 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 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. 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 on e-scooter use. Further, the Moran statistic or spatially autoregressive models could be used to further explore spatial auto-correlation in the data (Woudsma, Jensen, Kanaroglou, & Maoh, 2008). 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 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 distribution patterns are revealed which can contribute to how city planners and officials understand 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 use.

CHAPTER 3: SCOOT FURTHER: DETERMINANTS OF SHARED ELECTRIC SCOOTER TRIP DISTANCE AND FREQUENCY IN WASHINGTON D.C.

3.1 INTRODUCTION

The shared dockless electric scooter (e-scooter) is a growing mode of transport in North America. E-scooters first arrived in North American cities including Washington D.C. and Santa Monica, CA in September 2017 (Fonseca, 2019; Glambrone, 2019). By the end of 2018 e-scooters were available in 100 cities in the U.S. (NACTO, 2019). The National Association of City Transport Officials reported 38.5 million e-scooter trips across the United States, which comprised 46% of all micromobility trips in the country reported in 2018 (NACTO, 2019). Shared e-scooter companies have steadily expanded to additional cities, while also attracting pushback: by the beginning of 2020, e-scooters were available in 175 cities and banned in 31 cities across the U.S. (Smart Cities Dive, 2020). The private nature of the micromobility industry, which has attracted over a billion dollars of investment, is playing a role in driving the spread of e-scooters across North America (Möller et al., 2018). Further, operators are marketing shared e-scooters as first and last mile solutions to and from public transit (Lime, 2018). While e-scooter companies are known for entering cities without permission and then asking for forgiveness from North American cities, some cities such as Portland and Washington D.C. created pilot projects with dockless micromobility and are working to accommodate them with policies that describe the conditions that operators must comply with in order to have legal access to the public right of way (DDOT, 2019b; Irfan, 2018; Portland Bureau of Transportation, 2018d). Evidently, some American cities are exploring shared e-scooters as a possible method for shifting travel away from private vehicle use (DDOT, 2010, 2020; Portland Bureau of Transportation, 2018b).

City policymakers are motivated to decrease private vehicle use and increase public transit and active transport use because of the environmental, public health, and economic benefits associated with the transport mode shift (Xia, Zhang, Crabb, & Shah, 2013). Despite the potential for shared e-scooters to assist cities in meeting their transport goals, and shared e-scooter operators marketing their businesses as environmentally friendly transport, shared e-scooters have the potential to replace other active and public transport trips instead of trips that would otherwise have been made with personal vehicles. In fact, PBOT found that during the first year of their e-scooter pilot program, the mode that e-scooter trips most replaced was walking (Portland Bureau of Transportation, 2018c). Over a third of e-scooter trips replaced walking trips and just under 20% replaced taxi or ridehailing trips (Portland Bureau of Transportation, 2018c).

Despite cities' intentions to leverage e-scooter sharing to meet their sustainable transport goals, there is a policy gap. E-scooter operators are not incentivized to distribute e-scooters in ways that make them more likely to be used to support city transport goals. E-scooter distribution policies for shared e-scooter companies are often framed on a citywide level (i.e. caps on the number of e-scooters allowed per company in the central business district, and minimum numbers of e-scooters that must be deployed in "equity emphasis" areas) (Government of the District of Columbia, 2020). E-scooter parking guidelines are similarly vague. In Washington D.C., shared e-scooter companies are allowed to designate hubs (preferred parking locations), and the DDOT only requires that if an operator chooses to create a hub, they create one in each ward (Government of the District of Columbia, 2020). However, parking and distribution policies present an opportunity to influence how shared e-scooters are used. Specific policies can be generated to increase the number of e-scooter trips that support public transport and replace personal vehicle trips instead of replacing active and public transit trips.

To address this policy gap, we studied e-scooter trip length in Washington D.C. during the spring of 2019. Our research question focused on how different temporal, weather, transport infrastructure, and land use attributes impact e-scooter trip distances using distance decay curves and multi-level mixed effects regression models.

3.1.1 Literature review

Although e-scooters are a relatively new mode of transport in North America, they have similar characteristics to bikesharing which is more established. Compared to all other transport modes, cycling and e-scooters fall into the same "little vehicle" category as both types of vehicles are low-speed and have wheels, which are typically used for trips that are less than four kilometers long (Krizek & McGuckin, 2019). Cyclists and e-scooter riders are common in urban areas and both travel at similar average speeds – 17.9 kph and 19.6 kph respectively (Arellano & Fang, 2019; Krizek & McGuckin, 2019). Bikesharing systems and e-scooters are both available to travelers on an as needed basis and they offer the flexibility to be used for a one-way or round-trip, while the operators handle storage, maintenance, and security (Parkes et al., 2013). E-scooters and bikesharing are also both marketed as environmentally and socially sustainable modes of transport that can also support public transport by acting as first mile and last mile solutions (Bachand-Marleau et al., 2011; Bird, 2020b; Lime, 2019). Thus, studies about bikesharing, which is also more researched than e-scooters, can guide our approach to investigating e-scooters.

Distance decay functions and curves are a popular tool in the literature for understanding travel behavior (Bachand-Marleau et al., 2011; Larsen, El-Geneidy, & Yasmin, 2010). Distance decay curves are effective at comparing travel behavior, for example, between different modes, for different trip purposes, in different regions, and sociodemographic attributes (Bachand-Marleau et al., 2011; Larsen et al., 2010). In fact, both Bachand-Marleau and Larsen et al's studies employ distance decay curves to understand differences between walking and cycling travel (Bachand-Marleau et al., 2011; Larsen et al., 2010). This sets the precedence for us to study e-scooter travel behavior using distance decay curves.

The effects of the built environment, weather, sociodemographic, transport infrastructure and temporal characteristics have been shown to influence bikeshare ridership such as arrival and departure rates at stations (El-Assi et al., 2017; Imani et al., 2014). Both studies apply multi-level mixed effects regression models to investigate the determinants of bikeshare flows in Canadian cities because the models can indicate that observations were taken from the same station repetitively (El-Assi et al., 2017; Imani et al., 2014). Thus, El-Assi et al. and Imani et al. set the precedent for us to employ multi-level mixed effects regression models to study the influence of temporal, weather, sociodemographic, land use, and transport infrastructure on e-scooter trip distance.

3.2 METHODS AND DATA

3.2.1 Presence of e-scooters

Dockless shared e-scooters have been in Washington D.C. since the city launched a pilot program for them in September 2017, which made the city one of the earliest adopters of the transport mode in North America (Glambrone, 2019). Washington D.C. was selected for this study because it makes real time e-scooter data and descriptive data about the city publicly available through their District Department of Transport (DDOT) website and their Open Data platform (DC.GOV, 2019; DDOT, 2019a). Dockless shared e-scooter companies that have permits to function in Washington D.C. are required to provide live location data about vehicles not in use (DDOT, 2018). The data is publicly available through an application programming interface (API) (DDOT, 2018). Data from each of the six companies that operated e-scooters in Washington D.C.

in the spring of 2019 – Bird, Jump, Lime, Lyft, Skip, and Spin was available through APIs on the DDOT website. The APIs were used to collect e-scooter location data for this investigation. The data reported with each company's API varied, some only reported lat/long while others included unique vehicle identification numbers (IDs). In total, six full days of e-scooter location data was collected at five minute intervals in May and June 2019: Sunday May 12th, Monday May 13th, Tuesday May 14th, Thursday May 16th, Saturday June 1st, and Friday June 14th. Although data collection was conducted for three weeks between May and June, only six full days were achieved due to technical difficulties such as data collection being paused by the APIs.

3.2.2 Inferring trips

Companies with unique vehicle IDs were selected for this study in order to track the location and timestamp associated with e-scooter trip origin and destination. In order to determine which companies reported unique vehicle IDs, the number of unique vehicle IDs recorded per company per day was compared to the number of e-scooters the company was permitted to operate in Washington D.C. by the DDOT at the time (DDOT, 2019b). The number of unique vehicle IDs and the permitted number of e-scooter vehicles in 2019 are displayed in **Table 3.1**. Four companies were used for the analysis based on the closeness of the number of unique vehicle IDs and the number of e-scooters permitted. Although the number of unique vehicle IDs per day was reasonably close to the number of e-scooters permitted for Skip, the data was unusable because e-scooters reported in different locations at the same time had the same ID.

Table 3.1 Number of unique vehicles IDs vs how many vehicles are permitted per company in Washington D.C.

Company	Number of unique vehicle IDs per day (June 14th)	Number of e-scooters permitted
Bird*	9706	600
Jump	547	600
Lime	889	675
Lyft	862	720
Skip*	750	720
Spin	562	720

*Not included in dataset.

The unique vehicle IDs enabled us to track e-scooter trips based on the location data that we collected for e-scooters not in use and the associated timestamp. Thus, for each e-scooter, we generated a profile of its location and the associated timestamp based on our collected observations. Next, the Euclidean and time distance between each consecutive observation of the same e-scooter was calculated. A trip was defined as two consecutive observations whose Euclidean distance was greater than 30 meters, and a time distance less than one hour. These criteria were used to avoid a including a GPS reporting error or other technology related malfunctions, in the e-scooter trip dataset. Latitude and longitude reports from GPSs can be less accurate when there is interference such as many tall buildings nearby. Additionally, a trip that was reported as multiple hours long could have been recorded if an application did not register that a trip had finished. This analysis was performed separately for each day, since most of the days included in the data were not consecutive. As a result, we initially observed 118,702 trips over the course of six days. The route solver tool within the ArcGIS Network Analyst extension was used to calculate the trip distance along the Washington D.C. road network given the origin and destination of each trip. It should be noted that interstates were excluded from the Washington D.C. road network since we assumed that e-scooter trips would not take place on interstate roads because of their inhospitable conditions, see **Figure 3.3**. In order to incorporate the reality of e-scooter use, the direction of one-way streets was not used to generate the routes (this was controlled by a setting in Network Analyst), since e-scooters often ride against traffic and on sidewalks including on one-way streets. The route solver tool finds the shortest path along the road network, which is a reasonable assumption for commuting and shopping or errands related travel, however less so for recreation or social travel. In a survey of e-scooter users during their 2018 e-scooter pilot, PBOT found that 76% of those surveyed were Portlanders, and of those a total of 41% listed their last e-scooter trip purpose as commute related (to work, school, work related appointments, the bus or for errands), and 42% for recreation or social purposes (fun/recreation or social) (Portland Bureau of Transportation, 2018a). The survey was 24% tourists, or people who do not live in Portland, and they are less likely to take e-scooters for commuting, which would more likely be along the shortest route. The fact that we did not have access to trip purpose data or trip route data is thus a limitation of our analysis, and thus it did not reflect potential variations in travel behavior and route choice. However, 78.7% of the trips included in this analysis were within 1km long along the road network and 75% were 15 minutes or less in duration (see **Figure 3.6**), indicating that it is reasonable to assume that a good portion of the trips in this analysis would have taken relatively direct routes.

After calculating the trip distance along the road network for each of the 118,702 trips, the minimum trip length was 0 meters, despite the fact that consecutive observations of e-scooters with the same ID that had a Euclidean distance less than or equal to 30 meters apart, were filtered out during data cleaning. This discrepancy is explained by the difference between trip distance along the road network (which was used as the dependent variable and generated via the route solver network analyst tool in ArcMap) and Euclidean distance calculations between the observed origin and destination. Thus, in order to continue to filter out trips that may have been errors, we excluded e-scooter trips that were reported to be 30 meters or shorter in distance along the modified road network. Thus, our final count of e-scooter trips that were used in this study included 111,711 trips.

3.2.3 Covariates

The explanatory variables used in this study include time, weather, sociodemographic, land use, and transport infrastructure. Temporal variables were collected from the timestamp and date associated with each e-scooter origin and destination observation. They were used to examine how e-scooter trip lengths vary by time of day and day of the week. We divided the 24-hour day into four equally sized categories and included them in the data as dummy variables based on trip start and end time: 12AM – 6AM (late night), 6AM to 12PM (morning), 12PM to 6PM (afternoon), and 6PM to 12AM (evening). Further, we included if the trip took place on a weekend day as a dummy variable in the data.

Weather characteristics for the study time were collected from the Dark Sky API ("Dark Sky API," 2019). The weather data was collected to investigate how e-scooter trip length varies with weather conditions. The temperature, humidity, precipitation, wind speed, and cloud cover data were collected hourly. Temperature and humidity were highly correlated, so the heat index was generated based on the two measures, which describes a real feel measure. The equation used to generate the heat index in degrees Fahrenheit is below, where RH is relative humidity in percent and T is temperature in degrees Fahrenheit (NOAA/ National Weather Service, 2014):

$$\begin{aligned} \mathrm{HI} = {} & -42.379 + 2.04901523 * \mathrm{T} + 10.14333127 * \mathrm{RH} - .22475541 * \mathrm{T} * \mathrm{RH} \\ & - .00683783 * \mathrm{T} * \mathrm{T} - .05481717 * \mathrm{RH} * \mathrm{RH} + .00122874 * \mathrm{T} * \mathrm{T} * \mathrm{RH} \\ & + .00085282 * \mathrm{T} * \mathrm{RH} * \mathrm{RH} - .00000199 * \mathrm{T} * \mathrm{T} * \mathrm{RH} * \mathrm{RH} \end{aligned}$$

Cloud cover was highly correlated with the heat index so it was excluded from our study.

In order to examine the geographic characteristics associated with e-scooter trip origin and locations, Washington D.C. was divided into 1671 geographic grid cell square areas, called fishnets, that are 0.07 $miles^2$ (0.19 km^2) in size. Of the 1671 fishnets, 1,202 constituted the study area because at least one trip originated or ended in them. The sociodemographic, land use, transport infrastructure variables, and then the origin and destination locations of the e-scooter trips, were intersected with the fishnets.

Sociodemographic attributes of Washington D.C. were collected from the Census Bureau's On the Map platform, and maps on Washington D.C.'s Open Data platform that incorporated Census Bureau data (DC.GOV, 2019; U.S. Census Bureau, 2015). Sociodemographic attributes were used to depict characteristics of the populations near e-scooter trip origins and destinations. The population density (weighted in thousands) of the census tract that the fishnet is in, the number of jobs (weighted in thousands) per fishnet, and the median household income of the census tract that the fishnet is in were collected as variables in the data. The median household income was divided into three categories and treated as a dummy variable in the data: low income (less than $40,000), medium income (greater than or equal to $40,000 and less than $80,000), and high income (greater than or equal to $80,000). **Figure 3.1** shows that the outskirts of Washington D.C. exhibit lower population density, fewer jobs per fishnet, and higher median incomes. The more central areas of Washington D.C. have higher population densities, a higher number of jobs per fishnet, and lower median incomes than the outskirts of the city.

The land use variables from Washington D.C.'s Open Data platform were collected to investigate the type of places that people access with e-scooters (DC.GOV, 2019). They include the number of liquor licenses, restaurants and cafes, museums and marketplaces per fishnet. Additionally, if a fishnet is part of the central business district, on a college campus, or a national park, were included in the data as dummy variables. The number of restaurants and cafes, and liquor licenses in an area were found to be highly correlated, so the restaurants and cafes variable was excluded since many restaurants and cafes also have liquor licenses, and the list of liquor licenses was larger than the list of restaurants and cafes. The liquor licenses variable is referred to as bars and restaurants to capture this overlap. **Figure 3.2** demonstrates that the locations of services are more densely concentrated in the central part of Washington D.C. than the perimeter of the city.

The transport infrastructure characteristics were collected from the Washington D.C. Open Data platform in order to understand how e-scooter use interacts within the existing transport system and are depicted in **Figure 3.3** (DC.GOV, 2019). The presence of a bicycle lane in a fishnet was included as a dummy variable and the number of metro stations and bus stops per fishnet were included as continuous variables. The locations of services are shown in **Figure 3.2** and are also concentrated near the metro lines in the outer areas of Washington D.C. that are mapped in **Figure 3.3**.

Figure 3.1 Sociodemographic characteristics of Washington D.C.

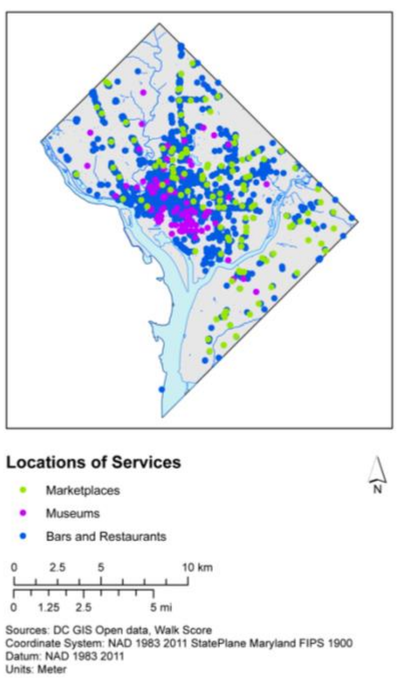


Figure 3.2 Land use in Washington D.C

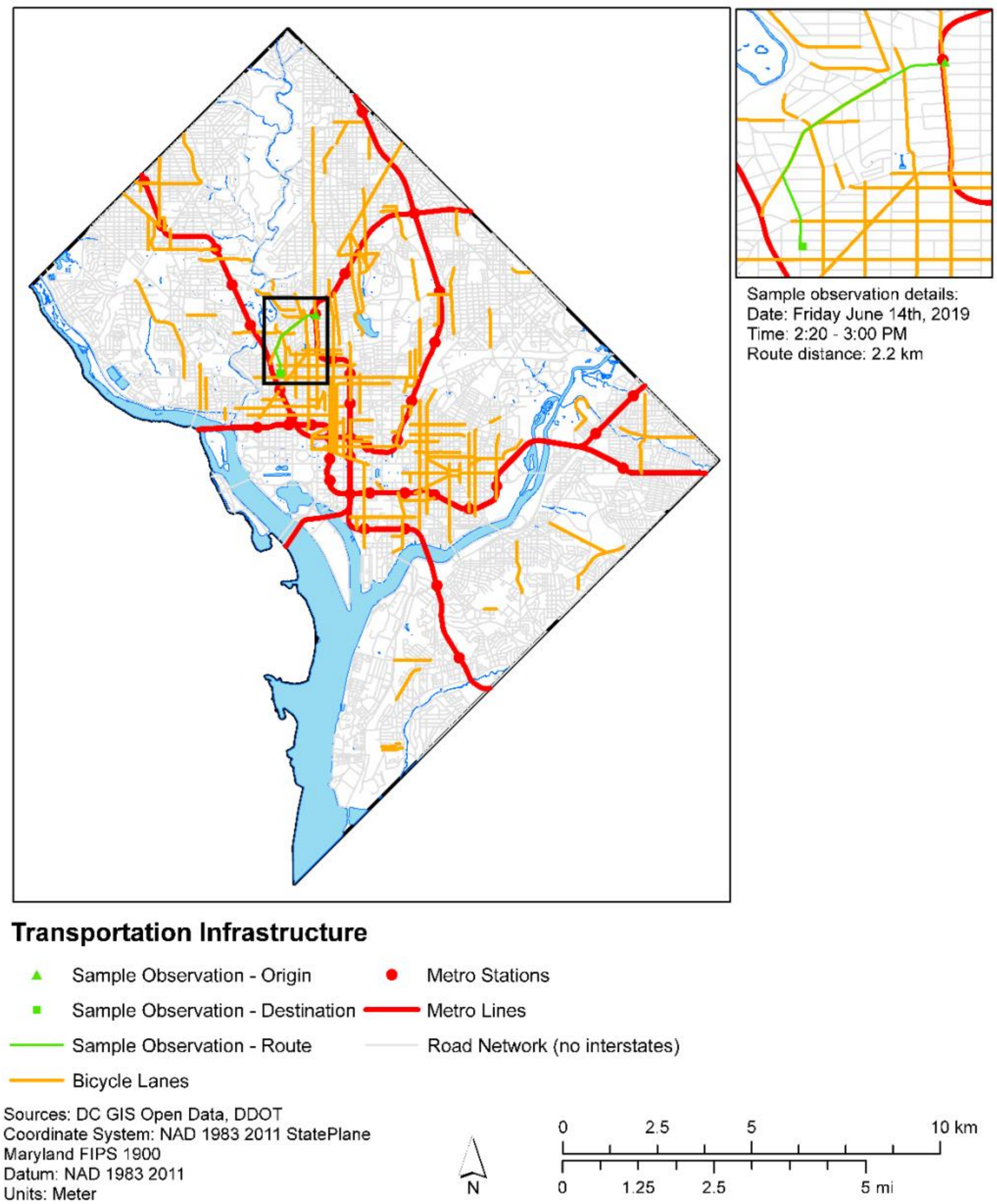


Figure 3.3 Transport infrastructure in Washington D.C.

3.2.4 Model development, processing and validation

To prepare the data for modeling, the trip distance in meters, and the temporal, weather, sociodemographic, transport infrastructure, and land use characteristics at the origin and destination of each observed trip were intersected.

The analysis of the impact of covariates on e-scooter trip distance is conducted through two types of analysis: an exploratory analysis of the covariates through generating distance decay curves and summary statistics, and a statistical analysis with two regression models. Five sets of distance decay curves were generated to depict how the frequency of e-scooter trip distances vary for the entire sample of trip observations, and how frequencies of e-scooter trips that are different lengths relate to varying times of day, heat indexes, and the presence of a bicycle lane or metro station. Distance decay curves were generated by categorizing the variables (i.e. low heat index, medium heat index, and high heat index), and counting the number of trips made within each category that were less than 3,500 meters long. Next, the trip counts within each variable category were counted at 100 meter intervals (i.e. the number of trips that were 0 – 100 meters, 100 – 200 meters, etc., long when the weather was observed to be a low heat index). It should be noted that the decay curves examining the presence of a bicycle lane and the presence of a metro station are generated for percent of trips per category instead of the raw frequency. This is because there is a large difference (over 6,000) in the number of trips between 0-100 meters if there is a bicycle lane near the origin and/or destination or not, and if there is a metro station near the origin and/or the destination or not. This would make the decay curves visually difficult to compare since the data included in the two categories would be at different scales. Thus, the distance decay curves are helpful in understanding the demand for e-scooters for different travel distances based on conditions. The distance decay curve based on travel time is generated using the same methodology, except the number of trips is counted for the trip time length instead of distance along the road network. The number of trips were counted at 5-minute intervals, and since the data was capped at trips that are less than one hour, so too was the decay curve for time. Summary statistics including the average trip distance and standard deviation were also calculated for each category of each covariate in order to compare the impact of those determinants on trip distance.

The natural log of the trip distance was generated and used as the independent variable because the distribution of trip distances skewed to the right, since there were many more short trips than long trips, see **Figure 3.4**. Correlation between variables was checked and used to decide which variables remained in the models. Additionally, the variance inflation factor (VIF) was used to check for multicollinearity among the variables that were kept after checking for correlation with a correlation matrix.

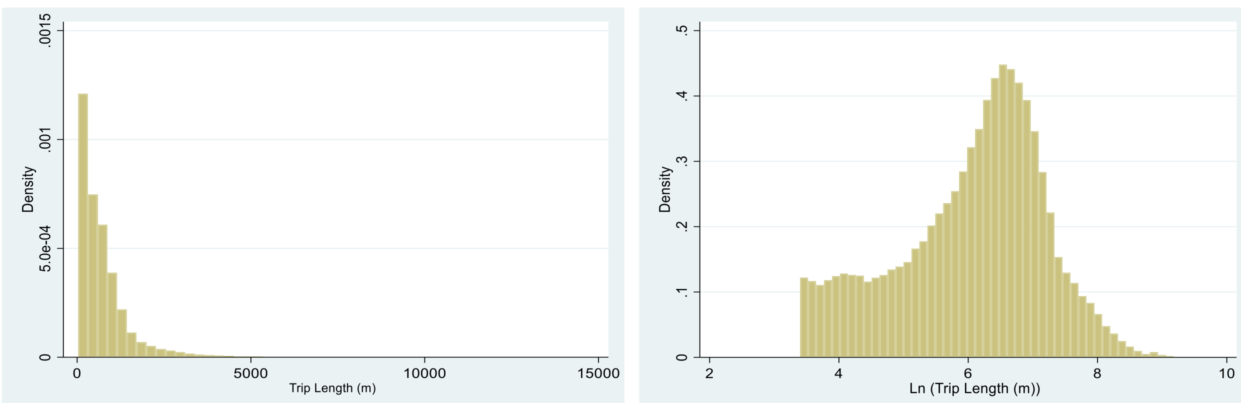


Figure 3.4 Histograms of trip length vs ln (trip length)

Multi-level mixed effects regression modelling was used because trips originated from places geographically near each other. Observations with trips originating from geographically close areas would result in estimation biases if they were used in a regular regression. In our models, trip origin observations are nested within census tracts as depicted in **Figure 3.5**. Since the observation includes the natural log of the trip distance and attributes associated with the origin and destination fishnet, the multi-level mixed effects regression model accounts for the similarities based on geographic location of the origin area that is not reflected in independent variables.

Further, we found that fishnet level was unsuitable to run the multi-level mixed effects regression modeling, since the distribution of observations across the 1,150 fishnets that trips originated from was sparse, which could have also introduced bias. Thus, the census tract level was selected as the level for the multi-level regression models, and the fishnets that trips originated from were clustered into 159 census tracts. The first multi-level regression model highlights selected independent variables (see **Table 3.4**) and the second model includes all of the covariates that were considered (see **Table 3.5**).

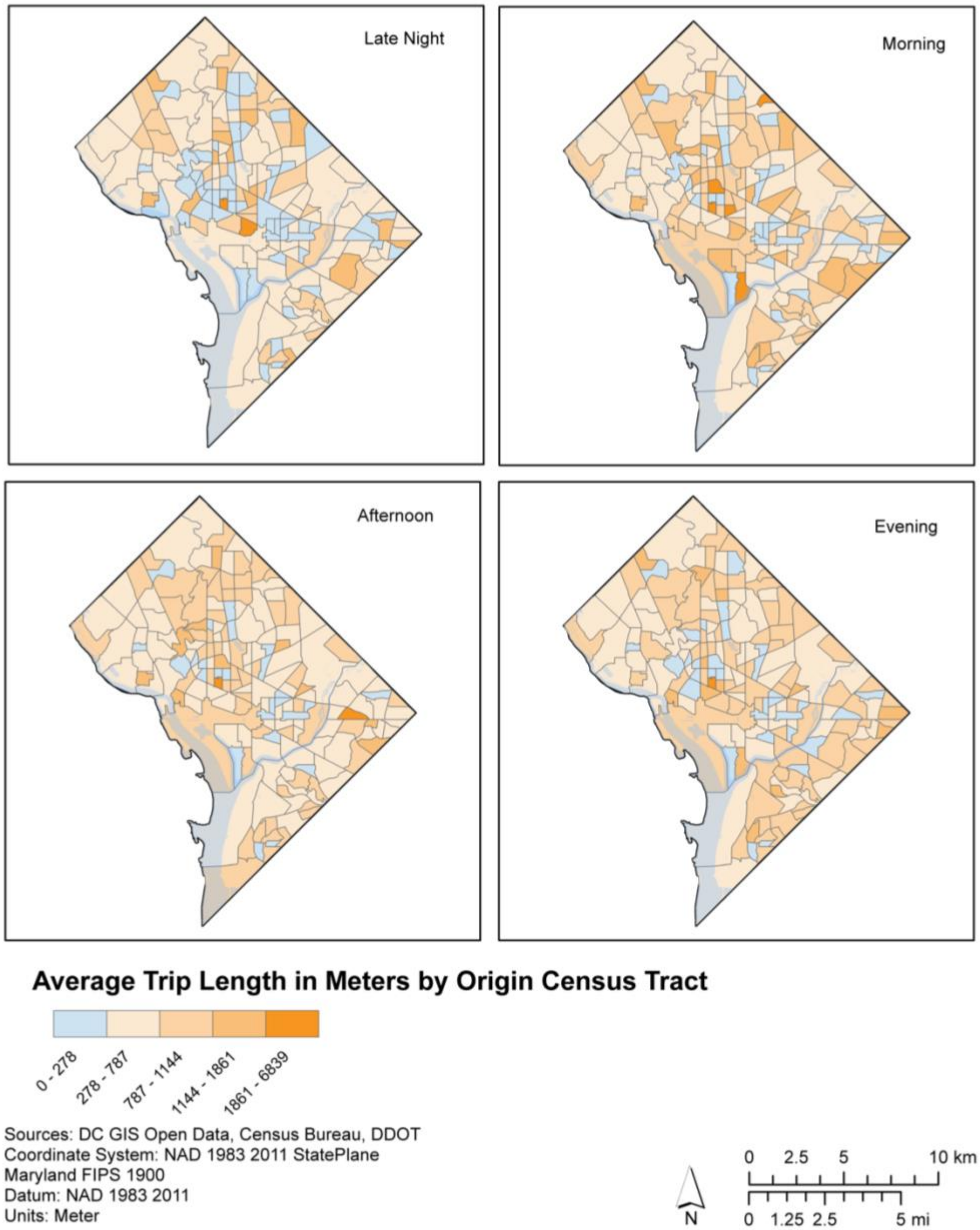


Figure 3.5 Average trip length by origin census tract and time of day

3.3 RESULTS AND DISCUSSION

3.3.1 Summary statistics

The summary statistics for the e-scooter trips included in this data as observations are presented in **Tables 3.2 & 3.3**. The mean, minimum, maximum, standard deviation, and number of observations of the sample of trip lengths used to generate the different decay curves is presented in **Table 3.2**. The number of observations for each category of decay curves (i.e. time of day) sum to 111,711 observations, the total number of observations in the data set.

Table 3.2 Decay curve summary statistics

		Mean	Min	Max	Standard Deviation	Observations: Total	Observations: Excluded from decay curve (over 3.5km)
	Trip length (meters)	723.55	30.00	14007.91	803.74	111,711	1624
	Trip length (minutes)	11.10	3.08	59.85	10.48	111,711	0
Time of day	Late night	638.18	30.00	14007.91	920.32	5,082	98
	Morning	691.15	30.03	11425.78	788.76	21,233	261
	Afternoon	710.10	30.00	10856.36	759.04	56,088	727
	Evening	787.56	30.01	11702.87	869.32	29,308	538
Heat index	Low heat index	728.89	30.00	11425.78	831.45	34,874	494
	Medium heat index	698.13	30.03	14007.91	773.75	30,204	395
	High heat index	736.02	30.00	10565.24	801.35	46,633	735
Bicycle lane	Bike lane near origin and/or destination	798.54	30.00	11425.78	834.27	49,375	825
	No bike lane near origin or destination	664.15	30.00	14007.91	773.57	62,336	799
Metro station	No metro station near origin or destination	755.13	30.02	9367.035	768.04	6,536	88
	Metro station near origin and/or destestination	721.59	30.00	14007.91	805.86	105,175	1536

The mean, minimum, maximum, and standard deviation, values of the population of observations is described in **Tables 3.2 & 3.3**. The summary statistics for explanatory and the dependent variables used in the regression models are presented in **Table 3.3**. They are distinguished between categorical variables and continuous variables. The frequencies and standard deviations are summarized for the categorical variables and the mean, minimum, maximum, and standard deviation values are described for the continuous variables.

Table 3.3 Variable summary statistics

Categorical Variables	Percent of Observations	Std. Dev
Weekend Day	31.16	0.46
12AM - 6AM	4.55	0.21
6AM - 12PM	19.01	0.39
12PM - 6PM	50.21	0.50
6PM - 12AM	26.24	0.44
Low Income Area - Origin (1000s)	39.27	0.49
Medium Income Area - Origin (1000s)	37.76	0.48
High Income Area - Origin (1000s)	22.97	0.42
Part of the CBD - Origin	3.30	0.18
Part of the CBD - Destination	3.28	0.18
Part of a College Campus - Origin	4.84	0.21
Part of a College Campus - Destination	4.91	0.22
Part of a National Park - Origin	42.42	0.49
Part of a National Park - Destination	42.51	0.49
Fishnet contains a Bicycle Lane - Origin	28.04	0.45
Fishnet contains a Bicycle Lane - Destination	27.97	0.45

Continuous Variables	Mean	Min	Max	Std. Dev
Heat Index	64.28	42.15	82.20	11.72
Precipitation Intensity (mm/hr)	0.00	0.00	0.08	0.01
Wind Speed (km/h)	6.57	0.00	12.96	3.50
Census Tract Population Density - Origin (1000s)	9.24	0.00	66.79	8.84
Census Tract Population Density - Destination (1000s)	9.15	0.00	66.79	8.70
Jobs - Origin (1000s)	0.29	0.00	24.95	1.21
Jobs - Destination (1000s)	0.28	0.00	24.95	1.20
Number of Bars & Restaurants - Origin	1.28	0.00	40.00	3.02
Number of Bars & Restaurants - Destination	1.29	0.00	40.00	3.06
Number of Museums - Origin	0.05	0.00	4.00	0.29
Number of Museums - Destination	0.05	0.00	4.00	0.28
Number of Marketplaces - Origin	0.12	0.00	3.00	0.42
Number of Marketplaces - Destination	0.12	0.00	3.00	0.42
Number of Capital Bikeshare Stations - Origin	0.21	0.00	3.00	0.49
Number of Capital Bikeshare Stations - Destination	0.21	0.00	3.00	0.48
Number of Metro Stations - Origin	0.03	0.00	1.00	0.18
Number of Metro Stations - Destination	0.03	0.00	1.00	0.18
Number of Bust Stops - Origin	2.66	0.00	19.00	3.11
Number of Bust Stops - Origin	2.63	0.00	19.00	3.09
Dependent variable = ln (trip length in meters)	6.04	3.40	9.55	1.14
Trip length in meters	723.55	30.00	14007.91	803.74

3.3.2 Distance decay curves

A distance decay curve for all e-scooter trips less than or equal to 3,500 meters long is depicted in **Figure 3.6**, where 49% of all e-scooter trips included in the curve are less than 500 meters long. The distance decay curve follows a negative exponential shape, where the rate of decrease in frequency is larger for trips that are shorter distances than trips at larger distances. The distance decay curve based on travel time in **Figure 3.6** depicts a low number of extremely short trips (within 5 minutes long), and a very high number of trips within 10 minutes long, and then it also follows a negative exponential shape. The curve shows that the majority of trips, 75%, are within 15 minutes long.

The distance decay curve for trips that take place in the afternoon, has a larger frequency of trips that are less than 3,000 meters long, than trips that take place during the late night, morning, and evening, which are in **Figure 3.6**. This increase in frequency for the majority of the data in the decay curve could be explained by the fact that nearly half of the total observed e-scooter trips occurred in the afternoon. Thus, our data showed a larger demand for e-scooters during the afternoon than any other time of day. Additionally, trips during the late night had the lowest average distance and during the evening had the highest average distance. The distance decay curves for morning and evening exhibit similar frequencies for the entirety of the decay curve. They are lower frequencies than the afternoon, but are not as low as the frequency of trips during the late night. This could be because there are far fewer trips that occur at the late night overall compared to the other times of day. The demand for e-scooters during our study was highest during the afternoon, then the evening, then the morning, and the demand was lowest during the late night.

The distance decay curves for travel during low, medium, and high heat index show that there are slightly larger frequencies of trips between when the heat index is high, than during low and medium heat indexes, as depicted in **Figure 3.6**, and larger frequencies of trips during high heat indexes than low or medium for trips between 300 – 900 meters. The more gradually decreasing distance decay curve for e-scooter trips when the heat index is high could also be explained by the larger number of observations overall that occurred during a high heat index. This indicates that the demand for e-scooter trips increases when the heat index, or real feel, is warmer than when it is colder in the spring.

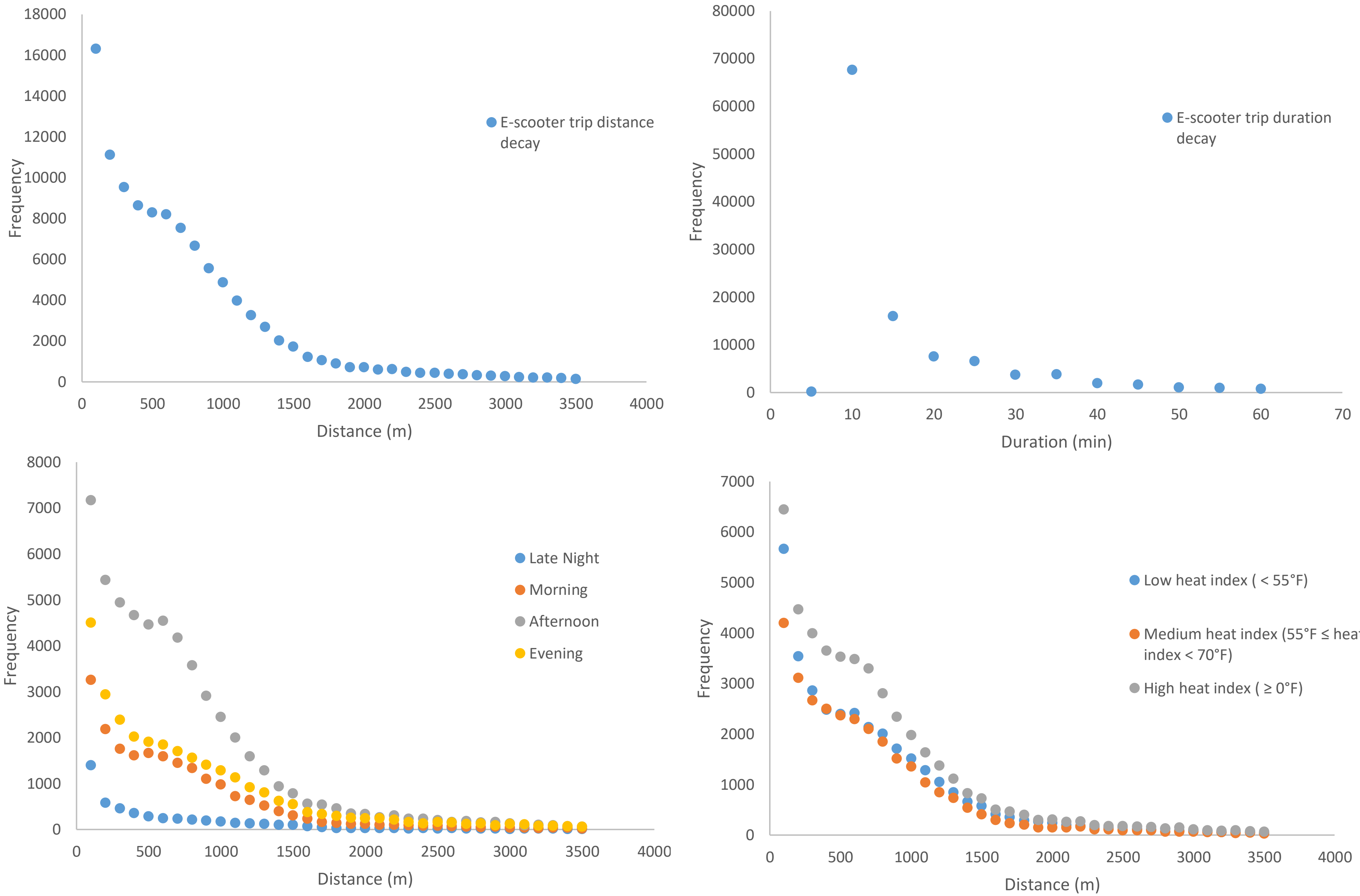
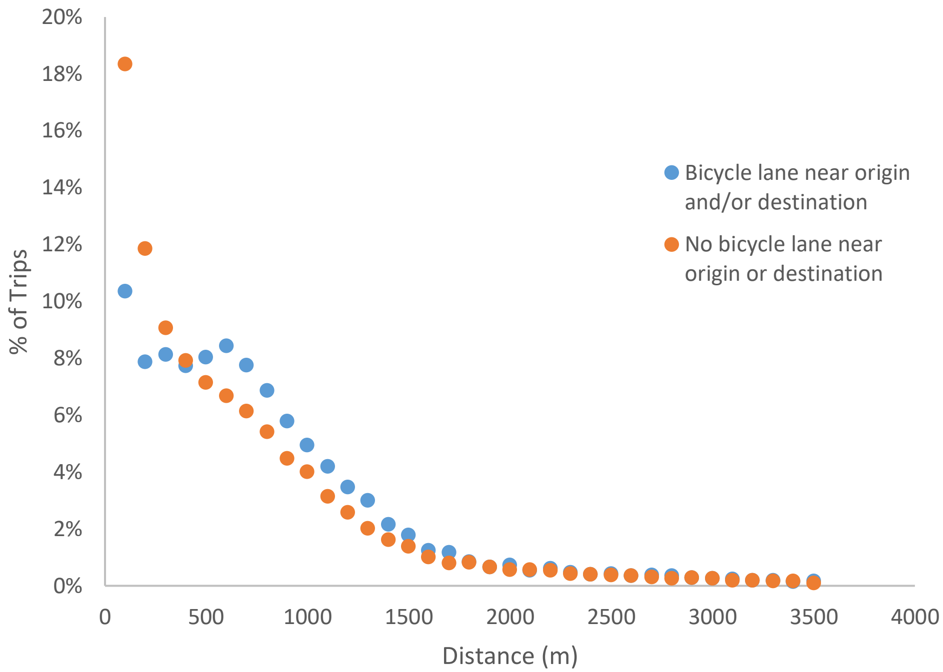


Figure 3.6 Distance decay curves - frequency vs distance (m) and duration (min)

The portion of e-scooter trips that are not near a bicycle lane at the origin and/or destination that are very short (less than 300 meters) is higher than the proportion of e-scooter trips that are very short and are near a bicycle lane at the origin or destination, as shown in **Figure 3.7**. Further, amongst e-scooter trips that start and/or end near a bicycle lane, e-scooter trips that are longer (400 – 700 meters) comprise a larger share than shorter trips (100 – 400 meters). Additionally, the proportion of trips that are between 400 – 1,500 meters is consistently larger for trips that originate and/or end near a bicycle lane than those that do not. Although there are far fewer e-scooter trips that originate and/or end near a bicycle lane, the difference in proportions of trips that are longer is reflected in the average trips distance of an e-scooter trip whose origin and/or destination is near a bicycle lane, which is 798.54 meters compared to the average distance of an e-scooter trip that does not start or end near a bicycle lane, which is 664.15 meters. Thus, the demand for longer trips on e-scooters is proportionally higher for trips that have origins and/or destinations near bicycle lanes. The number of e-scooter trips whose origin and/or destination is near a bicycle lane could be more than 12,000 fewer than trips that do not because of the sparsity and disconnected bicycle lane network outside of central Washington D.C.

The proportion of e-scooter trips that do not start and/or end near a metro station is nearly double the percent of e-scooter trips that have origins and/or destinations near metro stations for trips that are less than 100m long, as depicted in **Figure 3.7**. The proportion of trips between 100 – 400 meters long are similar for trips that have origins and/or destinations near metro stations and those that do not. However, the proportion of trips that are longer, 400 – 1,100 meters, is higher for e-scooter trips that start and/or end near metro stations than those that do not. This indicates that the relative demand for e-scooter trips between 400 – 1,100 meters in length is higher for e-scooter trips that are geographically associated with metro stations than those that are not. This relative demand for longer trips is also reflected in the larger average trip distance for e-scooter trips that begin and/or end near metro stations than those that do not (see **Table 3.2**). Notably, the number of e-scooter trips that have origins and/or destinations near metro stations is only 6% of the number of e-scooter trips that do not. This could be because the geographic density of metro stations in Washington D.C. is low.



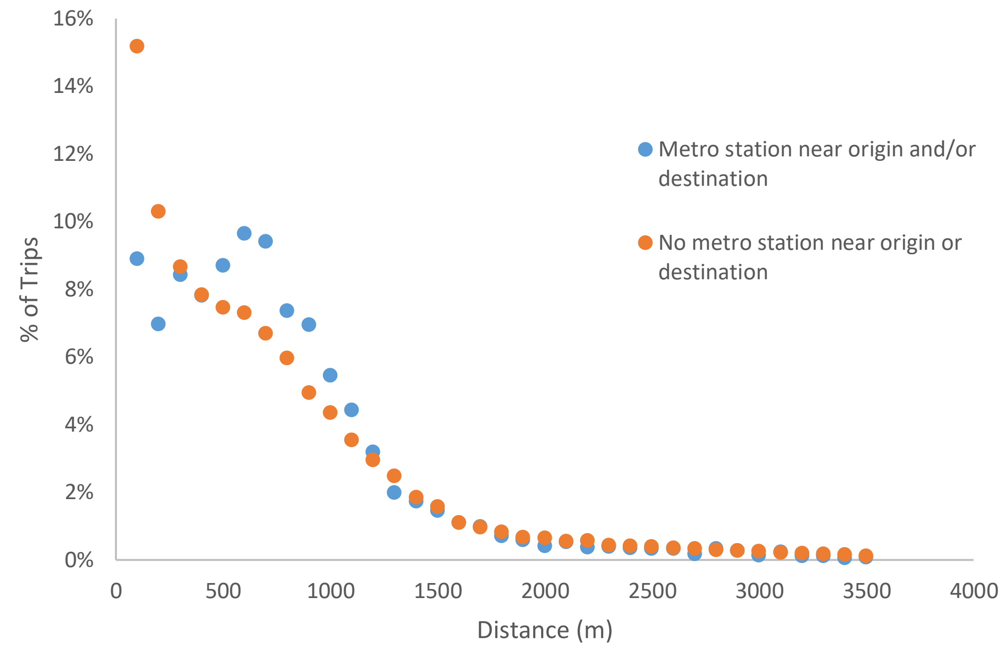


Figure 3.7 Distance decay curves - % of trips vs distance (m)

3.3.3 Regression results

Table 3.4 Model 1 regression results

		Coefficient	Significance	95% Confidence Interval	
Temporal	12PM - 6PM	0.0599	***	0.05	0.07
	Weekend Day	-0.0472	***	-0.06	-0.03
Weather	Heat Index	0.0022	***	0.00	0.00
	Precipitation Intensity (mm/hr)	-1.2047	*	-2.25	-0.16
Sociodemographic	Jobs - Origin (1000s)	0.0058		-0.01	0.02
	Jobs - Destination (1000s)	-0.0117	***	-0.02	-0.01
	Low Income Area - Origin (1000s)	0.1266		-0.01	0.27
	Medium Income Area - Origin (1000s)	0.0664		-0.07	0.21
Land Use	Number of Bars & Restaurants - Origin	0.0009		0.00	0.00
	Number of Bars & Restaurants - Destination	0.0035	**	0.00	0.01
Transportation Infrastructure	Fishnet contains a Bicycle Lane - Origin	0.0744	***	0.05	0.10
	Fishnet contains a Bicycle Lane - Destination	0.0378	***	0.02	0.05
	Number of Metro Stations - Origin	-0.1955	***	-0.25	-0.14
	Number of Metro Stations - Destination	0.0124		-0.03	0.05
	Constant	5.8827	***	5.76	6.01
	Number of observations		111,711		
	Log Likelihood		-172322.73		
	Interclass correlation		0.060174		
	Akaike's information criterion		344679.5		
	Bayesian information criterion		344843.1		

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

All variables included in model 1 exhibited statistical significance at the 5% significance level except the number of jobs at the origin, the median income of the origin areas, and the number of metro stations at the destination, all else held equal. If an e-scooter trip occurred in the afternoon, between 12PM – 6PM, it had a positive and significant impact on trip distance. All other variables held constant, if an e-scooter occurred during the afternoon, it increased the trip length by nearly 6%, potentially because of less availability of other transport options (off peak scheduling) and good visibility outside (it is daytime and thus light out). Meanwhile, e-scooter trips that occur on the weekend decrease the trip length by 4.7% compared to those that occur on weekdays, but all else equal. This could perhaps be due to a decrease in the need to travel or commute on the weekends.

All else held equal, the heat index (real feel) exhibited a positive and significant impact on trip length, possibly due to peoples' propensity to travel further outside when it feels warmer. An incremental increase in the heat index only results in a 0.22% increase in e-scooter trip distance, potentially signaling that an incremental increase in the heat index (one degree Fahrenheit) is not noticeable enough to change a rider's travel behavior. Conversely, precipitation intensity imparts a 120.47% decrease on e-scooter trip length, indicating that people use e-scooters for significantly shorter trips when it rains, perhaps because of slippery roads or perceived discomfort.

The number of jobs at the destination of the e-scooter trip decreased e-scooter trip distances by 1.17% if all else is held equal. The decrease in e-scooter trip length associated with job density could suggest that people do not rely on e-scooter trips for longer legs of their commute to work. The number of jobs at the origin, and if the origin area had a low or medium median income, did not have a statistically significant impact on e-scooter trip distance in this model. Although, if a trip originated in a low income area, had a significant impact in model 2, and is discussed in that context.

The number of bars and restaurants at the destination of an e-scooter trip have positive and significant impacts on e-scooter trip length, all else held equal. This could potentially be because people are willing to travel further than average to reach opportunities such as bars and restaurants, which are also concentrated in the central business district (CBD) and near other locations of services. Thus, the increase in trip length for e-scooter trips that end near bars and restaurants could also reflect the increase in distance that people will travel on e-scooters to reach opportunities more generally.

The presence of a bicycle lane at the origin or destination of an e-scooter trip both have positive and highly significant impacts on the length of the trip, all else equal. The presence of a bicycle lane near the origin or destination of an e-scooter trip increases the length of the trip by 7.44% and 3.78% respectively, potentially suggesting that people may use bicycle lanes for further e-scooter trips, or that they may be more likely to travel further on an e-scooter if using a bicycle lane for part of their trip. The presence of a metro station at the origin of an e-scooter trip has a significant impact on the length of a trip if all other variables are held constant at their mean. Interestingly, the presence of a metro station near the origin of an e-scooter trip decreases the trip length by 19.55%, potentially because there are higher densities of services and opportunities near metro stations, which decreases the need to travel far to reach a desired destination (see **Figures 3.2 & 3.3**). The presence of a metro station near the destination of an e-scooter trip is not a statistically significant indicator of e-scooter trip length in model 1, and is discussed in the context of model 2.

Table 3.5 Model 2 regression results

		Coefficient	Significance	95% Confidence Interval	
Temporal	Weekend Day	-0.0586	***	-0.08	-0.04
	12AM - 6AM	-0.3785	***	-0.41	-0.34
	6AM - 12PM	-0.0311	***	-0.05	-0.01
	12PM - 6PM	0.0446	***	0.03	0.06
Weather	Heat Index	0.0008	*	0.00	0.00
	Precipitation Intensity (mm/hr)	-1.2716	*	-2.31	-0.23
	Wind Speed (km/h)	-0.0089	***	-0.01	-0.01
Sociodemographic	Census Tract Population Density - Origin (1000s)	0.0073	***	0.00	0.01
	Census Tract Population Density - Destination (1000s)	0.0002		0.00	0.00
	Jobs - Origin (1000s)	0.0069		0.00	0.02
	Jobs - Destination (1000s)	0.0027		-0.01	0.01
	Low Income Area - Origin (1000s)	0.1370	*	0.01	0.27
	Medium Income Area - Origin (1000s)	0.0187		-0.11	0.15
Land Use	Part of the CBD - Origin	0.0465		-0.04	0.13
	Part of the CBD - Destination	0.0903	***	0.03	0.15
	Number of Bars & Restaurants - Origin	0.0054	**	0.00	0.01
	Number of Bars & Restaurants - Destination	0.0061	***	0.00	0.01
	Number of Museums - Origin	-0.1082	***	-0.17	-0.05
	Number of Museums - Destination	-0.0790	***	-0.12	-0.04
	Number of Marketplaces - Origin	-0.0345	**	-0.06	-0.01
	Number of Marketplaces - Destination	0.0408	***	0.02	0.06
	Part of a College Campus - Origin	0.2119	***	0.16	0.27
	Part of a College Campus - Destination	0.0382	*	0.01	0.07
	Part of a National Park - Origin	-0.0098		-0.03	0.01
	Part of a National Park - Destination	0.0185	*	0.00	0.03
Transportation Infrastructure	Fishnet contains a Bicycle Lane - Origin	0.0882	***	0.06	0.11
	Fishnet contains a Bicycle Lane - Destination	0.0353	***	0.02	0.05
	Number of Capital Bikeshare Stations - Origin	0.0010		-0.03	0.03
	Number of Capital Bikeshare Stations - Destination	-0.0140		-0.03	0.01
	Number of Metro Stations - Origin	-0.0436		-0.11	0.02
	Number of Metro Stations - Destination	0.1056	***	0.06	0.15
	Number of Bus Stops - Origin	-0.0181	***	-0.02	-0.01
	Number of Bus Stops - Destination	-0.0142	***	-0.02	-0.01
	Constant	6.0104	***	5.88	6.14
	Number of observations		111,711		
	Log Likelihood		-171894.19		
	Interclass correlation		0.0505513		
	Akaike's information criterion		343860.4		
	Bayesian information criterion		344206.8		

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

The trends noted in model 1 are further supported in model 2 (**Table 3.5**). Although the impact of median income at the origin of an e-scooter trip is not significant in model 1, if an e-scooter trip originates in a low income area, has a statistically significant impact on e-scooter trips length in model 2. All else constant, trips with origins in low income areas are 13.70% longer than e-scooter trips with origins in high income areas, potentially because of overlap with areas with higher population densities and locations of services in the more central parts of the city as compared to high income areas which are on the outskirts of the city. The positive coefficient is also confirmed in model 1, even though the variable for low median income at the origin is not significant.

The number of bars and restaurants at the origin and destination both have positive and significant impacts on e-scooter trip distance in model 2. The influence of the number of bars and restaurants at the destination is more significant and positive on e-scooter trip length than at the origin (0.61% compared to 0.54%, all else held equal), potentially reflecting the notion that people will travel further to reach opportunities, although will travel less far when already near opportunities.

Lastly, the presence of a metro station at the destination of an e-scooter trip has a significant impact on e-scooter trip length in model 2. Model 1 suggests that the number of metro stations at the origin of an e-scooter trip actually decreases the trip length, all else equal. Model 2 complements model 1 by clarifying that the presence of a metro station near the destination of an e-scooter trip increases the trip length by 10.56%, all else held constant, possibly suggesting that people will use e-scooters to travel further to reach metro stations.

3.3.4 Discussion

These results suggest a variety of policy opportunities for increasing e-scooter trip length to support city transport goals. These policies can be in the form of informing parking locations (i.e. designated parking hubs) and distribution guidelines.

The analysis suggests a connection with e-scooter use and metro stations at the destination of e-scooter trips, which is evident in model 1 and confirmed in model 2 (see **Tables 3.4 & 3.5**). Given that people are willing to walk within 0.5 km to access rail transit (El-Geneidy, Grimsrud, Wasfi, Tétreault, & Surprenant-Legault, 2014), and that riders are willing to travel further by e-scooter to access metro stations (see **Table 3.5**), e-scooters should be accessible between 0.5 – 1km of metro stations. Thus, e-scooters could be used as a first mile solution that extend the catchment area around metro stations.

The multi-level regression models also suggest a consistent positive impact of bicycle lanes on e-scooter trip length (see **Tables 3.4 & 3.5**). In order to increase the number of e-scooter trips that start and/or end near bicycle lanes, the supply of bicycle lanes in Washington D.C. should be increased. Additionally, e-scooter parking and distribution policies can incorporate proximity to bicycle lanes.

The decay curve and multi-level regression analyses showed that e-scooter trips during the afternoon and evening had a positive impact on e-scooter trip length and frequency. Thus, e-scooter distribution policies should ensure that e-scooters are specifically available in the afternoon and evening.

The socioeconomic and land use characteristics of areas in Washington D.C. also play a role in influencing e-scooter trip length that can be leveraged to encourage longer e-scooter trips. Namely, policies could require e-scooters to be placed in locations that have higher densities of people since the population density at the origin increases average e-scooter trip distance all else equal (see **Table 3.5**). The positive impact of the number of bars and restaurants at the destination of an e-scooter trip (see **Tables 3.4 & 3.5**), as well as locations of services, could indicate the e-scooters should be placed in locations that provide access to services but are not already near them (i.e. a catchment area for areas with higher concentrations of services such as bars and restaurants). Thus, although it might be difficult for policymakers to identify geographic areas that fit these sociodemographic and land use characteristics, e-scooters can fill in transport gaps that might otherwise be completed by short ridehailing trips, or could relieve transit.

3.4 CONCLUSIONS

In this study, we investigated the influence of temporal, weather, sociodemographic, land use, and transport infrastructure on e-scooter trip length and frequency.

The limitations of this study include that it was based on e-scooter presence data that trips were inferred from. Additionally, the trip distance was calculated based on passing the Washington D.C. road network, origin and destination locations through the route solver tool in ArcMap. Therefore, we may not have captured the actual e-scooter trip route and distance. Since route solver generates the shortest route along the road network, we did not account for trips that could be more circuitous, as it was not possible given the e-scooter location data. Additionally, the data does not include if an e-scooter was placed somewhere because of a redistribution effort or because of a traveler’s trip. Further, our dataset did not include observations from each company operating in Washington D.C. during the data collection period because two of the six companies did not report reliable e-scooter vehicle IDs. Lastly, the data was collected in the spring season, so it does not capture travel behavior outside of May and June 2019. These limitations highlight the importance of access to e-scooter trip data that include routes, origin and destination data. Further research could include incorporating e-scooter user and trip purpose attributes into the study of e-scooter trip length in order to better understand how different travelers use e-scooters. Additionally, the metro station entrances could be considered rather than just the stop location, since metro stops can have multiple entrances which might shed further light on the relationship between e-scooter use and public transit. Furthermore, future research could incorporate bicycle infrastructure into how routes along the city road network are generated as El-Assi et al. does when generating routes for active transport analysis (El-Assi et al., 2017). Further research could also include a larger data collection period and integrate additional bikeshare and e-scooter GPS breadcrumb data and previous studies to help identify route directness.

Based on our findings, we advocate for e-scooter parking and distribution policies to incorporate more specific considerations than at the city-scale. Policies regarding e-scooter parking and distribution could expand public transit catchment areas through e-scooter use, ensure access to e-scooters near bicycle lanes, and during afternoon/evening travel in order to support city transport goals. Geographic and socioeconomic contexts should also be considered in e-scooter distribution and parking policies. Areas that have a high population density, should have access to e-scooters. Similarly, e-scooter should be distributed such that they can be used to bring people into areas that have high concentrations of locations of services. Such policies would be geared towards increasing the length of e-scooter trips, which would be less likely to replace walking trips while potentially relieving transit or replacing personal vehicle or ridehailing trips.

CHAPTER 4: FIRST & LAST MILE TRAVEL BY E-SCOOTER IN WASHINGTON D.C.

4.1 RESEARCH QUESTION

The distance that people are willing to travel to and from public transit stations, known as the first mile last mile, is a major determinant of public transport use. Such distance is used to define a catchment or service area around every station (Hochmair, 2012). El-Geneidy et al. found that the mean walking distance to a metro station in Montreal is 564.80 meters and the 85th percentile of walking trips to a metro station are 873.35 meters (El-Geneidy et al., 2014). Similarly, Hochmair investigated the average cycling distance to public transit stations with trains in Los Angeles, Atlanta and the Twin Cities, and found that the mean travel distance is 4,495 meters, 1,694 meters, and 2,639 meters respectively, while the 85th percentiles of trips were 6,900 meters, 2,057 meters, and 4,843 meters long respectively (Hochmair, 2012). These findings led us to wonder, how far will people use shared electric scooters (e-scooters) to travel to and from metro stations? This research question is especially pertinent to transport planners and city transport officials because e-scooters are heavily marketed as first and last mile solutions that can support public transit (Bird, 2020b; Lime, 2019).

4.2 METHODS AND DATA

Washington D.C. was selected for this study because it requires e-scooter companies that operate in the city to make the real time e-scooter location data publicly accessible (DDOT, 2018). All e-scooters available for rent can be accessed through application programming interfaces (APIs), which are hosted on the District Department of Transport (DDOT) website (DDOT, 2019a). We collected the data at five-minute intervals over the course of six full days during the spring of 2019: Sunday May 12th, Monday May 13th, Tuesday May 14th, Thursday May 16th, Saturday June 1st, and Friday June 14th. The location data was collected for each of the six companies that operated in D.C. during that time: Bird, Jump, Lime, Lyft, Skip, and Spin. The location data that was collected included the lat/long of all the e-scooters available, the timestamp that it was collected at, and vehicle ID. The number of unique IDs per e-scooter company per day were compared to the number of vehicles permitted per company by the DDOT in order to determine if IDs were reliable. Thus, the data from Bird and Skip was not included in the dataset due to their unreliability.

E-scooter trips were derived from consecutive observations of the same e-scooter whose origin and destination had a duration less than one hour and distance of 30 meters or larger along the street and cycling network, excluding freeways. These criteria were used to exclude potentially erroneous data (e.g. – due to GPS interference or application technical difficulties). This resulted in 111,711 e-scooter trips. A map of Washington DC's metro station entrances (DC.GOV, 2019) was intersected with each trip origin and destination location to determine if the e-scooter was used to access or egress a metro station. We assumed that people riding e-scooters to metro stations would drop them near the station entrance, so first mile trips were defined as the trips that ended within 30 meters of a metro station entrance. We also assumed that people taking e-scooters after getting off the metro would be willing to look around for an available e-scooter, and thus considered any trip that originated within 100 meters of a metro station entrance to be a last mile trip. However, since we did not have access to trip purpose data or travel diaries, we cannot confirm that the e-scooters were in fact used as for first or last-mile travel, which is a major assumption of this analysis and limitation. The selected first and last mile trips were used to generate distance decay curves. The distance decay curves included trips less than 3.5 km, and were generated for all first mile and last mile travel, as well first mile and last mile travel by time of day. The number of trips during the late night, morning, afternoon and evening for first mile and last mile travel was observed to be zero for some distance ranges, but they were considered to be 0.1 in order to generate exponential trendlines for the decay curves (see **Figure 4.2** and **Table 4.1**).

4.3 FINDINGS

The summary statistics for the decay curves for first and last mile e-scooter trips are presented in **Table 4.1**. Distance decay curves follow negative exponential functions:

$$y = \alpha e^{\beta x}$$

y is the number of trips and x is the trip distance (m). α is the number of trips when x=0, and β defines the shape of the curve, where a larger absolute value indicates a steeper decline of the curve, and thus shorter trips.

Table 4.1 Decay curve summary statistics

		Mean	85th Percentile	Minimum	Maximum	Standard deviation	Total observations	Observations excluded from decay curve	Trendline description		
									β	α	Model fit (R^2)
	First mile	703.42	1230.31	30.06	14007.91	901.41	3050	42	-0.001	455.82	0.9723
	Last mile	708.34	1248.64	30.01	9339.23	834.98	12911	230	-0.001	1691.5	0.9768
First mile	Late night	715.76	1052.84	30.54	14007.91	1839.04	121	5	-0.001	7.102	0.5872
	Morning	708.84	1210.32	30.07	9462.44	991.60	771	12	-0.002	113.8	0.7543
	Afternoon	682.54	1171.23	30.18	7678.97	797.58	1504	16	-0.002	255.44	0.8833
	Evening	742.76	1327.22	30.06	4984.62	739.03	654	9	-0.002	139.07	0.8438
Last mile	Late night	500.48	923.05	30.24	9339.23	1003.41	623	10	-0.001	55.243	0.717
	Morning	630.14	1119.45	30.07	9312.03	748.47	2937	38	-0.002	430.62	0.9611
	Afternoon	720.40	1237.61	30.01	9298.40	809.81	6449	115	-0.001	901.26	0.9625
	Evening	805.28	1466.23	30.06	7961.23	914.87	2902	67	-0.001	332.38	0.9442

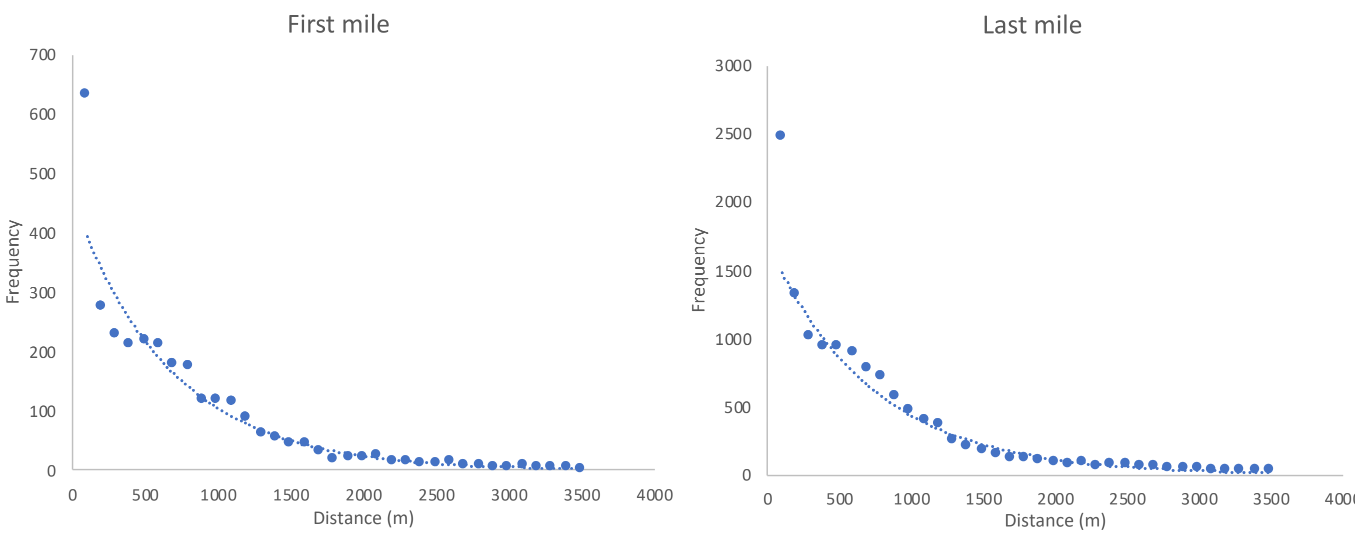


Figure 4.1 E-scooter first mile and last mile decay curves

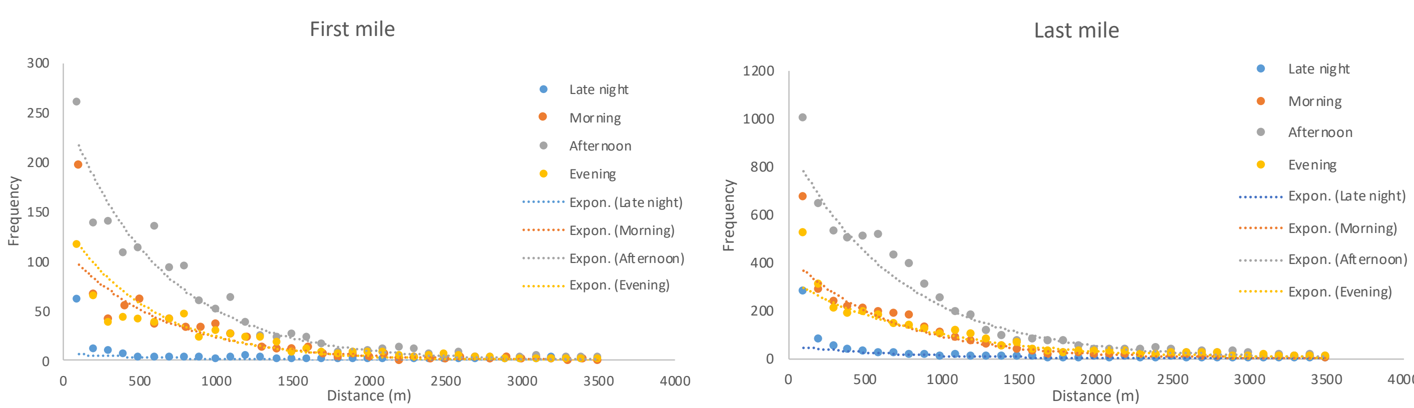


Figure 4.2 E-scooter first mile and last mile decay curves by time of day

The decay curves for first and last mile e-scooter trips are the same shape, indicating that in general people are willing to travel similar distances by e-scooter to and from metro stations. On average, people are willing to travel 703.42 meters to reach metro stations on e-scooter and 708.34 meters from a metro station on e-scooter. Compared to past findings (El-Geneidy et al., 2014; Hochmair, 2012), people are willing to use e-scooters to travel further than when walking to metro stations, although they are willing to bicycle further to metro stations than e-scooter. First mile e-scooter trips during the morning, afternoon, and evening, and last mile e-scooter trips in the morning, are shorter than first and last mile trips at other times of the day. E-scooters can be used to expand the catchment area around metro stations compared to walking.

CHAPTER 5: CONCLUSION

This research contributes to our understanding of e-scooter use based on analysis of location data collected in Washington D.C. during the spring of 2019. This is achieved through investigating the impact of time, weather, sociodemographic, land use, and transport infrastructure on e-scooter presence, variation in e-scooter presence, and e-scooter trip length, and frequency. First mile and last mile travel are also specifically examined in this thesis.

By studying the determinants of e-scooter presence in Chapter 2, we contribute to a more thorough comprehension of the factors that influence e-scooter presence in addition to variations of e-scooter presence. Among other findings detailed in Chapter 2, the four multi-level mixed effects regression models generated in the study suggest that e-scooters are available near bicycle lanes, and that the CBD has a significant impact on e-scooter presence. Further, the study indicates that there is a relationship between public transport and e-scooters, although it is unclear whether they provide a first-mile and/or last-mile solution. Ultimately, the utilization patterns that *Scoot over: Determinants of shared electric scooter presence in Washington D.C.* reveals can help engineers, city planners, and officials understand how e-scooters are used throughout Washington D.C. and how they interact with existing systems.

In building on the research conducted in Chapter 2, *Scoot further: Determinants of shared electric scooter trip distance in Washington D.C.* suggests a framework for inferring e-scooter trips based on e-scooter availability time and location data. Through the use of distance decay curves and two multi-level mixed effects regression models, the impact of determinants on e-scooter trip frequency and length are studied. Based on the analysis, we suggest policies to increase e-scooter trip length via parking and distribution of service policies that cities can implement in an effort to reach modal shifts. Our research suggests that e-scooter trips that originate or end near bicycle lanes are longer than the average e-scooter trip, and thus parking and distribution policies should incorporate bicycle infrastructure networks. Additionally, we found that e-scooter trips that have a metro station at their destination are longer than the average e-scooter trip, which implies that there is potential for e-scooters to be a first-mile solution to metro stations. Thus, city policies could encourage e-scooter use to increase the catchment area of metro stations. To achieve this, cities could create policies for e-scooters to be available further than 0.5 km away from metro stations, since it is accepted that people will walk 0.5 km to access a metro station (El-Geneidy et al., 2014). Additionally, since we found e-scooter trips to be longer and more frequent in the afternoon and evening, city policies can specify that vehicles must be available to meet that demand. The findings from this investigation also highlight the concept that people will travel further to reach opportunities, but will travel less far when they are already near opportunities. This is evident from the models, which showed that a higher density of services such as bars and restaurants near the origin or destination of an e-scooter trip increase e-scooter trip length compared to the average, but the positive impact is stronger for the number of bars and restaurants at the trip destination than the origin. Thus e-scooter distribution and parking policies should also take the sociodemographic characteristics of an area and built environment into account.

Chapter 4, *First and last mile travel by e-scooter in Washington D.C.*, continues our research about e-scooter trip length, which can help in solving the first and last mile problem in public transit planning. The research complements similar analyses conducted to investigate how far people are willing to walk and cycle to metro stations. The findings suggest that people are willing to travel on average 703.4 meters to a metro station by e-scooter, and 708.3 meters from a metro station.

Altogether, this thesis demonstrated how policymakers and transport analysts can study e-scooters in cities. It proposes a methodology for studying e-scooters based on data that is publicly available. The framework includes scraping e-scooter location data at five-minute intervals; combining the location data with publicly accessible sociodemographic, land use, and transport infrastructure data; and including observed weather and temporal characteristics based on the data collection timestamp. The study also relied on geographic grid cells as a way of grouping geographic traits. Additionally, this research built on previous active transport analyses (El-Assi et al., 2017; Imani et al., 2014), to validate the use of multi-level mixed effects regression models to understand active transport location, trip, and determinant data. The research in Chapter 2, 3, and 4 would all benefit if the data that they were based on included differentiation between e-scooters' presence due to rebalancing efforts or a traveler, and if each e-scooter had a unique and reliable vehicle ID. Thus, we suggest that cities ensure public access to e-scooter data that is more complete. More complete information about if an e-scooter was placed as part of a rebalancing effort or by a traveler, in addition full vehicle information, would enable researchers to help city policymakers understand how e-scooters are being used. This research can inform city policies on e-scooter parking and distribution to maximize the potential for e-scooters to help cities meet their goals.

Further research could be conducted that would build on the studies included in Chapter 2, 3 and 4. When generating e-scooter routes based on origin and destination data like in Chapter 3 and 4, it would be interesting to prioritize bicycle infrastructure and conduct trip length and determinant analyses. Additionally, a longer study period of available e-scooter location data collection could be helpful, especially with more seasonality in the data. If more complete e-scooter location data was available, we could incorporate if an e-scooter was placed by a redistributor or a traveler, the trip purpose, and the actual route of the e-scooter trip into our research.

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