A Segment-Level Model of Shared, Electric Scooter Origins and Destinations

Abstract

Electric scooters (or e-scooters) have quickly proliferated in cities worldwide, presenting a host of regulatory challenges. We analyze trip origins and destinations for shared e-scooter use at the street-segment level. Street segments are a relevant unit for policy analysis because users park scooters along the streets' curbside, and parking policies target specific street segments. We build Hurdle models for trip origins and destinations using data from Washington DC in 2019. Results show that street segments near tourist sites, hotels, and transit stops attract the most scooter-trip destinations. In contrast, the supply of available e-scooters is the dominant force shaping scooter-trip origins. We find preliminary evidence to suggest that scooters are complementing public transit. Like other studies, we find that areas with younger and more educated demographics correlate with higher e-scooter use. Finally, we demonstrate that the model can identify segments with a high demand for scooter parking.

Keywords: Micromobility, electric scooters, street segment, public transit, travel demand, built environment

1. Introduction: Understanding Scooter Parking Needs through a Segment-Level Model

Shared electric scooters, first introduced in Santa Monica in 2017 by Bird, have become one of the fastest-growing shared mobility modes, taking their place alongside bikesharing and ride-hailing before them (DuPuis et al., 2019; Populus, 2018). Shared e-scooters have been grouped alongside bikeshare under the rubric of "micromobility," i.e., shared mobility systems with small vehicles intended for single-person use at moderate speeds, faster than walking but

 https://doi.org/10.1016/j.trd.2021.102709

slower than automobile travel (DuPuis et al., 2019; Shaheen and Cohen, 2019). With their convenience, low cost, and intermediate-range, many analysts see the potential for micromobility to address a gap in urban transportation systems for moderate length trips, approximately 0.5-4 km in length, in some cases replacing car trips (DuPuis et al., 2019; Schellong et al., 2019). The excitement in the private sector over the potential of this new mode has resulted in a large number of companies forming to provide e-scooter services and rapid investment in e-scooter companies, with dozens of startups entering the market and two companies quickly achieving billion-dollar valuations (Agora Verkehrswende, 2019; Schellong et al., 2019). Although city-dwellers have already swiftly adopted e-scooters, analysts believe that their potential to transform the transportation landscape is as yet untapped; they envision significant further growth of e-scooter use in cities facilitating sustainable transportation systems (Gössling, 2020; Schellong et al., 2019).

With the quick introduction and proliferation of electric scooters in cities across the globe, city officials have often been in a bind when considering how to regulate the unprecedented aspects of shared e-scooters, i.e., that users park e-scooters in the public right-of-way without designated docking locations. While at first cities struggled with oversight, several non-profit authorities have developed necessary background information and regulatory guidance regarding e-scooters (Agora Verkehrswende, 2019; NACTO, 2019a, 2019b). Cities have responded a wide variety of ways to the introduction of scooters, including: Outright bans, limitations on the number of scooters permitted, requiring fees on a per-scooter basis, and issuing regulations about legal locations for riding scooters, parking scooters, and permissible speeds (DuPuis et al., 2019; Fang et al., 2018; McGeehan, 2019; Shaheen and Cohen, 2019).

 https://doi.org/10.1016/j.trd.2021.102709

Parking is a critical spatial management issue – cities must identify proper parking locations, provide signage and other guidance to promote appropriate parking, and handle mis-parked vehicles (Agora Verkehrswende, 2019; Brown et al., 2020; NACTO, 2019a). Some recommended techniques for managing e-scooter parking include identifying corrals and designated parking areas through means such as painting bike corrals in the furniture zone of the sidewalk or by repurposing on-street vehicle parking spaces into e-scooter parking (Agora Verkehrswende, 2019; NACTO, 2019b). Cities may identify no-parking areas in specific locations either via signage or through guidance provided via the e-scooter app.

Trip generation and trip attraction models help cities comprehend where the demand for scooters clusters in their city and therefore help cities plan their parking regulations (Capsi et al., 2020; Espinoza et al., 2020; McKenzie, 2019; Zuniga-Garcia and Machemehl, 2020). In particular, trip attraction models, i.e., models of destinations, can inform scooter parking regulations.

This paper breaks new ground regarding spatial patterns of scooter demand in two ways. Firstly, our unit of analysis is the street segment, rather than the traffic analysis zone or similar zone adopted by previous studies (Arnell et al., 2020; Bai and Jiao, 2020; Capsi et al., 2020; McKenzie, 2020; Zuniga-Garcia and Machemehl, 2020). Research at the street segment level provides a more useful policy development tool because cities implement scooter parking regulations on such segments. Besides, this finer unit of analysis may allow for a more precise analysis of the underlying factors of scooter travel demand. Every scooter trip begins and ends on a particular street segment. Zonal analyses aggregate many street segments together and may blur the effect of spatial variables on travel demand. Secondly, we motivate our study by

 https://doi.org/10.1016/j.trd.2021.102709

building upon the derived theory of travel demand, which suggests that destinations should drive scooter travel patterns. We examine such destinations as buildings, parks, and transit stops. Focusing on meaningful destinations is the best way to identify the spatial drivers of travel demand for scooters while also not double-counting potential destinations.

In the following sections, we review existing travel behavior studies of shared scooters, focusing on those that examine either trip origins, trip destinations, or trip purpose. Then we describe our study area and the data on scooter origins and destinations. In the results section, we describe the degree to which various demographic and built environment variables predict scooter trips and examine how well our model predicts street segments with high levels of scooter demand. Then we discuss possible interpretations of the results, limitations, and implications for planning for the spatial management of shared scooters.

2. Literature Review:

2.1 Shared E-Scooters and Regulatory Challenges

The rapid emergence of this new mode without adequate regulatory apparatus or infrastructure in many cases has resulted in public concerns and policy challenges. One problem is crashes and safety, as several fatalities have been documented among scooter-share riders (Greenfield, 2019). Safety for scooters is especially challenging because although cities may require helmets and although scooter companies themselves restrict the use of scooters to adults, determined riders can easily circumvent such regulations (DuPuis et al., 2019; Shaheen and Cohen, 2019). Furthermore, media organizations have noted cases of using electric scooters while under the influence of alcohol. Another hotly debated issue is whether shared scooters promote sustainability and decrease congestion (DuPuis et al., 2019; Shaheen and

 https://doi.org/10.1016/j.trd.2021.102709

Cohen, 2019). If scooters reduce vehicle use and encourage public transit, they could lead to a more sustainable transportation system overall. Also, electric scooters' energy use is relatively small compared to other vehicular modes (Agora Verkehrswende, 2019). A third major issue is curb space management. Critics commonly object to scooters for at least two different reasons. Firstly, when riders use e-scooters on public sidewalks, they may pose a hazard to pedestrians (Agora Verkehrswende, 2019; Shaheen and Cohen, 2019). Secondly, when scooters are parked improperly, they can pose an obstacle to those walking or using wheelchairs to navigate pedestrian space (Agora Verkehrswende, 2019; Gössling, 2020; NACTO, 2019a).

The quick spread and adoption of shared e-scooters as a transportation mode in cities has led to a regulatory challenge for civic authorities, as discussed above. Regulations can be categorized roughly as non-spatial and spatial. Non-spatial regulatory concerns include permitting, insurance, scooter caps, vehicle requirements, rider requirements, app requirements, pricing regulation, marketing, and public education, helmet laws, equipment maintenance, safety regulations such as speed limitations, and data sharing (Agora Verkehrswende, 2019; NACTO, 2019a). Spatial regulations concern the proper location for riding and parking scooters and the provision of appropriate infrastructure. The spatial management of shared e-scooters is more difficult because most cities have little infrastructure dedicated to micromobility. On the other hand, the wealth of real-time information on scooters from APIs facilitates regulatory oversight. Besides proper places for riding and parking, the geographic balance of available scooter locations is also a concern. Several cities have identified disadvantaged areas and require companies to offer a minimum supply of scooters in these areas for equity purposes (Arnell et al., 2020; Clewlow et al., 2018; Smith and Schwieterman,

 https://doi.org/10.1016/j.trd.2021.102709

2020a). Other cities may want to discourage an oversupply of scooters in congested central areas (Agora Verkehrswende, 2019). Finally, cities may wish to know about spatial patterns of demand to supply better infrastructure for this burgeoning mode. In particular, if cities see e-scooters and micromobility as part of a first-mile, last-mile solution connecting people to significant destinations through a combination of transit and micromobility, improved micromobility infrastructure takes on a heightened priority (DuPuis et al., 2019; Fang et al., 2018; Shaheen and Cohen, 2019).

2.2 Travel Behavior of Scooter Users

The research community has taken to the advent of e-scooters with alacrity, likely because of the abundance of available location data. Unlike existing modes such as walking, biking, personal vehicle travel, and transit, the location of scooters is often accessible as public information every few minutes through Application Programming Interface (APIs), including the General Bikeshare Feed Specifications (GBFS) or the Mobility Data Specification (MDS) published by the Los Angeles DOT (2018). Researchers can sometimes use such data to derive trip origins and destinations with a high degree of precision. So a great deal of spatial and temporal data is available for transportation behavior analysis.

Thus far, researchers have examined diverse questions about e-scooter travel behavior such as utilization, trip distance, trip duration, spatial patterns, trip purposes, temporal patterns, mode substitution, and equity. Studies from several US cities shows that trips per vehicle per day ranges from about 4.0 in the most intensively used cities to as low as 1.0 trip per day in places with a low level of utilization. Inadequate rides per vehicle per day could undermine system profitability (Schellong et al., 2019). An analysis of scooter use in Indianapolis (Mathew et al.,

https://doi.org/10.1016/j.trd.2021.102709

2019) found an average utilization of 3.1 trips per day or 40 minutes per day (median). Trip lengths vary across studies. The interquartile range (IQR) for trip distances in Indianapolis was 0.6-2.2 km with IQR for travel time of 4.3-16 minutes (Mathew et al., 2019), while a different study in Washington DC found a shorter mean trip distance of 0.6 km and a mean trip length of just 5 minutes (McKenzie, 2019). Still, another study found a mean trip distance of 3 km in Chicago (Smith and Schwieterman, 2020b). Relatively few studies (Arnell et al., 2020; NACTO, 2019b) have examined the same data across multiple cities, leaving open the question of generalizability across contexts for many of these results. With scooter use being seasonal in cold weather climates, travel demand patterns may vary substantially across seasons (Younes et al., 2020).

In this study, we focus on trip origins and destinations, which are linked to the related topic of trip purpose. Concerning trip purposes, survey respondents from pooled, multi-city data identify commuting, connecting to transit, social, and recreational trip purposes as equally common trip purposes (NACTO, 2019b). Espinoza et al. (2019) examined detailed point of interest (POI) data in Atlanta to identify likely trip origins and destinations. They disaggregated trip purposes into ten land use categories. They identified the top trip purposes (destinations) as business, parking, food, and recreation, with business-to-business and parking-to-business being the most common OD pairings. McKenzie's (2019) analysis of trip patterns in Washington DC observed that riders were most likely to employ e-scooters for social, recreational, and tourism trips, with a majority of trips starting in non-residential areas. McKenzie found that the most common land-use destination types were public/recreational (28.2%), followed by commercial (19.5%). Capsi, Noland, and Smart (2020) found that, in Austin, many land uses,

 https://doi.org/10.1016/j.trd.2021.102709

including residential, commercial, and recreational, were correlated with both trip origin and trip destinations, as were the presence of bus stops. By contrast, Zuniga-Garcia and Machemehl (2020) suggested that various transit service availability indicators did not predict spatial patterns of trips in Austin.

3. Materials and Methods: Trip Origins, Trip Destinations, Built Environment, and Demographic Variables

3.1 Scooters in Washington DC

We analyze Washington DC due to the availability of a wide range of open data, including built environment data, and the maturity of its shared mobility market. Washington DC has been a leader in micromobility since the launch of its bikeshare program in 2008. The city started permitting dockless bikeshare in 2017 and soon after started an electric shared scooter pilot in 2018 (DuPuis et al., 2019). When we gathered data for this study (2020), the following companies were permitted to operate up to 2,500 dockless vehicles in Washington DC: Bird, Bolt, Hellbiz, Lime, Jump, Lyft, Razor, Skip, and Spin. DDOT has a comprehensive set of terms and conditions that apply to shared dockless vendors (DDOT, 2020). These terms and conditions include parking regulations, vehicle distribution, speed controls, geofencing, customer payment options, performance-based fleet expansion criteria, data reporting requirements, insurance, and permitting fees. Geographical distribution criteria include not allowing vehicles on federal land, limiting the number of scooters in the central business district, providing a minimum of 20 vehicles in each ward during daylight hours, and providing at least 25% of vehicles in Equity Emphasis Areas (DDOT, 2020). Equity Emphasis Areas account for areas of concentrated low-

 https://doi.org/10.1016/j.trd.2021.102709

income or minority populations, including African-Americans, Asian-Americans, or Hispanic/Latinos (National Capital Region Transportation Planning Board, 2018).

We inferred scooter trip origins and destinations from the real-time scooter data, which is available through public APIs developed by each vendor.[1] We aggregate origins and destinations over the entire day and do not differentiate the time of arrival or departure. Following McKenzie (2019), we scrape the scooter status data every minute. We have been collecting the data in this way since February 2019. For this study, we use four weeks of data between June 17 – July 14, 2019; we select this period because it represents the month of highest use. From this period, we choose data for four weeks of weekdays, Monday-Thursday, for a total of 16 weekdays, and four Saturdays. The data standard that scooter companies use is called General Bikeshare Feed Specification (GBFS). GBFS data attributes include scooter ID, latitude and longitude of scooter location, and battery level. To protect users' privacy, only the data of "free vehicles" (scooters not in use) is available from the APIs. GBFS does not standardize how vendors report scooter IDs. Accordingly, vendors have adopted different scooter ID generating strategies: Helbiz, Razor, Skip, Spin, and Jump provide a consistent ID for the same scooter over time; Bird changes the ID for a vehicle only when users start a trip; and Lime and Lyft changes the IDs of all e-scooters every minute.[2]

We infer scooter trip origins and destinations by observing how the scooter ID field changes over time. For scooters with consistent IDs, their disappearance from the scraped GBFS data indicates the start of a trip (i.e., trip origin), and their reappearance into the GBFS data suggests

[1] These APIs and related documentation can be found at https://ddot.dc.gov/page/dockless-api.
[2] Note that companies may change how they report scooter IDs over time (usually from reporting consistent IDs for the same scooter to dynamic ones), possibly due privacy complaints.

 https://doi.org/10.1016/j.trd.2021.102709

the end of a trip (i.e., trip destinations). For scooters with IDs that change after each use, the first appearance of a scooter ID is a trip destination, and the last is a trip origin. Finally, we aggregate the trip origins and destinations to streets via spatial joins to the nearest segment.

3.2 Variables predicting scooter demand at the street segment level

Based on the principles of derived demand to scooter origins and destinations, we seek to identify the influence of built environment variables. Trips can start or find their destination at buildings, transit stops, parks, or major attractions. Washington DC tracks building square feet for commercial buildings, residential buildings, and condominium buildings (Data source: https://opendata.dc.gov/); they also provide street data at the segment level. We spatially join and aggregate building square feet for each of these three categories to all street segments within 30 meters. Likewise, we spatially join and aggregate total acres of city parks and National Parks to street segments within 100 meters; the higher buffer is because parks are sometimes set back a distance from streets. GTFS provides locations of metro stops, bus stops, streetcar stops, and circulator stops. We count the number of each of these types of stops along each street segment. We likewise count the number of hotels and the number of prominent tourist attractions along each street segment. We obtain hotel location data from the DC Open Data Portal. We identify significant attractions from the top 30 Washington DC attractions listed on Trip Advisor (See Appendix A – Top Attractions in Washington DC).

We gather demographic data at the census tract level from American Community Survey 2014-2018 5-year estimates, including population density, percent of residents holding bachelor's degrees, median age, percent white, median household income, percent of households in poverty, and percent household car ownership. We then convert the census-tract-level data to

 https://doi.org/10.1016/j.trd.2021.102709

the street segments level, accounting for the fact that a street segment may intersect with several census tracts. If the street segment intersects several census tracts, we take the average value across these tracts.

We also control for several variables that are not related to trip attractions or demographics. We account for street segment length (logged) because longer segments are more likely to be origins and destinations than shorter ones, all other factors held equally. We control for distance from each segment to the start-of-day scooter centroid to account for the effects of pre-existing scooter locations. Most scooter trips in the sample are relatively short (most are 3 kilometers or less). Therefore, where scooters are at the start of the day influences which destinations are visited.

We also create a supply variable to help predict scooter trip origins. Unlike destinations, scooter trip origins can only start from a segment if a scooter is already present. Therefore, we calculate the total number of scooters available for each segment's average weekday or Saturday. The total number of scooters available is the sum of scooters available at the start of the day (at 6:00 AM) plus the total number of scooters whose trips end on that segment, divided by the number of sample days. We call this variable "scooter supply" or "supply." Also, street segments that never have a scooter available are removed from the analysis, resulting in smaller sample sizes for these analyses.

We remove limited access roadways where one could not reasonably begin or end a scooter trip. We also exclude some trips that we believed to be atypical, such as vehicle-charging trips or falsely inferred trips resulting from GPS tracking errors and vehicle relocations. Following Zou et al. (2020), we exclude trips if they meet the following criteria: distance is shorter than 0.02

 https://doi.org/10.1016/j.trd.2021.102709

mile or longer than ten miles, average travel speed is above 20 miles per hour, and duration is less than two minutes or longer than 90 minutes. After data cleaning was complete, 13,643 street segments are available for analysis for destinations. For Saturday origins, 5,098 street segments have at least one scooter present, and for weekday origins, 7,470 street segments have at least one scooter present. So only these segments are part of the analysis data set for trip origins.

As shown in Table 1, the non-count variables display a wide range of scales, necessitating the use of standardized variables. Most variables display a high coefficient of variation, as indicated by a high standard deviation relative to the mean. However, median age and car ownership show somewhat less contrast than the other variables. As can be seen in the descriptive statistics for count variables in Table 2, a large number of street segments have zero counts for these features, i.e., 99.5% of street segments do not have a metro stop, although 36.1% do have a bus stop, the most common count feature. The most active street segments on Saturday have as many as 734 scooter-trip destinations and 764 scooter-trip origins, and on weekdays have as many as 2,464 destinations and 2,595 origins over the four weeks.

 https://doi.org/10.1016/j.trd.2021.102709

Table 1: Descriptive Statistics for non-Count Variables

	Minimum	Mean	Standard Deviation	Maximum
Segment Length (Meters)	6	134	124	4,055
Distance to Centroid (Meters)	47	5,264	2,392	10,561
Park Acres	0.00	1.95	11.10	165.53
National Park Acres	0.00	37.34	211.64	2024.41
Commercial Building Square Feet	0	236,743	582,770	6,904,255
Condominium Building Square Feet	0	8,713	37,830	986,382
Residential Building Square Feet	0	23,107	24,815	266,977
Median Age	19.8	36.1	6.0	47.6
Median HH Income	$13,750	$97,226	$49,038	$250,001
Percent BAs	1%	58%	28%	100%
Percent HH Car Ownership	20%	72%	16%	100%
Percent White	0%	43%	32%	100%
Percent Poverty	0%	15%	11%	70%
Population Density (persons/acre)	24	13,647	10,012	64,909

Note: Data sources include Washington DC Open Data Portal ([Dataset] Washington DC, 2020), American Community Survey 2014-2018 5-year estimates ([Dataset] US Census Bureau, 2020), TripAdvisor.com. Sample size = 13,643.

Table 2: Descriptive Statistics for Count Variables

	Percent Zeros	Mean	Max
Saturday Destinations	65.1%	5.08	738
Saturday Origins	13.8%	13.62	764
Weekday Destinations	47.8%	21.33	2464
Weekday Origins	11.9%	39.02	2595
Saturday Supply	NA	24.42	1190
Weekday Supply	NA	77.45	5161
Attractions	98.8%	0.02	6
Hotels	93.6%	0.09	6
Metro Stops	99.5%	0.00	1
Bus Stops	63.9%	0.64	9
Streetcar Stops	99.9%	0.00	2
Circulator Stops	98.1%	0.03	3

Note: Data sources include GTFS, TripAdvisor.com, Washington DC Open Data Portal. Sample size = 13,643.

 https://doi.org/10.1016/j.trd.2021.102709

4. Calculation: The Hurdle Model

After data cleaning, there are a total of 13,643 street segments available for analysis. The number of segments with zero destinations is very high, with 65.1% having no scooter destinations on Saturday, for example. For this reason, we employ Hurdle models to estimate the number of trip origins and trip destinations for each segment. Except for count variables and segment length, we standardize all other variables for ease of coefficient comparison.

The Hurdle model is a combined model with the first part of the model predicting zeros or no trips and the second part predicting a positive count of trips. The first part of the model is a binomial model with a logit link, and the second part of the model is a truncated negative binomial model with a log link (Zeileis et al., 2008). The negative binomial model allows for overdispersion in the error variance, which is accounted for by a parameter theta. The model is fit by maximum likelihood methods. More formally,

$$f_{zeroinfl}(y; x, z, \beta, \gamma) = g_{zero}(0; z, \gamma)I(0) + \big(1 - g_{zero}(0; z, \gamma)\big)h_{count}(y; x, \beta)$$

Where $f_{zeroinfl}$ is the combined Hurdle function, $g_{zero}(\cdot)$ is the zero-hurdle model, $h_{count}(\cdot)$ is a truncated negative binomial function (left-truncated at y = 1), *x* and *z* are given independent variables, y is the given dependent variable, β and γ are estimated parameters.

For variable selection, we start with a model including all built environment variables. Then we subtract out variables one at a time using likelihood ratio tests with a threshold of $p = 0.05$. After removing unneeded built environment variables, we add in demographic variables one at a time. We include or exclude variables from both levels of the model at once. VIF tests show no significant multicollinearity among the built environment variables, but the demographic

 https://doi.org/10.1016/j.trd.2021.102709

variables are highly correlated. For this reason, we have only examined percent of adults with bachelor's degrees, percent of households with vehicles, population density, and median age among the demographic variables. The final models for each situation consider the following variables: Scooter supply variable (for trip origins models), distance to start-of-day vehicle centroid, log of street segment length, commercial building square feet, residential building square feet, condominium building square feet, park acreage, National Park acreage, count of attractions, count of metro stops, count of bus stops, count of streetcar stops, count of circulator stops, percent car ownership, median age, percent bachelor's degrees, and population density.

5. Results: Correlates of E-Scooter Trip Origins and Destinations

We present the detailed results for the four hurdle model results in **Appendix B – Hurdle Model Results**. For each model, the negative binomial count model comes before its corresponding zero-hurdle model. The tables display control variables first, then standardized built environment variables, then count built environment variables, and finally, standardized demographic variables. The tables show coefficients, standard errors, estimated Z-Scores, p-values for each independent variable. Note that positive values in both portions of the model correspond with higher scooter trip counts. If an independent variable shows different signs in the two levels of the model, whether it has a marginal positive or marginal negative effect depends on that variable's exact prior value.

Because the models have two parts, a zero-prediction model followed by a count model, interpreting the coefficients' effect is challenging. For this reason, we report the impact of a one-standard-deviation increase (or decrease, if the marginal effect is negative) for all non-

 https://doi.org/10.1016/j.trd.2021.102709

count variables and of a one-unit change for all count variables. For the count variables, a very high number of zeros results in a small standard deviation; therefore, reporting the effect of one standard deviation change underrepresents the significance of these features.

Table 3 shows the effect of a one-unit increase (or decrease, as appropriate) for each standardized variable.

For the two destinations models, the single variable with the most considerable effect in both the weekday and the Saturday models is distance from the start-of-day centroid. This suggests that the scooters are highly clustered in the central part of Washington DC. Since such scooters are predominantly used for shorter trips, they tend to remain centrally clustered throughout the day. Commercial and condominium square feet have small positive correlations with destinations per day, while residential square feet have a slight negative correlation for both weekdays and Saturdays. Median age, the percentage of bachelor degrees, and population density have slightly stronger relationships with weekday destinations and Saturday destinations than the built environment variables. Proportion of car owners is only significant in the Saturday destinations model and has a similar order of magnitude relationship with the built environment variables. The percentage of people with bachelor's degrees has a larger marginal effect on Saturdays than on Weekdays.

The origin models are quite different than the destinations models, though many of the significant variables remain the same. The scooter supply variable is the strongest predictor of trip origins, which is not surprising. Next is the distance to the start-of-day centroid, emphasizing the importance of central location in predicting trip origins. The built environment variables also have a statistically significant relationship with trip origins – commercial square

 https://doi.org/10.1016/j.trd.2021.102709

feet and condo square feet are positively correlated. In contrast, residential floor space, parks, and national parks are negatively correlated. However, all of these effects are smaller than in the corresponding trip destinations models. Likewise, for the demographic variables, median age, percentage of bachelor's degrees, and population density, each has a statistically significant but smaller effect in their relationship with scooter trip origins.

While each independent variable's effect is minor, their aggregate influences on trip demand can be considerable because of multiplicative effects. For instance, for weekday destinations, the predicted trips per segment can reach as high as 429 trips, whereas, on Saturdays, the predicted trips per day can reach 309.

Table 3: Effect of +1 Standard Deviation on Mean Trips

	Weekday Destinations	Saturday Destinations	Weekday Origins	Saturday Origins
Baseline	1.00	1.00	1.00	1.00
Supply	NA	NA	2.84	2.47
Saturday Distance to Centroid (-)	NA	3.31	NA	1.58
Weekday Distance Centroid (-)	3.59	NA	2.03	NA
Commercial SF	1.21	1.14	1.14	1.08
Condo SF	1.09	1.36	1.04	1.03
Residential SF (-)	1.18	1.31	1.17	1.20
Park Acres (-)	NA	NA	NA	1.05
National Park Acres (-)	NA	NA	1.05	NA
Median Age (-)	1.31	1.20	1.20	1.07
% BA Degrees	1.37	1.93	1.27	1.27
% Car Ownership (-)	NA	1.27	NA	NA
Population Density	1.33	1.33	1.07	1.04

NB. This table shows the expected number of daily trip origins and destinations for a street segment with a one standard deviation increase or decrease in the underlying independent variable. In the case the independent variable has a negative marginal effect, the effect of a one standard deviation decrease is shown. The baseline number of trips is normalized to 1.0 in all cases.

Table 4 illustrates the effect of a one-unit increase in tourist attractions, hotels, and transit stops of various sorts. Although these phenomena are present on relatively few street

 https://doi.org/10.1016/j.trd.2021.102709

segments, a unit increase in these built environment factors has a relatively sizable effect compared to the standard deviation increases in Table 3.

For the most part, the weekday and Saturday destination results are quite similar. The number of attractions and the number of metro stops show the largest marginal increases in scooter trip destinations. The marginal effect of attractions is larger on Saturdays than weekdays. Hotels, streetcar stops, and circulator stops all approximately double the number of expected scooter destinations, with the number of bus stops having a smaller effect.

The trip origin models are also similar between weekdays and Saturdays, but they are markedly different from the trip destination models. After accounting for scooter supply, metro stops do not have a statistically significant correlation with trip origins. Attractions drop out of the weekday origin model and have only a small relationship with Saturday trip origins. Hotels, circulator stops, and bus stops have weak, positive relationships with the count of scooter trip origins. Streetcar stops appear to have the largest effect on both weekday and Saturday trip origins.

Table 4: Effect of + 1 Unit on Mean Trips

	Weekday Destinations	Saturday Destinations	Weekday Origins	Saturday Origins
Baseline	1.00	1.00	1.00	1.00
Attractions	2.19	3.20	NA	1.13
Hotels	2.00	2.20	1.18	1.16
Metro Stops	2.70	3.32	NA	NA
Bus Stops	1.32	1.26	1.10	1.04
Streetcar Stops	2.14	1.78	1.51	1.34
Circulator Stops	1.99	1.98	1.36	1.25

NB. This table shows the expected number of daily trip origins and destinations for a street segment with a one-unit increase in the underlying independent variable. The baseline number of trips is normalized to 1.0 in all cases.

 https://doi.org/10.1016/j.trd.2021.102709

Table 5 illustrates the model's ability to predict the most utilized segments, i.e., approximately those in the top 5% of trip origins or trip destinations. The first column displays the number of street segments in the top 5% in terms of scooter visits; this number varies a bit because there are many ties. The second column indicates how many the model identifies correctly as being in the top 5%. As the third column shows, the correct prediction percentage ranges from 56.0-77.0%. This modest level of prediction accuracy may be due to missing variables or a lack of differentiation in the independent variables, i.e., treating all tourist attractions and commercial buildings as equivalent. Adding more variables into the model and adopting a machine-learning approach to predict scooter demand would likely improve predictive accuracy (Yan et al., 2020).

Table 5: Predictions for Highly Utilized Segments

	# of Segments in Top 5%	# in Predicted in Top 5%	Prediction Percentage
Saturday Destinations	668	374	56.0%
Saturday Origins	257	198	77.0%
Weekday Destinations	687	411	59.8%
Weekday Origins	373	280	75.1%

 https://doi.org/10.1016/j.trd.2021.102709

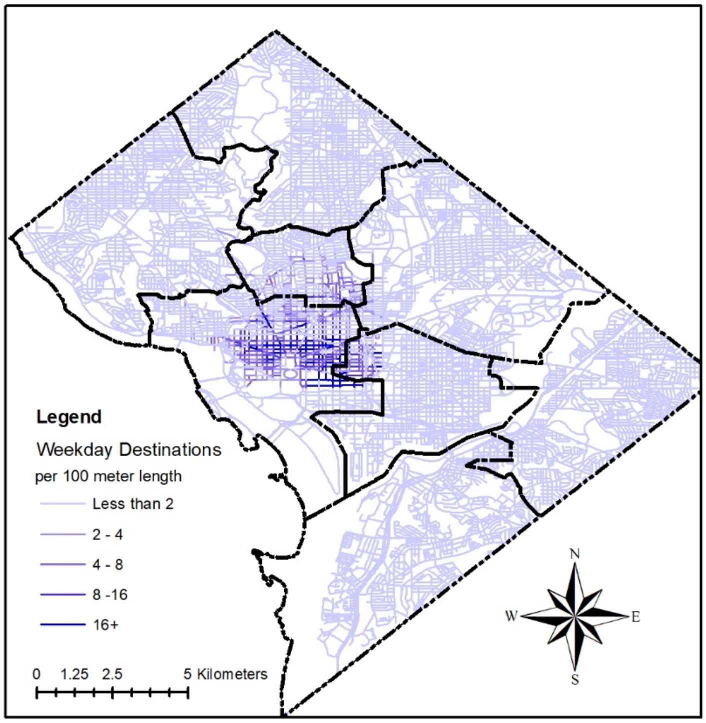

Figure 1: Predicted Destinations by Segment for Weekdays

Figure 1 illustrates the predictions for the weekday destinations model on a map of Washington DC wards. We present predicted trips on an average weekday per 100 meters of segment length. Normalizing by segment length allows a more direct comparison of attractiveness between long and shorter segments. The data is presented on a logarithmic scale because many street segments see almost no scooter arrivals, whereas others see a great deal. Practically all street segments on the outer wards have less than one expected trip per day per 100 meters. The areas of predicted high scooter traffic are almost all in the downtown area, near the Mall, the White House, and Congress. Some segments in Ward 1 immediately north of downtown also display higher-than-average scooter destinations.

 https://doi.org/10.1016/j.trd.2021.102709

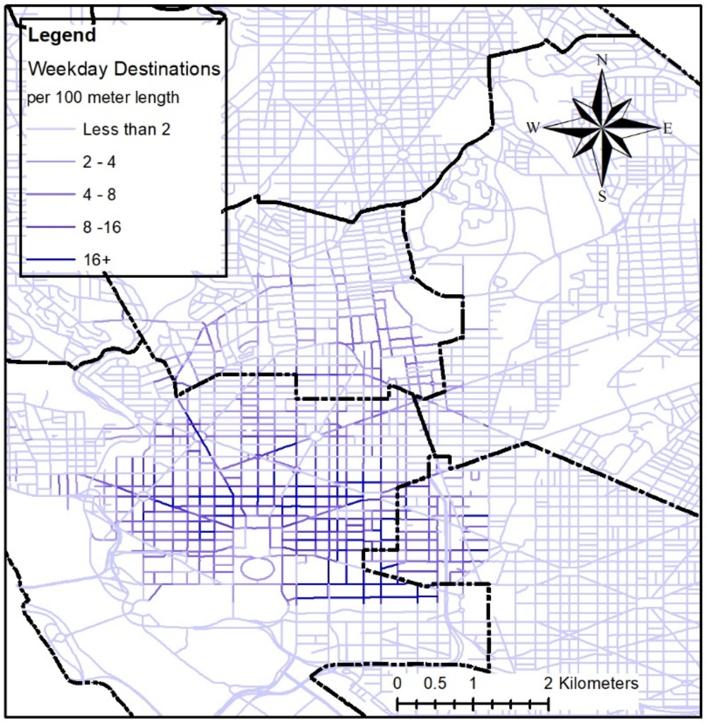

Figure 2: Predicted Destinations by Segment for Weekdays, Downtown Area

In Figure 2, we highlight the downtown and Mall area. Although streets with many forecast destinations are clustered in the downtown area, there is still a great deal of variation across street segments, with segments in each of the four frequency categories present within the downtown figure. The model can distinguish a high-demand segment nearby a low-demand one.

Figure 3 illustrates model residuals for the Saturday destinations model, again for the downtown area. In this figure, green lines indicate a residual smaller than one in absolute value; most segments are in this range, especially in the outer wards, so we focus the figure on the area of most considerable variation. The model overpredicts destinations in red and yellow segments and underpredicts destinations for dark and light blue segments. No distinct spatial

 https://doi.org/10.1016/j.trd.2021.102709

pattern emerges in this map, as the blue and red lines are often quite close. However, the variation in residuals is highest in areas with the highest scooter demand.

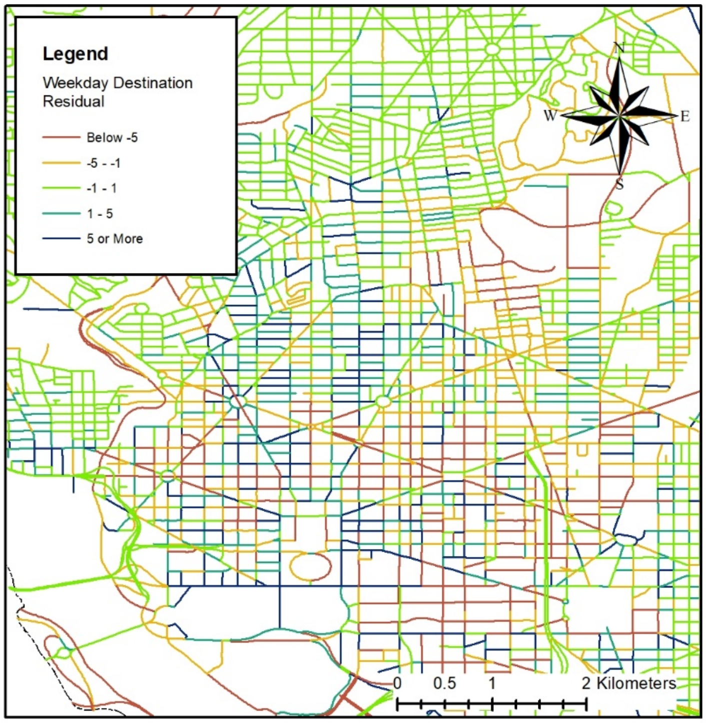

Figure 3: Residuals by Segment for Weekday Destinations, Downtown Area

6. Discussion: What Drives the Location E-Scooter Use?

The above results offer a clear picture of trip generation and trip attraction sources for shared e-scooter trips in Washington DC. Both built environment and demographic factors matter. Tourism appears to be a considerable driver in scooter use; tourist attractions, hotels, and metro stops are all predictive of higher destinations, with a larger effect on Saturdays than on weekdays. Unlike some previous studies (Espinoza et al., 2020; Zuniga-Garcia and Machemehl, 2020), we find a strong correlation between scooter use and the presence of all transit stops types. Metro stations, circulator stops, streetcar stops, and bus stops show a positive

 https://doi.org/10.1016/j.trd.2021.102709

association with scooter destinations at the segment level, even when accounting for many other built environment factors. The effect is much smaller concerning scooter trip origins but is still present for circulator stops, streetcar stops, and bus stops.

Taken alone, the correlations of scooter origins and destinations with transit stop locations are open to an ambiguous interpretation. Travelers could be using scooters for transit access or egress, or they could be using e-scooters to get to station areas, where destinations happen to concentrate. However, we believe the evidence is more persuasive that riders are using scooters for transit access and egress. By leveraging a derived-demand framework, we have attempted to control for the most common types of origins and destinations for scooter travel – residences, commercial areas, tourist stops, parks, and hotels. The fact that transit stops are still significant after controlling for these other destination types suggests that the stops themselves are likely attractor for scooter trip destinations.

Models for scooter trip origins and scooter trip destinations displayed markedly different results. Presumably, this is because only trip origins are constrained by the supply of available scooters. Unsurprisingly, the availability of scooters on a segment over a day is the best predictor of scooter trip origins. Most of the same demographic and built environment variables have relationships with trip origins as in the trip destinations models, except that metro stops drop out and that the effects are weaker.

There are no large contrasts between the weekday and Saturday results for both the destination models and the origin models. Centralized location is a powerful predictor in both sets of models. We think the importance of centralized location reflects both the concentration of destinations in the downtown and the start of day location of the scooters. Most scooters

 https://doi.org/10.1016/j.trd.2021.102709

are used for short trips, so if they start downtown, they tend to stay in the downtown area. Tourist attractions and metro stops show slightly stronger effects on Saturdays' destination counts, as does the percentage of population with bachelor's degrees.

Concerning built environment variables, those variables that correspond to a more intensive built environment have positive correlations with trip origins and destinations. In contrast, those variables that correspond to a less intensive built environment have negative correlations. Commercial square footage, condominium square footage, and population density all have positive correlations, whereas park acreage, National Park acreage, and non-condo residential have negative correlations with scooter trip origins and destinations. Though people may take scooters to parks on occasion, overall, the relationship between park acreage and scooter use is negative.

While we do not doubt that demographic factors play a role, we want to sound a note of caution – demographic data is derived from residential locations (at the census tract level). However, it is not necessarily local residents who are taking trips from or to a given area. If an out-of-town tourist uses a scooter in a location where the median age is 30, our analysis will not pick up on the user's actual age; it will just adopt the median age for the nearby census tract. Considering results from other studies, however, our study corroborates the evidence that shared mobility users tend to be younger and college educated (Clewlow and Mishra, 2017; Fishman, 2016; Rayle et al., 2016). Surprisingly, we found little relationship between auto ownership rates and scooter trip origins and destinations after controlling for other built environment variables.

 https://doi.org/10.1016/j.trd.2021.102709

Our results have implications in particular for planning for scooter parking and parking enforcement. Based on these results, logical locations for scooter corrals or other designated parking locations for large numbers of scooters might include nearby metro stops, streetcar stops, circulator stops, tourist attractions, and hotels. Notably, providing better parking facilities for e-scooters at transit stops is likely to encourage the greater combined use of e-scooters and public transit. Commercial areas are generally attractive for scooter traffic but apparently in a less concentrated way, meaning that perhaps scooter parking could be permitted to be scattered throughout commercial regions in niche locations. Likewise, the same places should be areas of focus for enforcement of scooter parking regulations.

The generalizability of these results is limited by their location and timing – Washington DC in July of 2019. Washington DC is a national and international tourist hub, and the role of tourist destinations and hotels as shared scooter origins and destinations may be more marked here than elsewhere. However, the tourist market is likely a sizable market segment for scooter riders in many other cities too. Also, there may be unaccounted spatial error effects due to omitted variables. We account for a wide range of built environment characteristics; however, we have not captured all factors in our analysis. For example, we have not controlled for the effect of nearby colleges and universities on scooter demand. Another drawback is that we could not use data from all scooter companies, as time-varying scooter IDs make it challenging to determine the precise location of their scooters' origins and destinations.

7. Conclusion: Learning from a Segment-Level Model

What drives spatial patterns of shared e-scooter use? Although there are several previous studies of e-scooter origins and destinations, we build the first segment-level model, which

 https://doi.org/10.1016/j.trd.2021.102709

allows for capturing built environment variables more precisely; in addition, segments are the unit of analysis cities must plan scooter parking policies and parking infrastructure. Another strength of this paper is that we have accounted for the supply of scooters at a given street segment in the trip origin models, which mitigates endogeneity concerns.

We build Hurdle models for trip origins and destinations using data for scooter use data from June-July 2019 in Washington, DC. This model choice accounts for the high number of segments with no scooter trips and the overdispersion in segment-level variance. The results indicate that the tourists are a significant part of the Washington DC scooter market, with tourist attractions and hotels explaining a considerable portion of scooter trip origins and destinations. Furthermore, we find that, after controlling for other types of destinations, public transit stops of all kinds – metro stops, bus stops, circulator stops, and streetcar stops - are predictive of scooter destinations and to a much lesser extent origins. Demographic variables, including younger median age and the percentage of adults with bachelor's degrees, were also significant, positive predictors of trip origins and trip destinations. Both trip origins and destinations are highly centralized in Washington DC and anchored to the scooters' start-of-day locations. Unlike destinations, trip origins are primarily predicted by the supply of scooters available on a given segment over the course of a day.

Our model has a moderate ability to identify segments with high levels of expected scooter demand, correctly identifying 56-60% of segments in the top 5% of usage in trip destinations. Therefore, transportation planners can use this model or similar ones customized for their city to identify street segments with a high demand for scooter parking, including to predict areas of redevelopment that will likely need the provision of scooter parking. We believe the

 https://doi.org/10.1016/j.trd.2021.102709

predictivity could be improved by the inclusion of additional predictors and machine-learning techniques.

Shared scooters are a rapidly emerging mode, and travel demand patterns for this mode may not have stabilized. As shared scooters become more ubiquitous and as equity programs become more widespread, the demographics that comprise the shared scooter market may expand. Although electric scooter use has declined during COVID, it could rebound rapidly, especially if travelers start to substitute scooters for transit on some shorter trips. Alternative shared mobility modes such as electric bicycles and mopeds could broaden the appeal of micromobility to different market segments. Understanding the demographics most likely to use shared mobility modes is expected to be a moving target for at least the next several years. Moreover, as we point out in the discussion, the models here cannot identify patterns of where scooters are in demand but are undersupplied. When no scooters are present in a location, no scooter trips are possible even if the potential demand for the service is high. This latent demand for e-scooter services is a crucial spatial consideration in need of further investigation.

Glossary

APIs – Application programming interfaces. An application programming interface (API) is a computing interface that defines interactions between multiple software intermediaries. It describes the kinds of calls or requests programs can make, how to make them, the data formats that should be used, from one program to another.

DOT – Department of Transportation

ID – A unique identifier for a scooter, possibly reset to a new ID upon scooter booking or end of the trip.

 https://doi.org/10.1016/j.trd.2021.102709

GBFS – A common data standard for sharing data on the location of micromobility devices.

Hurdle – Hurdle model. A model used to predict counts with a large number of zeros and overdispersion.

Micromobility – Small, shared vehicles serving one individual at a time such as shared bikes, shared electric bikes, and shared electric scooters.

Acknowledgments

We would like to thank the Washington DC District Department of Transportation and others at the Washington DC Open Data Portal for providing the data that supported this research.

References

[Dataset] US Census Bureau, 2020. American Community Survey, 2014—2018 ACS 5-Year Data Profile.

[Dataset] Washington DC, 2020. Open Data DC.

Agora Verkehrswende, 2019. Shared E-Scooters: Paving the Road Ahead. Policy Recommendations for Local Government (No. 29-2019- EN). Berlin.

Arnell, B., Noursalehi, P., Huntley, E., Zhao, J., 2020. Shared Electric Scooters and Transportation Equity: A Cross-City Analysis. Transp. Res. Board 99th Annu. Meet.

Bai, S., Jiao, J., 2020. Dockless E-scooter usage patterns and urban built environments: a comparison study of Austin, TX, and Minneapolis, MN. Travel Behav. Soc. 20, 264–272.

Brown, A., Klein, N.J., Thigpen, C., Williams, N., 2020. Parking Violations : The Frequency of Improper Scooter, Bike , and Car Parking, in: Transportation Research Board 99th Annual Meeting. Washington DC.

 https://doi.org/10.1016/j.trd.2021.102709

Capsi, O., Noland, R.B., Smart, MJ, 2020. Spatial associations in dockless shared e-scooter usage, in: Transportation Research Board 99th Annual Meeting.

Clewlow, R., Foti, F., Shepard-Ohta, T., 2018. Measuring Equitable Access to New Mobility: A Case Study of Shared Bikes and Electric Scooters.

Clewlow, R.R., Mishra, G.S., 2017. Disruptive transportation: The adoption, utilization, and impacts of ride-hailing in the United States (No. UCD-ITS-RR-17-07). Davis, CA.

DDOT, 2020. Shared Dockless Terms and Conditions.

DuPuis, N., Griess, J., Klein, C., 2019. Micromobility in Cities. A History and Policy Overview. Natl. Leag. Cities 1–30.

Espinoza, W., Howard, M., Lane, J., Van Hentenryck, P., 2020. Shared E-Scooters: Business, Pleasure, or Transit, in: Transportation Research Board 99th Annual Meeting. Washington DC.

Espinoza, W., Howard, M., Lane, J., Van Hentenryck, P., 2019. Shared E-scooters: Business, Pleasure, or Transit? 1–16.

Fang, K., Agrawal, A.W., Hooper, A., 2018. Electric Kick Scooters on Sidewalks in Virginia but Not in California ? A Review of How States Regulate Personal Transportation Devices 1–6.

Fishman, E., 2016. Bikeshare: A Review of Recent Literature. Transp. Rev. 36, 92–113. https://doi.org/10.1080/01441647.2015.1033036

Gössling, S., 2020. Integrating e-scooters in urban transportation : Problems , policies , and the prospect of system change 79.

Greenfield, J., 2019. Not-so-easy riders. ChiciagoReader.com 5.

LA DOT, 2018. Mobility Data Specification.

Mathew, J.K., Liu, M., Seeder, S., Li, H., Bullock, D.M., 2019. Analysis of E-Scooter Trips and Their Temporal Usage Patterns. ITE J. 44–49.

McGeehan, P., 2019. Riding While Drunk and Other Dangers of the Electric Scooter Craze. New York Times.

McKenzie, G., 2020. Urban mobility in the sharing economy: A spatiotemporal comparison of shared mobility services. Comput. Environ. Urban Syst. 79, 101418. https://doi.org/10.1016/j.compenvurbsys.2019.101418

McKenzie, G., 2019. Spatiotemporal comparative analysis of scooter-share and bike-share usage patterns in Washington, DC. J. Transp. Geogr. 78, 19–28. https://doi.org/10.1016/j.jtrangeo.2019.05.007

NACTO, 2019a. Guidelines for Regulating Shared Micromobility 56.

NACTO, 2019b. Shared Micromobility in the US: 2018. New York, NY.

National Capital Region Transportation Planning Board, 2018. Methodology for Equity Emphasis Areas.

Populus, 2018. The micro-mobility revolution: The introduction and adoption of electric scooters in the United States.

Rayle, L., Dai, D., Chan, N., Cervero, R., Shaheen, S., 2016. Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. Transp. Policy 45, 168–178. https://doi.org/10.1016/j.tranpol.2015.10.004

Schellong, D., Sadek, P., Schaetzberger, C., Barrack, T., 2019. The promise and the pitfalls of e-scooter sharing.

Shaheen, S.A., Cohen, A.P., 2019. Shared Micromoblity Policy Toolkit: Docked and Dockless Bike and Scooter Sharing. https://doi.org/10.7922/G2TH8JW7

Smith, C.S., Schwieterman, J.P., 2020a. Context-Sensitive Approaches for Evaluating the Potential Benefits and Performanceof Micro-Mobility. Transp. Res. Board 99th Annu. Meet.

Smith, C.S., Schwieterman, J.P., 2020b. Context-Sensitive Approaches for Evaluating the Potential Benefits and Performanceof Micro-Mobility, in: Transportation Research Board 99th Annual Meeting.

Yan, X., Liu, X., Zhao, X., 2020. Using machine learning for direct demand modeling of ridesourcing services in Chicago. J. Transp. Geogr. 83, 102661. https://doi.org/https://doi.org/10.1016/j.jtrangeo.2020.102661

Younes, H., Zou, Z., Wu, J., Baiocchi, G., 2020. Comparing the Temporal Determinants of Dockless Scooter-share and Station-based Bike-share in Washington, D.C. Transp. Res. Part A Policy Pract. 134, 308–320. https://doi.org/10.1016/j.tra.2020.02.021

Zeileis, A., Kleiber, C., Jackman, S., 2008. Regression models for count data in R. J. Stat. Softw. 27, 1–25. https://doi.org/10.18637/jss.v027.i08

Zou, Z., Younes, H., Erdogan, S., Wu, J., 2020. Exploratory Analysis of Real-Time E-Scooter Trip Data in Washington, DC. Transp. Res. Rec. https://doi.org/10.1177/0361198120919760

Zuniga-Garcia, N., Machemehl, R.B., 2020. Dockless Electric Scooters and Transit Use in an Urban/University Environment, in: Transportation Research Board 99th Annual Meeting.

Appendix A – Top Attractions in Washington DC

Table A.1: Top 30 Washington DC Attractions according to TripAdvisor

Rank	Attraction Name
1	Smithsonian National Museum of Natural History
2	US Capitol
3	National Museum of African American History and Culture
4	Lincoln Memorial
5	National Gallery of Art
5	National Gallery of Art
6	United States Holocaust Memorial Museum
7	Library of Congress
8	National Air and Space Museum
9	Vietnam Veterans Memorial
10	Newseum
11	National Mall
12	Korean War Veterans Memorial
13	National Portrait Gallery
14	Washington Monument
15	Museum of the Bible
16	Georgetown
17	Ford's Theatre
18	National World War II Memorial
19	The National Archives Museum
20	United States Botanic Garden
21	Washington National Cathedral
22	Capitol Hill
23	Jefferson Memorial
24	Tidal Basin
25	Hillwood Estate, Museum & Gardens
26	Martin Luther King, Jr. Memorial
27	White House
28	Smithsonian American Art Museum
29	National Museum of American History
30	Basilica of the National Shrine of the Immaculate Conception

Source: Tripadvisor, https://www.tripadvisor.com/, 2020.

https://doi.org/10.1016/j.trd.2021.102709

Appendix B – Hurdle Model Results

Table B.1: Saturday Destinations Hurdle Model

	Coefficient	Std. Err.	Z-Value	p-value
(Intercept)	-4.68	0.24	-19.65	0.000
log(SegLength)	1.06	0.05	22.20	0.000
SatMedCenStd	-0.82	0.04	-20.42	0.000
Comm_Std	0.09	0.02	4.38	0.000
Condo_Std	-0.02	0.02	-1.07	0.285
Resid_Std	-0.31	0.02	-17.24	0.000
AttractionCount	0.54	0.06	8.47	0.000
MetroCount	0.65	0.20	3.28	0.001
BusCount	0.15	0.02	7.67	0.000
StreetCarCount	0.44	0.20	2.23	0.026
CirculatorCount	0.53	0.08	6.68	0.000
HotelCount	0.26	0.04	6.39	0.000
PctBachStd	0.33	0.04	9.01	0.000
PctCarStd	-0.10	0.03	-3.31	0.001
MedAgeStd	-0.11	0.03	-3.51	0.000
PopDenStd	-0.03	0.02	-1.21	0.225
Log(theta)	-0.87	0.06	-15.41	0.000

	Coefficient	Std. Err.	Z-Value	p-value
(Intercept)	-5.83	0.23	-25.68	0.000
log(SegLength)	0.98	0.05	20.77	0.000
SatMedCenStd	-1.29	0.04	-32.89	0.000
Comm_Std	0.13	0.04	3.67	0.000
Condo_Std	0.12	0.03	4.38	0.000
Resid_Std	-0.04	0.03	-1.41	0.157
AttractionCount	1.53	0.38	3.99	0.000
MetroCount	1.30	0.47	2.74	0.006
BusCount	0.24	0.03	9.54	0.000
StreetCarCount	0.77	0.54	1.43	0.152
CirculatorCount	0.71	0.16	4.48	0.000
HotelCount	0.77	0.12	6.32	0.000
PctBachStd	0.72	0.04	19.57	0.000
PctCarStd	-0.28	0.04	-6.72	0.000
MedAgeStd	-0.20	0.03	-6.81	0.000
PopDenStd	0.35	0.03	10.14	0.000

 https://doi.org/10.1016/j.trd.2021.102709

Table B.2: Weekday Destinations Hurdle Model

	Coefficient	Std. Err.	Z-Value	p-value
(Intercept)	-3.57	0.18	-20.38	0.000
log(SegLength)	1.08	0.04	29.82	0.000
WkdyMedCenStd	-1.05	0.03	-38.90	0.000
Comm_Std	0.15	0.02	8.18	0.000
Condo_Std	0.02	0.02	1.28	0.201
Resid_Std	-0.28	0.01	-19.15	0.000
AttractionCount	0.38	0.06	6.89	0.000
HotelCount	0.33	0.04	9.00	0.000
MetroCount	0.90	0.18	5.04	0.000
BusCount	0.20	0.02	12.50	0.000
StreetCarCount	0.51	0.18	2.88	0.004
CirculatorCount	0.47	0.07	6.88	0.000
MedAgeStd	-0.25	0.02	-11.18	0.000
PctBachStd	0.16	0.02	7.25	0.000
PopDenStd	0.05	0.02	2.61	0.009
Log(theta)	-0.68	0.03	-21.00	0.000

	Coefficient	Std. Err.	Z-Value	p-value
(Intercept)	-4.04	0.20	-19.99	0.000
log(SegLength)	0.89	0.04	20.55	0.000
WkdyMedCenStd	-1.31	0.03	-37.78	0.000
Comm_Std	0.16	0.04	4.39	0.000
Condo_Std	0.17	0.04	4.81	0.000
Resid_Std	0.15	0.03	5.09	0.000
AttractionCount	2.07	0.88	2.35	0.019
HotelCount	1.65	0.23	7.23	0.000
MetroCount	0.63	0.55	1.13	0.258
BusCount	0.30	0.02	11.95	0.000
StreetCarCount	1.08	1.00	1.08	0.280
CirculatorCount	0.92	0.23	4.01	0.000
MedAgeStd	-0.17	0.02	-7.00	0.000
PctBachStd	0.49	0.03	18.57	0.000
PopDenStd	0.74	0.04	18.77	0.000

https://doi.org/10.1016/j.trd.2021.102709

Table B.3: Saturday Origins Hurdle Model

	Coefficient	Std. Err.	Z-Value
(Intercept)	-0.53	0.17	-3.19
Supply_Std	0.94	0.03	32.77
log(SegLength)	0.44	0.03	13.15
SatMedCenStd	-0.49	0.02	-21.00
Comm_Std	0.08	0.02	4.29
Condo_Std	0.03	0.02	1.73
Resid_Std	-0.20	0.02	-12.42
Parks_Std	-0.06	0.02	-2.86
AttractionCount	0.10	0.04	2.80
HotelCount	0.15	0.03	6.06
BusCount	0.04	0.01	2.81
CirculatorCount	0.25	0.05	5.31
StreetCarCount	0.28	0.13	2.22
MedAgeStd	-0.07	0.02	-4.10
PctBachStd	0.26	0.02	13.55
PopDenStd	0.03	0.02	2.01
Log(theta)	0.26	0.04	6.79

	Coefficient	Std. Err.	Z-Value
(Intercept)	0.56	0.47	1.19
Supply_Std	2.81	0.31	8.99
log(SegLength)	0.48	0.09	5.13
SatMedCenStd	-0.65	0.06	-11.67
Comm_Std	0.32	0.12	2.71
Condo_Std	0.06	0.07	0.96
Resid_Std	-0.06	0.06	-1.09
Parks_Std	-0.06	0.03	-1.77
AttractionCount	0.95	0.78	1.21
HotelCount	0.28	0.18	1.57
BusCount	0.15	0.05	3.07
CirculatorCount	0.17	0.28	0.59
StreetCarCount	8.18	351.20	0.02
MedAgeStd	-0.14	0.05	-2.87
PctBachStd	0.32	0.04	7.32
PopDenStd	0.23	0.07	3.35

 https://doi.org/10.1016/j.trd.2021.102709

Table B.4: Weekday Origins Hurdle Model

	Coefficient	Std. Err.	Z-Value	p-value
(Intercept)	-0.06	0.14	-0.42	0.676
Supply_Std	1.09	0.03	37.26	0.000
log(SegLength)	0.51	0.03	18.14	0.000
WkdyMedCenStd	-0.69	0.02	-35.22	0.000
Comm_Std	0.10	0.02	6.73	0.000
Condo_Std	0.03	0.01	2.56	0.010
Resid_Std	-0.17	0.01	-12.21	0.000
NParks_Std	-0.04	0.01	-2.71	0.007
HotelCount	0.12	0.03	4.88	0.000
BusCount	0.09	0.01	7.48	0.000
StreetCarCount	0.32	0.13	2.54	0.011
CirculatorCount	0.26	0.05	5.62	0.000
MedAgeStd	-0.18	0.01	-11.99	0.000
PctBachStd	0.22	0.02	14.35	0.000
PopDenStd	0.04	0.01	2.90	0.004
Log(theta)	0.09	0.03	3.49	0.000

	Coefficient	Std. Err.	Z-Value	p-value
(Intercept)	-0.17	0.39	-0.43	0.668
Supply	0.03	0.00	10.25	0.000
log(SegLength)	0.47	0.08	5.58	0.000
WkdyMedCenStd	-0.77	0.05	-14.27	0.000
Comm_Std	0.44	0.14	3.11	0.002
Condo_Std	0.08	0.07	1.18	0.239
Resid_Std	-0.05	0.06	-0.89	0.375
NParks_Std	-0.13	0.03	-4.07	0.000
HotelCount	0.68	0.31	2.19	0.029
BusCount	0.12	0.04	2.88	0.004
StreetCarCount	9.87	303.86	0.03	0.974
CirculatorCount	0.86	0.53	1.65	0.100
MedAgeStd	-0.19	0.04	-4.19	0.000
PctBachStd	0.33	0.04	7.97	0.000
PopDenStd	0.34	0.07	4.61	0.000

 https://doi.org/10.1016/j.trd.2021.102709