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Factors Influencing the Usage of Shared E-scooters : A Case Study of Chicago

Farzana Mehzabin Tuli
University of Arkansas, Fayetteville

Factors Influencing the Usage of Shared E-scooters : A Case Study of Chicago

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Farzana Mehzabin Tuli
Bangladesh University of Engineering and Technology
Bachelor of Civil Engineering, 2016

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University of Arkansas

This thesis is approved for recommendation to the Graduate Council.

_____
Suman Mitra, Ph.D.
Thesis Director

_____   _____
Sarah Hernandez, Ph.D.   Andrew Braham, Ph.D.
Committee Member   Committee Member

ABSTRACT

The rapid popularity growth of shared e-scooters creates the necessity of understanding the determinants of shared e-scooter usage. This thesis estimates the impacts of temporal variables (weather data, weekday/weekend, and gasoline prices) and time-invariant variables (socio-demographic, built environment, and neighborhood characteristics) on the shared e-scooter demand by using four months (June 2019- October 2019) period of data from the shared e-scooter pilot program in Chicago. The study employs a random-effects negative binomial (RENB) model that effectively models shared e-scooter trip origin and destination count data with over-dispersion while capturing serial autocorrelation in the data. Results of temporal variables indicate that shared e-scooter demand is higher on days when the average temperature is higher, wind speed is lower, there is less precipitation (rain), weekly gasoline prices are higher, and during the weekend. Results related to time-invariant variables indicate that densely populated areas with higher median income, mixed land use, more parks and open spaces, public bike-sharing stations, higher parking rates, and fewer crime rates generate a higher number of e-scooter trips. Moreover, census tracts with a higher number of zero-car households and workers commuting by public transit generate more shared e-scooter trips. On the other hand, results reveal mixed relationships between shared e-scooter demand and public transportation supply variables. This study's findings will help planners and policymakers make decisions and policies related to shared e-scooter services.

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Chapter 1. Introduction

Many cities in the USA and Europe are experiencing a rapid change in the mode of micromobility with the introduction of the shared e-scooters. In 2017, the shared e-scooter was first introduced as a new mode of micromobility in the United States. By the end of 2018, shared e-scooters overtook the place of station-based pedal bikes as the preferred vehicle by making two million more trips (NACTO, 2019). As a form of sustainable transportation, shared e-scooters have the potential to transform urban transportation systems by reducing traffic congestion and fuel use (Shaheen and Cohen, 2019). However, as shared e-scooters are relatively new to us, cities and transportation researchers are still at the early stage of discovering how these services play within cities and existing transport systems. So, policymakers and city planners are struggling to implement policies and regulations to harness and maximize the social and environmental benefits of these innovative transportation modes. To implement effective policies relating to shared e-scooter services, it is critical to understand the role of these services, their usage pattern, and factors related to shared e-scooter usage.

While emerging shared e-scooter studies have focused on the usage pattern of shared e-scooter services (e.g., see Noland, 2019; Mathew et al., 2019a; Mathew et al., 2019b; Younes et al., 2020; Jiao and Bai, 2020), additional data and research are needed to understand the various potential determinants of shared e-scooter usage. This thesis aims to fill this gap by analyzing the recently released shared e-scooter data in the Chicago region. The objective of this study is to determine the factors associated with the usage of shared e-scooters with a focus on the temporal variables (weather data, weekday/weekend, and gasoline prices) and time-invariant variables (socio-demographic, built environment, and neighborhood characteristics).

This study makes several novel contributions to the existing literature, including (i) analyzing a new publicly available data source (first to use data from outside of Austin, NYC, Atlanta, and Washington DC), (ii) using a different modeling approach to model shared e-scooter usage, (iii) incorporating new factors (e.g., parking price, commute mode share, multimodal network density, and crime records) into the shared e-scooter demand model specification, thus, (iv) uncovering new and important relationships between several key determinants and shared e-scooter demand. Understanding the relationship between e-scooter usage and built environment, transportation infrastructure, zonal socio-demographics, parking, crime, etc. can provide significant value to: i) transportation regulators and policymakers interested in policies related to pricing, parking, legislation and management, and incentives and/or disincentives for e-scooter in specific areas of a city; and ii) transportation planners tasked with making multimodal planning decisions. Moreover, this study employs a random-effects negative binomial (RENB) model to effectively model shared e-scooter trip count data with overdispersion while capturing serial autocorrelation in the data.

The thesis consists of five sections: following the introduction, a section of the literature review is built up describing previous studies related to the e-scooter usage pattern and bikesharing demand models. Then, the data and methodology of the study is presented in the third section. The fourth section explains the result of the RENB model. Finally, the paper concludes with a summary of key findings, policy implications, limitations, and directions for future research.

Chapter 2. Literature Review

This section discusses studies related to modeling e-scooter usage and the factors influencing e-scooter demand (Section 2.1). Section 2.2 reviews determinants of bikeshare demand.

2.1 Factors Influencing E-scooter Usage

While E-scooters are becoming an attractive mode of transportation in the urban environment

and researchers expect the growth of its usage in the coming years (Gössling, 2020), there are a

handful of studies on e-scooters. This is due, in part, to the relative infancy of e-scooter

platforms and available usage data. Existing literature evaluate the usage pattern and travel

behavior associated with this mode, mainly focusing on the temporal (e.g., Noland, 2019;

Mathew et al., 2019a; Mathew et al., 2019b), socio-demographic (e.g., Jiao and Bai, 2020; Reck

and Axhausen, 2021), and built-environment variables (e.g., Younes et al., 2020; Caspi et al.,

2020). There is also an increasing interest in the relationship between e-scooter usage and transit

(e.g., Espinoza et al., 2019; Laa and Leth, 2020; Nikiforiadis et al., 2021).

2.1.1 Temporal variables and e-scooter usage pattern

Noland (2019) applies an ordinary least square regression model to analyze the weather effects

on the usage of e-scooters in Kentucky. He finds that rain and snow reduce daily trips, while

higher wind speeds are responsible for lowering e-scooter trip distances. Using different data

(historical e-scooter hourly trip data from Indianapolis) and a different model (negative

binomial), Mathew et al. (2019a) also conclude that the amount of snowfall and rainfall, and

mean temperatures are important variables in modeling the hourly number of e-scooter trips.

Younes et al. (2020) compare the determinants of dock-less scooters-share (DSS), and station-

based bike-share (SBBS) rides in Washington D.C. by incorporating economic variables like

gasoline prices along with the weather variables. The study observes that the DSS users are more

sensitive to the changing of the gasoline prices while less sensitive to the weather factors than the

SBBS users. However, in their model specification, Younes et al. (2020) do not incorporate any

time-invariant variables (e.g., socio-demographic, built environment variables).

Using the same data set, McKenzie (2019) compares the spatial and temporal patterns of DSS and SBBS systems. The results indicate that bike-sharing services within Washington, D.C., are primarily used by individuals commuting to and from work. In contrast, dockless scooters are mainly used for leisure, recreation, and tourism activities. Mathew et al. (2019b) also find a low e-scooter usage for morning commuting to work in Indianapolis. Similarly, Bai and Jiao (2021) observe that e-scooter use has a significant correlation with daily dining, drinking, shopping, and recreational activities in Austin, Texas.

2.1.2 Socio-demographic Variables

Using the same data set from Austin, Jiao and Bai (2020) find that more higher education residents are associated with more E-scooter trips. Aguilera-García et al. (2020) apply an ordered logit model to analyze data from an online survey in different Spanish cities and find that the people who used bikeshare or car share before are more likely to be the user of shared e-scooter. Reck and Axhausen (2021) compare three shared micromobility user groups using multivariate probit models: shared dockless e-scooters, shard docked e-bikes, and dockless e-bikes. The result shows that e-scooter users are younger and lower-income people comparing to other shared micromobility modes. In Seoul, Korea, Lee et al. (2021) find that young people dissatisfied with the town bus are more willing to use e-scooters.

2.1.3 Built-environment Variables

Motivated by the importance of land use and the built environment on travel behavior (Ewing and Cervero,2010), researchers have made various attempts to analyze the built-environment and land-use factors associated with shared e-scooter usage. Analyzing the Austin data set, Caspi et al. (2020) explore the e-scooter sharing services to examine the impact of the built environment, land use, and demographic variables on the e-scooter trip generation. The spatial regression

model applied in the study finds that areas with high employment rates and bicycle infrastructure are associated with higher e-scooter usage. Bai and Jiao (2020) conduct further analysis to compare the e-scooter usage pattern between Austin, TX, and Minneapolis, MN. The study applies an NB model targeting five built environment elements (i.e., distance to the city center, transit accessibility, land use diversity, land use entropy, and dominant land use type). Both cities show that proximity to the city center, better transit accessibility, and complex land uses are positively related to e-scooter usage. Liu et al. (2020) analyze the e-scooter data of the City of Indianapolis across three different land-use regions: an urban mixed-use region, an institutional-oriented mixed-type region, and the downtown region. The result reveals that the downtown and institutional-oriented area produces the highest number of non-recreational trips. At the same time, the urban mixed-use region has the smallest proportion of non-recreational trips.

Hawa et al. (2020) use multi-level mixed-effects linear regression models to analyze data from Washington D.C. and find that population density, the density of places of interest (POI) are associated with higher e-scooter usage. Using the same data set, Zou et al. (2020) find that the arterials and local streets with large traffic movements to be popular with e-scooter users. Moreover, the study observes the streets having bike lane facilities attract more e-scooter trips. Similarly, by applying a multilevel negative binomial model to the e-scooter sharing data from five cities (Austin, Minneapolis, Kansas City, Louisville, and Portland), Huo et al. (2021) find a positive association between bicycle density and density of e-scooter trips. Hosseinzadeh et al. (2021a) apply the Geographical Weighted Regression method to examine the influence of built-environment factors on e-scooter trips in Louisville, Kentucky. The study shows that the percentage of commercial land use, public and semi-public land use, intersection density,

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average elevation, walk score, park score, and job proximity index positively impact the density of e-scooter trips.

2.1.4 E-scooter usage and transit

Transportation researchers, planners, policymakers, and transit agencies have considerable interest in the relationship between e-scooter services and transit, primarily because of its potential to solve the 'first- and last-mile" problem of public transportation. By analyzing data from Manhattan, New York, Lee et al. (2019) find that the e-scooter trips substitute trips from access trips to public transit. On the other hand, analyzing usage data of Bird e-scooters in the city of Atlanta, Espinoza et al. (2019) find that the use of e-scooters in connection with transit is small due to the relatively high additional cost. In Austin, Texas, Jiao and Bai (2020) find that increased e-scooter usage is associated with the presence of transit stations. Similarly, Hosseinzadeh et al. (2021b) also find a positive association between the e-scooter trip density and the transit Score in Louisville, Kentucky.

On the other hand, based on both an online survey and field observation in Vienna (Austria), Laa and Leth (2020) indicate that e-scooters replace walking, public transit, and private car trips. Nikiforiadis et al. (2021) reinforce their findings by conducting 578 questionnaires (271 by e-scooter users and 307 by non-users) in Thessaloniki, Greece. Their results show that shared e-scooters mostly replaced walking and public transport trips while people traveling by bicycle or motorcycle were not attracted by e-scooters. In addition, Mitra and Hess (2021) find that most walking and transit trips would be replaced by shared e-scooters in Toronto and surrounding municipalities in Canada. Besides, from a road survey organized in Paris, Christoforou et al. (2021) conclude that the users of free-floating electric scooters are moving towards e-scooters by replacing their walking and public transportation trips.

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2.1.5 Summary

Although only a few studies analyze the determinants of e-scooter demand, Table 1 can help identify similarities and differences in the existing studies. Table 1 provides a summary of studies in the literature that analyze e-scooter trip data. The temporal analysis of the studies shows that temperature and visibility are positively associated with e-scooter demand, while snow and rainfall show a negative association with e-scooter trips. Though Younes et al. (2020) find more e-scooter trips on weekends, Hawa et al. (2020) observe more e-scooter trips on a weekday.

From the socio-demographic perspective, studies reveal that young male people with lower income are mainly associated with e-scooter demand. Conversely, the study of Lee et al. (2021) in Seoul and analysis of Bai and Jiao (2020) in Minneapolis find that income is positively associated with the e-scooter demand. There is consistency in findings related to built-environment variables, which show that population density, land use mix, transportation facility, open space, and parks are positively associated with e-scooter usage. Only Bai and Jiao (2020) find a negative association between e-scooter usage and land use mix. On the other hand, increases in the distance to the city center and transit stations decrease the e-scooter demand. While the results from U.S. studies enhance the possibility of using e-scooters to solve the first-mile-last-mile problem, three European studies and one study from Canada find that e-scooter trips replace walking and transit trips.

Although existing studies mentioned above examine various parameters affecting e-scooter usage and patterns, less attention has been put toward incorporating socio-demographic, spatial, and temporal characteristics together. This study estimates the impacts of temporal variables (weather data, weekday/weekend, and gasoline price) and time-invariant variables

Table 1: Summaries of E-scooter Studies

Study	Location and Year	Modeling Approach	Dependent Variable	Spatial Scale	Weather	Socio-demographic	Built-environment	Transit	Travel Characteristics	Others
Noland (2019)	Louisville, Kentucky, 2018-2019	OLS	Daily trips/, Average daily distance	Metro area	-Rain -Snow -Wind speed					
Mathew et al. (2019a)	Indianapolis, 2018	Negative binomial regression	Hourly number of trips	Citywide	-Snow -Rain +Visibility -Gusts -Freeze below					
Younes et al. (2020)	Washington D.C., 2018-2019	Negative binomial regression	Hourly trip data	Citywide	+Temperature +Visibility +Humidity -Wind speed -Precipitation +Midday					+Gasoline price +weekend
Lee et al. (2019)	Portland, Austin, Chicago (Estimating model only)	Log-log regression analysis	Ln (total number of e-scooter trips)	Zip Code			+ln (population*age ratio) -ln (labor area)			+ln (e-scooter fleet size)
Jia and Bai (2020)	Austin (Texas) 2019	Negative binomial regression	Total number of trips	Census block group		+Gender (male) -Age -Income level +Education	+Population density -Distance to city center -Distance to transit +Land use mix +Open space and parks	+Transit facilities		

Table 1: Summary of E-Scooter Studies (Cont.)

Study	Location and Year	Modeling Approach	Dependent Variable	Spatial Scale	Weather	Socio-demographic	Built-environment	Transit	Travel Characteristics	Others
Hosseinzadeh et al. (2021a)	Louisville, KY 2018-2019	Geographically weighted regression	The density of e-scooter trip destinations	TAZ		+Age +Male	+ Density of intersections -Density of bike lanes +Walk score +Job proximity index			
Hosseinzadeh et al. (2021b)	Louisville, KY 2018-2020	Generalized additive model	The density of e-scooter trip destinations for peak time trips and all trips	TAZ		+ Age 18-29 years old (all trips) - Age 18-29 years old (peak time trips)	+Schools -Density of intersection -Density of local roads +Job proximity index +High employment zones +Walk score + Bike score	+ Transit score		
Hawa et al. (2020)	Washington D.C. 2019	Multi-level mixed effect linear regression models	Difference in the average number of e-scooters present by hour	Fishnets (0.07 miles^2)	+ Temperature -Rainfall	- Income	+Population density +CBD	+ Metro stations		+Weekday +Capital bikeshare stations +Bicycle lane
Aguilera-García, et al. (2020)	Different Spanish urban areas 2018	(Online survey) Ordered logit model	Frequency of use of scooter-sharing	Urban areas		+Age (26 to 34) -Income +Shared housing			+Ever driven a scooter/ moto or used car-share +Never using private car -Never travelling on foot +Bikesharing	

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Table 1: Summary of E-Scooter Studies (Cont.)

Study	Location and Year	Modeling Approach	Dependent Variable	Spatial Scale	Weather	Socio-demographic	Built-environment	Transit	Travel Characteristics	Others
Huo et al. (2021)	Austin (2018), Minneapolis (2018), Kansas City (2019), Louisville (2019), and Portland (2019)	Multilevel mixed-effects negative binomial model	The density of e-scooter trips in the CBG in the city	Census block group		+Median income -No vehicles -Median age	+Population density Employment density -Distance to city center +Road density +Intersection density +Land use mix School and university + Restaurant density	+Bus stop density	+Proportion of public transit riders	
Reck and Axhausen (2021)	Zurich, Switzerland (2020)	Univariate probit model and multivariate probit model	Shared dockless e-scooter usage (binary)	Zurich municipality		-Age -Female +Driver's license -Education -Employment +Income -No. of children -No. of adults			-Travel priority: environment -Travel priority: time -Travel priority: flexibility - # of cars	
This study	Chicago (2019)	Random-Effects Negative Binomial	Daily Trip Counts in Origin/ Destination	Census Tract	+Temperature -Rain -Wind speed	+Age (destination model) + Income	+ Population density +Land use mix **+Multi-modal network density** (Origin model) + Parks and open space	-Bus Stops (origin model) + Rail station (origin model)	+ # of zero car households **+ Transit to work**	+Gasoline price + Weekend +Bike station **+Parking cost** **-Crime records**

Notes: positive/negative signs mean the corresponding explanatory variable positivily/negatively affects e-scooter usage; in **bold** are the variables in this study that were not included in previous studies.

(socio-demographic, built environment, and neighborhood characteristics) on the shared e-scooter demand.

2.2 Factors Influencing Bikeshare Demand

Understanding the factors related to bikeshare demand is important as there are some similarities between these two systems. Given comparatively a more extended history of bikeshare programs in cities, particularly large cities, across the U.S. and in Europe, there is well-established literature related to bikeshare demand modeling that is relevant to the demand for e-scooter services (e.g., El-Assi et al., 2015; Tran et al., 2015; Faghih-Imani et al., 2017; Sun et al., 2017; Hyland et al., 2018; Shen et al., 2018). Researchers are motivated by the temporal, socio-demographic variables, built environment variables, and transit facilities to analyze the factors associated with bikeshare usage.

Studies on temporal analysis (Gebhart and Noland, 2014; Hyland et al., 2018; Shen et al. 2018; Wang et al., 2018; Kutela and Teng, 2019; and Scott and Ciuro, 2019) show that temperature is positively associated with bikeshare demand while high humidity, rainfall, and snow have negative impacts on bikeshare trips. On the other hand, Heaney et al. (2019) find that the increase of temperature above 26-28ºC (78-82º F) decreases the bikeshare usage. Moreover, the hourly studies (Faghih-Imani et al., 2017; Shen et al., 2018; and Noland et al., 2019) show the bike-share demand is high during midday and afternoon.

In terms of socio-demographic variables, studies (e.g., Lewis, 2011; Ursaki and Aultman-Hall, 2015; Fishman, 2016; Hosford and Winters, 2018) find a positive relationship between income and bikesharing demand. Using data from Washington D.C., Buck and Buehler (2012) observe that an area with a higher number of car-less households is associated with higher bike-sharing demand. On the contrary, Chen et al. (2020) find that having a car increases the usage of

dockless bikeshare. Besides, Fishman et al. (2015) find that having a personal bike increases the bikeshare usage while mandatory rules of wearing a helmet reduce the usage rate.

Population and employment density (Tran et al., 2015; Rixey, 2013; Lee and Noland, 2021) are found as positive built-environment factors to increase bike sharing demand. However, these relationships are not consistent across studies. For example, Noland et al. (2016) find that the employment density positively impacts bikeshare on weekdays while negatively affecting weekends. Moreover, a study in Singapore by Shen et al. (2018) shows that public residential density and industrial land use are negatively related to hourly bike trips.

Bicycle infrastructure always plays an important role in bikeshare usage. For example, bikesharing capacity (El-Assi et al., 2015; Tran et al., 2015; Jäppinen et al., 2013; Romanillos et al., 2018) and supply of bicycle lanes (Buck and Buehler, 2012; Buehler and Pucher, 2012; Noland et al., 2016; Wergin and Buehler, 2017) are found to be critical factors that positively increase the demand of bikeshare. The numbers of roadway intersections are also vital components for determining bikeshare usage. Though Fishman et al. (2015) find the number of intersections is negatively associated with the bikeshare demand, other studies find a positive relationship with bikeshare demand (Buck and Buehler, 2012; Noland et al., 2016).

Literature reveals mixed relationships between public transit and bikeshare demand. Previous studies find the proximity of bikeshare stations to any transit stations as a positive factor to increase the bikeshare demand (Buck and Buehler,2012; Noland et al., 2016; El-Assi et al., 2015; and Shen et al., 2018). Tran et al. (2015) specifically indicate nearness to railway stations increase the biking demand of a bikeshare station. In contrast, Sun et al. (2017) claim that the hourly metro frequency rate reduces bikeshare usage. Faghih-Imani et al. (2017) conclude that the relationship between subway and path train stations with the bikeshare demand

depends on the types of users. For annual members, subway and path train stations are positively related to the bikeshare demand, while these variables negatively impact daily customer's bikesharing demand.

Fishman et al. (2015) emphasize the neighborhood characteristics of a bikeshare station as an important factor in determining the bikeshare demand. The study finds that docking stations near the grocery stores and within 250m of a workplace increase bikeshare demand. Faghih-Imani et al. (2017) observe that the number of restaurants is positively related to the bikeshare demand of annual members, which is opposite for the daily customers of bikeshare. Besides, the crime rate of an area is negatively associated with the bikeshare demand. (Sun et al., 2017; Hyland et al., 2018)

The review of existing e-scooter and bikeshare literature reveals some similarities and differences between factors influencing bikeshare and e-scooter usage. For example, the effects of weather variables are similar on both bikeshare and e-scooter demand. On the other hand, while most bikeshare studies show that income is positively associated with bikeshare usage, most e-scooter studies find a negative association between e-scooter use and income. Bicycle infrastructure is found to be a positive factor in increasing both bikeshare and e-scooter trips. Moreover, literature on bikesharing demand reveals some significant temporal, socio-demographic, built environment, and transit-related factors that suggested explanatory variables for the model.

Chapter 3. Data and Methodology

3.1 E-scooter Pilot Program

This study uses the data of a shared e-scooter pilot program in Chicago, which is publicly available in the City of Chicago Data Portal (E-scooter Share Pilot Program, 2020). The City of Chicago organized the shared e-scooter pilot program for four months (15 June 2019 to 15 October 2019) to evaluate the performance of e-scooters as a safe, sustainable, and equitable mode of transportation for the residents. The pilot region covers 50 square miles, including 251 census tracts (Figures 1 and 2). The pilot area is divided into three sections that are somewhat more demographically diverse than the City of Chicago. Two priority areas were established within the pilot area to ensure equity and provide service to underserved community areas. The south priority area contains mainly black residents with the highest rate of households living under the poverty line and the lowest household density. Hispanics and Latinx are predominant in the north priority area. The remaining area has a higher share of white people with a higher median household income and higher density of household and employment. The diverse demographic characteristic of the pilot area enabled the City to assess the impact of e-scooters to access transit and other mobility modes.

The pilot study permitted ten e-scooter companies (Bird, Sherpa, Bolt, Gruv, Jump, Lime, Lyft, Spin, Veoride, and Wheels) to operate 250 e-scooters each within the specific region. To ensure equity, the e-scooter companies were supposed to distribute at least 25 percent of e-scooters in the south and north priority area at the beginning of each day. Some companies were better at achieving the rebalancing requirements than others. Still, none consistently ensured that 25 percent of their e-scooters were available in the priority areas throughout the pilot. Though the e-scooter companies failed to achieve the metric, the deployment requirements made the distribution of e-scooters to be the most equitable during the morning. To further regulate the

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geographical operation of e-scooters, the City used geofencing technology to set e-scooter boundaries to remain within the pilot area. More information regarding pilot study design can be found here (E-scooter pilot evaluation, 2020).

3.2 E-scooter Data

The dataset contains a total of 821,615 unique trips reported by the participating companies. Due to data downloading issues stemming from the difficulty of achieving perfect data compliance, 664,975 trips were available for analysis. The dataset provides the start and end times with the location (latitude and longitude of the centroids of the pickup and dropoff census tracts), trip duration, and trip distance corresponding to each trip ID. The study analyzes the shared e-scooter trips at the census tract levels. It is to be noted that a significant proportion of trips recorded the geographic coordinates of the start/end census tracts centroid but not the census tract ID. The study recovered those IDs by using ArcGIS. While this procedure found 253 distinct origin census tracts and 273 distinct destination census tracts, this study considers 251 census tracts within the pilot program's boundary. The participating e-scooter companies applied a geofence function that required the e-scooter to slow down automatically and stop within a quarter of a mile when it had crossed the pilot program's boundary. Because of this, we found 12 census tracts, which were either partially within the pilot boundary or at the border of the boundary (Figures 1 and 2). The final origin and destination trip data sets consist of 239 and 237 census tracts, respectively, where at least one trip was originated or ended during the pilot program period.

The study aggregated the e-scooter origin and destination trips according to each census tract on each day during the period to generate the dependent variable y_{it}, the count of e-scooter trips in census tract i on day t. The dependent variable's mean is 20.65 and 20.71 in the origin

and destination model datasets with a standard deviation of 77.13 and 70.23, respectively. While

the standard deviation values indicate a significant variance across census tracts and days for

both datasets, there are not many differences in the spatial distribution of the number of shared e-

scooter trips between these two data sets (Figures 1 and 2).

3.3 Explanatory Variables

Following the literature review and considering the study area's context, the study includes

different independent variables to model the determinants of shared e-scooter usage. These

variables are categorized into four broader groups: i) temporal variables, ii) socio-demographic

and commuting characteristics, iii) built environment variables, iv) neighborhood characteristics.

Table 2 includes detailed information about each of the variables considered in the study.

3.3.1 Temporal variables

This study's temporal or time-variant variables include the weather variables, day of the week,

and weekly gasoline price. Since it is a known fact that natural environment components such as

weather and climate have a significant impact on both bicycle usage and frequency of usage

(Sears et al., 2012), we expect that these variables will also influence e-scooter use. Mathew et

al. (2019a) find that the amount of snowfall, rainfall, and temperature is the most predominant

variable for predicting the hourly number of e-scooter trips. To capture these effects, the model

includes the following weather variables: average temperature of the day, total precipitation (rain

in mm), average wind speed (mph). The snowfall variable is not included in the model

specification since there was no snow day in Chicago during the study period (June to October

2019). These weather data were obtained from Wunderground (2019) and the National Oceanic

and Atmospheric Administration (NOAA. 2019). These variables vary daily but are assumed to

be the same for all the census tracts under the study area during the same day. The number of e-scooter trips is expected to negatively affect the total precipitation (rain) and wind speed. In contrast, more e-scooter trips are expected to be generated on warmer days.

We expect that there will be variation in e-scooter usage patterns during weekdays and weekends as bikeshare studies have identified the influence of calendar attributes (weekday and weekends) on the bikeshare system usage (Corcoran et al., 2014; Gebhart and Noland, 2014). Weekend reflects changes in the routine activities of individuals and families, which can bring about both increased and reduced prevalence in the spatio-temporal patterns of e-scooter trips (Corcoran et al., 2014). Moreover, during weekends, the number of fun/recreation rides may increase. To capture the variation of e-scooter demand during weekdays and weekends, we include a binary variable specifying whether the trip was performed during a weekday or weekend.

Previous research highlights the importance of gasoline price (taxes) on the use of alternative and sustainable modes of transport (Litman 2005; Gimenez-Nadal and Molina, 2019). Prior research has found negative price elasticities of gasoline for auto vehicle miles traveled (Hymel & Small, 2015; Labandeira et al., 2017; Chen et al., 2017; Goetzke and Vance, 2018), and the opposite relationship is found in transit ridership (Currie and Phung, 2007). In addition, previous studies have also shown that the weekly gasoline price is positively associated with bikeshare trips (He et al., 2020) and e-scooter usage (Younes et al., 2020). So, we hypothesize that higher gas prices will increase e-scooter demand as people may switch to a readily available energy-friendly mode for budget adjustments, at least in the short term. To test this relationship, following Younes et al. (2020) and He et al. (2020), this study includes the weekly gasoline
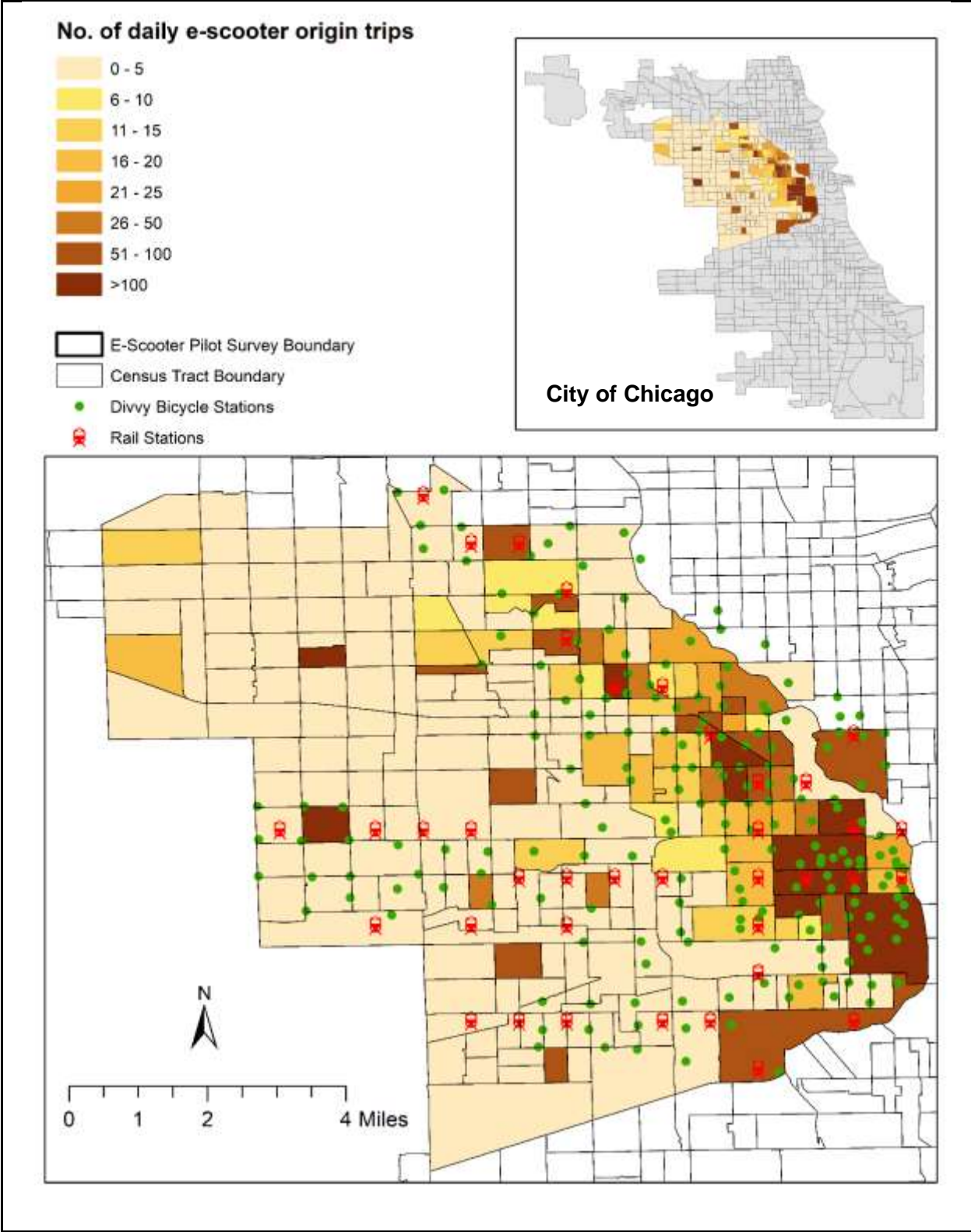
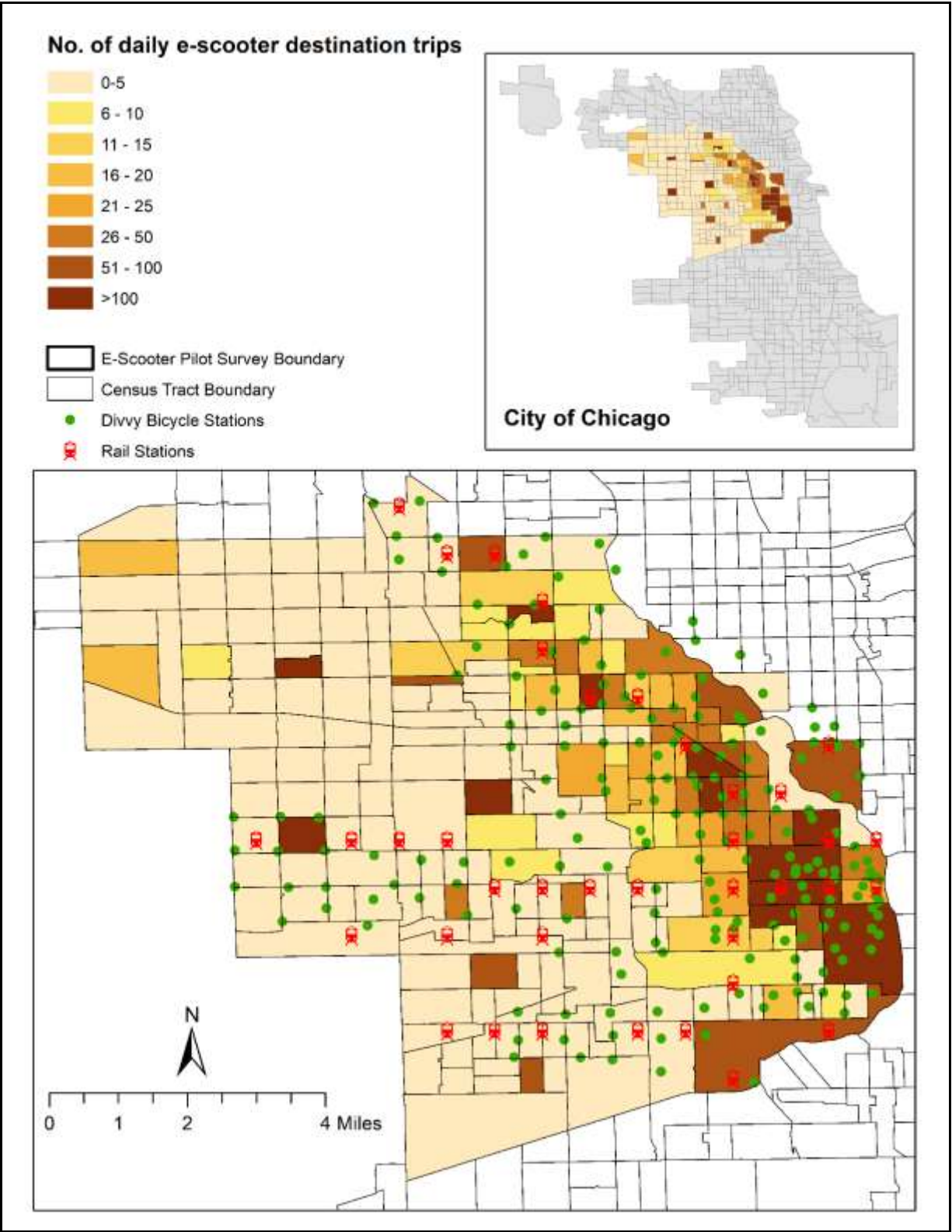**Figure 1:Spatial distribution of number of daily shared e-scooter origin trips in Chicago**

Figure 2: Spatial distribution of number of daily shared e-scooter destination trips in Chicago

Table 2: Model Variables and Summary Statistics

Variables	Units	Source	Expected Relationship	Time Variant?	Mean	Std. Dev.	Min	Max
Dependent Variables								
Number of trips originated per day per census tract (Origin)	Count	CDP[1]	N/A	Yes	20.65	77.13	0	1453
Number of trips per day per census tract (Destination)	Count	CDP[1]	N/A	Yes	20.71	70.23	0	1305
Explanatory Variables (Census tract level)								
Temporal Variables								
Average temperature	Celsius	NOAA	+	Yes	72.11	8.08	46	88
Total precipitation (Rain)	mm	NOAA	-	Yes	0.14	0.29	0	1.54
Average wind speed	mph	Wunderground	-	Yes	8.94	2.57	4.2	16.8
Binary 1: if weekend	-	CDP	+	Yes	2.98	2.01	0	6
Weekly gasoline price	$/gallon	EIA	+	Yes	2.89	0.16	2.6	3.27
Socio-demographic and Commuting Characteristics								
Median age	years	ACS	?	No	32.49	4.59	21.9	59.3
Median income[2]	$	ACS						
Binary 1: Low median income (baseline)	-		?	No	0.51	0.50	0	1
Binary 1: Medium median income	-		?	No	0.46	0.50	0	1
Binary 1: Higher median income	-		?	No	0.03	0.16	0	1
Number of zero car hhlds (in thousand)	%	ACS	+	No	0.28	0.22	0.01	1.83
% of workers commuting by public transit	%	ACS	+	No	28.61	11.2	3.99	70.45
Built Environment Variables								
Population density (in thousand)	prs/sq.mile	ACS	+	No	18.62	8.28	1.93	40.71
Land use mix[3]	-	LEHD	+	No	0.49	0.14	0.22	0.85
Network density in terms of facility miles of multimodal links per square mile	miles/sq.mile	SLD	+	No	8.25	7.24	0	42
Number of CTA bus stops	Count	CDP	?	No	12.74	8.26	0	51
Binary 1: if a census tract has at least one CTA rail station	Count	CDP	?	No	0.14	0.35	0	1
Parking cost ($/hour) in census tract	$/hour	CMAP	+	No	0.29	0.34	0	3.06
Binary 1: if a census tract has at least one Divvy bikeshare station	Count	CDP	?	No	0.45	0.50	0	1
Neighborhood Characteristics								
Total number of parks and open spaces (in 100s)	Count	CMAP	+	No	1.57	1.66	0	9
Number of crime records (in 100s)	Count	CDP	-	No	4.53	3.80	0.57	19.56

Notes: CDP=Chicago Data Portal; NOAA= National Oceanic and Atmospheric Administration; EIA=Energy Information Administration of the US Department of Energy; ACS= American Community Survey; LEHD= Longituidinal Employer Household Dynamics; SLD=Smart Location Database; CMAP= Chicago Metropolitan Agency for Planning;1 E-scooter Pilot Survey-2019, Chicago; data available through CDP;[2] Expected relationship with the base category;[3] Calculated by the authors.

prices of Chicago for the study period by assuming that the price of gasoline is constant throughout the week. The gasoline price data is collected from the Energy Information Administration of the US Department of Energy (US DOE, 2019), which compiles average weekly gasoline prices for major cities in the US.

3.3.2 Socio-demographic and commuting characteristics

Several studies reviewed in Section 2 find an association between the e-scooter/ bikeshare usage and different socio-economic variables (e.g., Mathew et al., 2019b; Lee et al., 2019; Younes et al., 2020; Jiao and Bai, 2020; Caspi et al., 2020). To capture these effects, we include variables such as age, household income, and education. The median age of the census tract residents is included in the model to capture the age distribution of a census tract. It is to be noted that while the categorical age variable might be more appropriate to represent age, we could not include the categorical variable due to the multi-collinearity issue. The income variable is included as categorical variables based on the definition of the Pew Research Center (2016): low income if the median income of a census tract is less than $45,000 (baseline), middle-income if median income is between $45,000-$125,000, and higher-income if the median income is greater than $125,000. We also include the percentage of people with bachelor's degrees to control for education. However, the final model specification does not have this variable due to the multi-collinearity issue.

An examination of the empirical evidence indicates that car-ownership plays an important role in the usage pattern of alternative transportation modes (e.g., bicycle, e-scooter, or public transportation) (Van Acker and Wiltox, 2010; Fishman et al., 2014; Tao et al., 2019). Previous studies find that carless households are more likely to rely on alternative transportation modes to fulfill daily travel needs (Brown, 2017; Mitra et al., 2020). To capture the effects of car

ownership on e-scooter usage, this study includes the number of zero car households in each census tract with the expectation that a census tract with a higher number of zero car households will generate more e-scooter trips. In addition, this study includes the commuting characteristics of working people of a census tract, namely the percentage of workers who commute by public transit. The working hypothesis is that census tracts with a higher percentage of public transit commuters are likely to have more e-scooter usage because these census tracts include residents who are already using other alternative transportation options. Besides, public transit commuters can use e-scooters to solve their first and last-mile problems. These socio-demographic and commuting characteristics data are available through the United States Census Bureau (2018).

3.3.3 Built-environment variables

The built environment variables are directly related to the demand for a transportation mode (Kemperman and Timmermans, 2009; Ewing and Cervero,2010). Ewing and Cervero (2010) identified different "D" variables as a measure of the built environment. This study considers *Density, Diversity*, and *Design* variables to understand the built environment's impact on e-scooter usage (Cervero and Kockelman, 1997). The urban environment, which has a higher job and population density with a greater mix of land use, and better accessibility to transit stations, is expected to provide a suitable environment for e-scooter usage, as it is the case for bikeshare usage (Ewing and Cervero, 2001; Cervero et al., 2009; Teschke, 2010). This study includes population density and employment density to represent the *Density* variable. The United States Census Bureau (2018) provides data for the population at the census tract level. The study collects employment density data for each census tract from Longitudinal Employer-Household Dynamics (United States Census Bureau, 2015). However, the final model does not include the employment density due to the multi-collinearity issue.

Jiao and Bai (2020) indicate the land use mix as the most influential variable for generating e-scooter trips. Therefore, we calculate the land-use entropy index based on the parcel-level data from the Chicago Metropolitan Agency for Planning (CMAP) 's Land use Inventory for Northeastern Illinois (Chicago Metropolitan Agency of Planning, 2013). This study calculates the land use entropy index using Eqn. 1 (Cervero and Kockelman, 1997):

$$\text{Land use entropy index} = \frac{-\left[\sum_{j=1}^{k} P^j * \ln(P^j)\right]}{\ln(k)} \tag{1}$$

where j indicates the number of land-use types. In Eqn. 1, j includes six land-use types (i.e. residential, commercial, industrial, institutional, transportation/communication, agriculture). P^j represents the percentage of land use in the jth land-use class. The entropy index ranges from 0 to 1, where larger values indicate a more balance layout of land use mixes, and 0 indicates a single land-use type. Since a complex land use mix produces different activities (e.g., residential, recreational, and business purpose), the study expects a higher entropy index to generate more e-scooter demand.

The *Design* variables measure the street network characteristics within an area. Different measures of design variables were used in the travel behavior literature, such as average block size, the proportion of four-way intersections, and the number of intersections per square mile. (Ewing and Cervero, 2010). To capture the multimodal characteristics of street networks, we include network density in terms of facility miles of multimodal links per square mile. In addition, this variable works as a proxy variable for the city's bicycle infrastructure, as Caspi et al. (2020) found a positive association between bicycle infrastructure (on-street bike lanes and off-road bike paths) and e-scooter usage. This data is extracted from the smart location database

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of the U.S. Environmental Protection Agency (EPA, 2014). The smart location database grouped streets into facility categories (e.g., auto-oriented links, multimodal links, and pedestrian-oriented links, etc.). The multimodal facilities are defined by any arterial or local streets where autos and pedestrians must be permitted on the link. These multimodal facility categories are summarized for each central block group (CBG) to obtain the total facility per saure mile. The summary results of facility miles were divided by the total land area for each CBG to obtain the network density (EPA, 2014). Additionally, the network density is weighted to reflect connectivity for pedestrian and bicycle travel (for more detail, see pages 21-23 of EPA, 2014). The starting hypothesis is that higher multimodal network density will produce more e-scooter trips.

In addition to these three "Ds," transit supply variables are used in travel research with different measures such as shortest route distance to the nearest transit station, transit route density, the distance between transit stops, or the number of stations per unit area (Ewing and Cervero, 2010). The current study includes the number of transit stops as explanatory variables in the model. We separate the transit count variables into two types: bus stops and rail stations. The rail station count variable is included as a dummy variable indicating the presence of at least one rail station in a census tract. While the shared e-scooter is considered a quick, convenient, and inexpensive vehicle that has the potential to solve the first-and last-mile problem of access to public transportation (Shaheen & Cohen,2019), there is no clear theoretical reasoning for the directionality of transit supply variables on e-scooter demand.

Another 'D' variable, *Demand management,* includes parking supply features which appear in a few travel behavior studies (Cervero and Kockelman, 1997; Ewing and Cervero, 2010). This study includes parking cost ($/hour) as parking supply variables to expect census

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tracts with higher parking costs to produce more e-scooter trips. The parking cost data is collected from the CMAP (Chicago Metropolitan Agency of Planning, 2013). CMAP provided the parking cost data for Northeast Illinois for each Traffic Analysis Zone (TAZ) in 2015. Following Ghaffar et al. (2021), we converted the parking cost data from TAZ-level to census tract-level datasets by taking the average parking costs of all TAZs that a census tract comprises.

The City of Chicago has had a public dock-based bike-sharing system named Divvy since 2013, with stations located throughout the city. While there are comparative studies between traditional bike-sharing systems and e-scooter systems (e.g., McKenzie, 2019; Younes et al., 2020), it is unknown from the existing literature how the traditional bike-sharing systems influence e-scooter usage. This effect can be captured by incorporating the bikeshare usage data in the model. However, incorporating the bikeshare demand in the model may raise endogeneity issues as many of the explanatory variables in the model may influence the bikeshare demand. To overcome this problem, we used the bikeshare station variable as a proxy variable for bikeshare demand as previous studies found the number of bikeshare stations as one of the significant determinants of bikeshare demand (Rudloff and Lackner, 2014; Eren and Uz, 2020; Xu and Chow, 2020). Therefore, to understand the effect of Divvy bike-sharing stations on shared e-scooter usage, we include a binary variable indicating the presence of a Divvy bike-sharing station in a census tract (baseline: no Divvy station). There is no priori of the Divvy stations' directionality on shared e-scooter usage because shared e-scooter could be a competitive mode to the existing bike-sharing system, or Divvy riders could be included in different markets.

3.3.4 Neighborhood characteristics

The neighborhood characteristics include the number of parks and open spaces in a census tract as well as the crime rate. Previous studies found that the presence of parks and open spaces are

important determinants of bike-share trips in Chicago (Hyland et al., 2018) and e-scooter usage in Austin (Jiao and Bai, 2020). This study includes the number of parks and open spaces in each census tract as covariates. It is to be noted that we have also included other points of interest variables such as museums, restaurants, and banks. These variables are not statistically significant in any of the models and thus are not reported in the final model results.

Hyland et al. (2018) also find that the crime rate in terms of the number of homicides is negatively associated with the number of bikeshare trips in Chicago. The effects of crime on shared e-scooter usage may have temporal lag and immediate effect, but the power and the extent are unknown (Hyland et al., 2018). Hence, the current study includes the cumulative number of criminal records in each census tract between January 2015-October, 2019. The crime records include homicide, assaults, robbery, and battery counts. This data is available through the Chicago Data Portal (2020).

3.4 Modeling Approach

To model the determinants of shared e-scooter usage, we employ a random-effects negative binomial (RENB) regression model. In this research, the shared e-scooter trip count data is a discrete and non-negative integer and has the possibility of being random and sporadic. Poisson or Negative Binomial (NB) is a common way to model this kind of data, and both models assume that trip counts in a census tract *i* for any day *t* are independent. A critical constraint of the Poisson model is that the mean must be equal to the variance. So, suppose the data are found to be significantly over-dispersed (i.e., the variance is much greater than the mean). In that case, the Poisson model estimation will incorrectly estimate the likelihood of e-scooter trip demand. The equi-dispersion of trip count data is unlikely to be truly observed, as trip-count data are typically over-dispersed, which is also true for this study's shared e-scooter trip dataset.

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Unobserved dispersion in this data set can arise when the covariates are not fully capable of capturing the heterogeneity across the census tracts in the city. The over-dispersion could result from the omission of important exogenous variables, model misspecification, or excess zero counts (Camron and Trivedi, 2013), resulting in a biased estimated standard error and incorrect test statistics in the Poisson model. Besides, the time-series nature of the multiday data of this study presents serial correlation issues. Both overdispersion and serial correlation need to be addressed in a modeling framework to produce efficient estimates (Hausman et al., 1984). We first adopt a negative binomial model to account for the over-dispersion in the number of e-scooter trips in census tract i during day t.

The NB specification provides the probability $P(y_{it})$ of y_{it} median trip counts for census tract i in period t as:

$$P(y_{it}) = \frac{\Gamma(\theta + n y_{it})}{\Gamma(\theta) y_{it}!} u_{it}^{\theta} (1 - u_{it})^{y_{it}} \tag{2}$$

Where, $u_{it} = \frac{\theta}{(\theta + \lambda_{it})}$, $\theta = \frac{1}{\alpha}$, $\Gamma(\cdot)$ is a gamma function, and λ_{it} is given by,

$$ln \ \lambda_{it} = \mathbf{X}_{it}\boldsymbol{\beta} + \epsilon_{it} \tag{3}$$

here $\mathbf{X}_{it}$ represents the covariates in period t, $\boldsymbol{\beta}$ is the vector of estimable coefficients, and $\exp(\epsilon_{it})$ expresses the gamma-distributed error with mean 1 and variance α. The relation between the mean and the variance can be obtained by,

$$\text{Var}\ [y_{it}] = E(n_{it})[1 + \alpha E(y_{it})] \tag{4}$$

If α has a significant difference from zero, the variance is greater than the mean and indicates the data to be over-dispersed or under-dispersed. On the other hand, having the value of α equal to zero reduces the NB model to Poisson distribution. Therefore, in negative binomial, the standard maximum likelihood function can be used to estimate the λ_{it} as follows

$$L(\lambda_{it}) = \prod_{i=1}^{N}\prod_{t=1}^{T} \frac{\Gamma(\theta + y_{it})}{\Gamma(\theta)y_{it}!} \left[\frac{\theta}{(\theta + \lambda_{it})}\right]\left[\frac{\lambda_{it}}{(\theta + \lambda_{it})}\right] \qquad (5)$$

where T is the last day of the trip data and N is the total number of census tracts. Although the NB model accounts for overdispersion conditions, it does not allow location-specific effects or serial correlation over time for census tract-level trip counts. One way to overcome this problem is by adding temporal and spatial variability in the data using indicator variables for locations and a "trend" variable for the temporal effect. However, it is unlikely that these variables will capture all unobserved heterogeneity—especially when heterogeneity exists at the observation level. Since the data used in this model have census tract-specific effects that are randomly distributed across locations and are likely to have negative or positive serial correlation as well as unobserved heterogeneity, a negative binomial panel model appears most appropriate (Hausman et al., 1984).

Moreover, after examining the random-effects and fixed-effects negative binomial models for panel data, Hausman et al. (1984) suggested that the random-effects negative binomial model (RENB) is more appropriate where the location-specific effect (in this case, census tract) is randomly distributed across locations. This effect can cause negative or positive serial correlation depending on how the effect deviates from the "average location". On the other hand, the fixed-effects negative binomial (FENB) model is conditioned on the total number of trips and does not allow for location-specific variation. Because of the census tract constraints in the dataset, it is reasonable to believe that e-scooter trip counts are associated with location-specific effects that are randomly distributed across locations and serially correlated. In this case, therefore, the random-effects negative binomial (RENB) model appears appropriate to model the e-scooter trip frequency with *n* number of location groups and *t* periods (days).

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For the random-effects overdispersion models, let y_{it} be the trip count of the *t*th observation in the *i*th census tracts. We begin with the model $y_{it}| Y_{it} \sim$ Poisson (Y_{it}), where $Y_{it} \mid \delta_i \sim$ gamma ($\lambda_{it}, 1/\delta_i$) with $\lambda_{it} = $ exp ($\mathbf{X}_{it}\boldsymbol{\beta} + \epsilon_{it}$) and δ_i is the dispersion parameter and exp (ϵ_{it}) expresses the gamma-distributed error with mean 1 and variance α. This yields the model:

$$\text{Pr}\ (Y_{it} = y_{it}\ |\mathrm{x}_{it}, \delta_i\ ) = \frac{\Gamma(\lambda_{it}+y_{it})}{\Gamma(\lambda_{it})\ \Gamma(y_{it}+1)} \left[\frac{1}{(1+\delta_i)}\right]^{\lambda_{it}} \left[\frac{\delta_i}{(1+\delta_i)}\right]^{y_{it}} \tag{6}$$

Looking at within-census tract effects only, this specification yields a negative binomial model for the *i*th census tract with dispersion (variance divided by the mean) equal to $1 + \delta_i$, i.e., constant dispersion within a census tract. Note that this parameterization of the negative binomial model differs from regular parameterization of negative binomial (Equation 3), which has dispersion equal to $[1 + \alpha E(y_{it})]$.

For a random-effects negative binomial model, we allow δ_i to vary randomly across census tracts; namely, we assume that $\frac{1}{(1+\delta_i)} \sim$ Beta (r, s). The joint probability of the counts for the *i*th census tract is

$$\text{Pr}\ \left(Y_{i1} = y_{i1}, \dots, Y_{in_i} = y_{in_i}\middle| \boldsymbol{X}_i\right) = \int_0^\infty \prod_{t=1}^{n_i} \text{Pr}\ (Y_{it} = y_{it}\ |\mathrm{x}_{it}, \delta_i\ )\ f(\delta_i)\ d\delta_i$$

$$= \frac{\Gamma(\text{r}+\text{s})\Gamma(\text{r}+\sum_{t=1}^{n_i} \lambda_{it})\Gamma(\text{s}+\sum_{t=1}^{n_i} y_{it})}{\Gamma(\text{r})\Gamma(\text{s})(\text{r}+\text{s}+\sum_{t=1}^{n_i} \lambda_{it}+\sum_{t=1}^{n_i} y_{it})} \prod_{t=1}^{n_i} \frac{\Gamma(\lambda_{it}+y_{it})}{(\lambda_{it})\Gamma(y_{it}+1)} \tag{7}$$

For $\boldsymbol{X}_i = (x_{i1}, \dots, x_{in_i})$ and where f is the probability density function for δ_i , the resulting log-likelihood is

$$lnL = \sum_{i=1}^{n} w_i [\ln\Gamma(r+s) + \ln\Gamma\left(r + \sum_{k=1}^{n_i} \lambda_{ik}\right) + \ln\Gamma\left(s + \sum_{k=1}^{n_i} y_{ik}\right) - \ln\Gamma(r) - \ln\Gamma(s)$$

$$- \ln\Gamma\left(r + s + \sum_{k=1}^{n_i} \lambda_{ik} + \sum_{k=1}^{n_i} y_{ik}\right) \tag{8}$$

$$+ \sum_{k=1}^{n_i} \{\ln\Gamma(\lambda_{it} + y_{it}) - \ln\Gamma(\lambda_{it}) - \ln\Gamma(y_{it} + 1)\}]$$

Where $\lambda_{it} = \exp(\mathbf{X}_{it}\boldsymbol{\beta} + \epsilon_{it})$ and w_i is the weight for the ith census tract (Hausman et al., 1984). This formulation allows the within-census tract effect to varying over time even when the exogenous vectors of attributes are constant, thereby better accounting for unobserved heterogeneity (Shankar et al., 1998). The parameters r, s, and the coefficient vector $\boldsymbol{\beta}$ can be estimated using standard ML algorithms (Camron and Trivedi, 2013).

Chapter 4. Results and Discussion

4.1 Model Diagnostic and Fit

StataMP 16 (StataCorp, 2019) is used to estimate the origin and destination models. The final datasets for the origin and destination models have 29,397 and 29,151 longitudinal e-scooter trips records of 123 days from 239 and 237 census tracts, respectively. The multicollinearity is not an issue in the data set, as the largest variance inflation factor (VIF) among the explanatory variables is equal to 2.88. Tables 3 and 4 provide coefficient estimates for the Random-effect Poisson, standard negative binomial (NB), and RENB model for shared e-scooter trips origin and destination, respectively. The results do not include any variables which are statistically insignificant in both models. To facilitate the comparison between the origin and destination models, we include those variables which are statistically significant in at least one of the models.

The Wald Chi-squared for the full random-effect Poisson and RENB models and the

Likelihood Ratio Chi-squared for the NB are significant in both the origin and destination

models, indicating that the overall models are significant in all three cases. The alpha (α)

parameter in the NB model and the Likelihood-Ratio (LR) test of α parameter in the Poisson

model are significant, illustrating the presence of over-dispersion in the e-scooter daily trip data.

Therefore, the NB model appears to be plausible than the Poisson model. On the other hand, the

RENB model is superior to the NB model in terms of AIC, BIC, and log-likelihood in both

origin and destination models. Besides, the beta-distribution parameters *r* and *s* are also

significant, indicating autocorrelation between multiple observations of the same census tract.

Again, the likelihood test shows that the panel estimator (RENB model) performs better than the

pooled estimator (NB model). The *F* statistic of the Wooldridge test (Wooldridge, 2010) for

serial autocorrelation is significant in both origin and destination models, illustrating the

necessity of using the RENB model over the standard NB model and fixed-effect NB model. We

also performed the Hausman test (Hausman, 1978) for the random- versus fixed-effects, which

leads to a rejection of the fixed-effect model (insignificant test statistic). Likewise, the Breusch

and Pagan Lagrangian multiplier test (Breusch and Pagan,1979) for random-effects indicates the

RENB model's appropriateness for this data set. Since the RENB model outperforms the

random-effects Poisson and NB models in every aspect, the following section discusses the

RENB results exclusively.

To facilitate interpretation, the coefficients of the RENB model have been transformed

into incidence rate ratios (IRRs) (i.e., e^{β} rather than β) (Tables 3 and 4). If the IRR of a given

variable is much greater than 1.0, then an increase in the variable's value is associated with

higher usage of shared e-scooters. Conversely, if the IRR is much less than 1.0, an increase in the

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Table 3: Results of Origin Models

Variables	RE Poisson Coefficient	NB Coefficient	RENB Coefficient (IRR)
Temporal Variable			
Average temperature	0.031***	0.053***	0.048 (1.05) ***
Total precipitation (Rain)	-0.208***	-0.266***	-0.228 (0.80) ***
Average wind speed	-0.025***	-0.039***	-0.039 (0.96) ***
Binary: 1 if weekend	0.032***	0.029***	0.040 (1.04) ***
Weekly gasoline prices	0.313***	0.492***	0.805 (2.24) ***
Socio-demographic and Commuting Characteristics			
Median age	0.007	0.003	0.004 (1.00)
Income (baseline: *Low median income*)			
Binary 1: Medium median income	0.398	0.433***	0.445(1.58) ***
Binary 1: Higher median income	1.375**	1.414***	0.693(2.03) ***
Number of zero car households (in thousand)	0.138	0.154*	0.353 (1.43) ***
% of workers who commute by public transit in census tract	0.01	0.009***	0.025(1.02) ***
Built Environment Variable			
Population density (in thousand)	0.073***	0.073***	0.006 (1.00) **
Land use mix	2.248***	2.175***	0.214 (1.23) *
Network density in terms of facility miles of multimodal links per square mile	0.037*	0.037***	0.009 (1.01) ***
Number of CTA bus stops	0.002	0.003***	-0.006 (0.99) **
Binary 1: if a census tract has a CTA rail station	1.569***	1.558***	0.115 (1.13) ***
Parking cost ($/hour) in census tract	-0.5	-0.489***	0.103 (1.11) **
Binary 1: if the census tract has at least one Divvy bike station	0.616**	0.610***	0.410 (1.51) ***
Neighborhood Characteristics			
Number of parks in a census tract (in 100s)	0.274***	0.272***	0.093 (1.10) ***
Number of crime records (in 100s)	-0.052	-0.050***	-0.040 (0.96) ***
Constant	-4.846***	-6.747***	-7.793***
Model Diagnostics and Fit			
Wald Chi2 (19)	46321.99***		6901.86***
LR Chi2 (19)		6650.45***	
Ln (Alpha)	0.815***	1.800***	
LR test for alpha=0 Chi-squared (1)	9.6e+05***	1.0e+06***	
LR test vs. Pooled (Chi squared)			2.1e+04***
Ln_r			-0.445***
Ln_s			0.399***
AIC	300273.4	151961.1	128258.2
BIC	300447.5	152135.2	128440.6
Log-L	-150115.72	-62258.899	-64107.104
Wooldridge test for serial autocorrelation F (1,238)			56.253***
Hausman test for Fixed vs Random Model, Chi-square (5)			0.00
Breusch and Pagan Lagrangian multiplier test for random effects Chi-square (01)			1.1e+06***
N (Number of observations)	29,397	29397	29,397
n (Number of groups)	239	239	239
T (Number of days)	123	123	123

Note: RE Poisson: Random-Effect Poisson Model. * Significance at 10%. ** Significance at 5%. *** Significance at 1%. Dependent Variable: Number of shared e-scooter trips originating from a census tract per day

Table 4: Results of Destination Models

Variables	RE Poisson Coefficient	NB Coefficient	RENB Coefficient (IRR)
Temporal Variable			
Average temperature	0.031***	0.053***	0.047 (1.05) ***
Total precipitation (Rain)	-0.209***	-0.259***	-0.217 (0.80) ***
Average wind speed	-0.025***	-0.037***	-0.040 (0.96) ***
Binary: 1 if weekend	0.032***	0.029***	0.037 (1.04) ***
Weekly gasoline prices	0.309***	0.445***	0.760 (2.14) ***
Socio-demographic and Commuting Characteristics			
Median age	0.010	0.006	0.011 (1.01) ***
Income (baseline: *Low median income*)			
Binary 1: Medium median income	0.642 **	0.672***	0.576 (1.78) ***
Binary 1: Higher median income	1.423**	1.455***	0.791 (2.21) ***
Number of zero car households (in thousand)	0.261	0.283**	0.397 (1.49) ***
% of workers who commute by public transit in census tract	0.006	0.006***	0.023 (1.02) ***
Built Environment Variable			
Population density (in thousand)	0.072***	0.072***	0.019 (1.02) ***
Land use mix	1.913**	1.850***	0.223 (1.25) **
Network density in terms of facility miles of multimodal links per square mile	0.032*	0.032***	0.002 (1.00)
Number of CTA bus stops	0.004	0.005**	0.002 (1.00)
Binary 1: if a census tract has a CTA rail station	1.423***	1.455***	-0.012 (0.99)
Parking cost ($/hour) in census tract	-0.519	-0.506***	0.091 (1.09) **
Binary 1: if the census tract has at least one divvy bike station	0.638**	0.629***	0.418 (1.52) ***
Neighborhood Characteristics			
Number of parks in a census tract (in 100s)	0.266***	0.263***	0.101 (1.11) ***
Number of crime records (in 100s)	-0.039	-0.038***	-0.037 (0.96) ***
Constant	-4.780***	-6.564***	-8.094***
Model Diagnostics and Fit			
Wald Chi2 (19)	46000.93***		7394.81***
LR Chi2 (19)		6917.44***	
Ln (Alpha)	0.709***	1.682***	
LR test for alpha=0 Chi-squared (1)	9.3e+05***	1.0e+06***	
LR test vs. Pooled (Chi squared)			2.1e+04***
Ln_r			-0.317***
Ln_s			0.709***
AIC	300943.4	158444.5	134551.4
BIC	301117.3	158618.4	134733.6
Log-L	-150450.71	-79201.24	-67253.71
Wooldridge test for serial autocorrelation F (1,236)			55.15***
Hausman test for Fixed vs Random Model, Chi-square (5)			0.00
Breusch and Pagan Lagrangian multiplier test for random effects Chi-square (01)			1.1e+06***
N (Number of observations)	29,151	29,151	29,151
n (Number of groups)	239	239	239
T (Number of days)	123	123	123

Note: RE Poisson: Random-Effect Poisson Model. * Significance at 10%. ** Significance at 5%.
*** Significance at 1%. Dependent Variable: Number of shared e-scooter trips ending in a
census tract per day.

variable's value is associated with a significant decline in shared e-scooter demand. Otherwise, the variable does not affect the e-scooter demand.

4.2 Parameter Estimates

4.2.1 Temporal variables

All three weather variables are statistically significant in both the origin and destination models. While higher average temperature produces more e-scooter trips, precipitation (rain) and wind gust are negatively associated with e-scooter usage. The IRR value indicates that a one-millimeter increase in the rain (standard deviation (sd): 0.29) is associated with a 20%[1] (both models) reduction in e-scooter usage while holding all other variables in the model constant. This is not surprising, given that rain makes it harder to ride e-scooters. Besides, while riding in the rain on an e-scooter is said to be safe, manufacturers do not exactly encourage it, especially if it is heavy (Scooter Sight, 2017). Moreover, the model's overall weather results are consistent with the previous studies (e.g., see Corcoran et al., 2014; Noland, 2019; Mathew et al., 2019a; Younes et al., 2020).

The time of week binary variable shows a higher e-scooter usage during the weekend in both the origin and destination models. One possible reason for this observation may be that most casual e-scooter riders use it for leisure purposes (Espinoza et al., 2019; McKenzie, 2019), leading to higher e-scooter demand during weekends as more people go out for non-work purposes during weekends.

The final time-variant variable of the model is the weekly gasoline prices. The study finds a significant positive relationship between the weekly gasoline prices and shared e-scooter

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[1] IRR=0.80; percentage change = (0.80-1) *100 = -20%

usage, which is in line with Younes et al. (2020). The IRR values of both models (Origin: 2.24

and destination: 2.14) indicate that a one-dollar increase in weekly per gallon gasoline price (sd:

0.16) results in a 124%[2] and 114% increase in e-scooter ridership in origin and destination

census tracts, respectively. The main reason behind this finding may be that people prefer to

avoid car trips when gasoline prices are higher, and these trips shift to more e-scooter trips as

higher gasoline taxes (prices) are related to greater use of "green" transportation modes (Moreau

et al., 2020). However, these shifts may be a temporary adjustment to maintain their travel

behavior in the short-term rather than a long-term behavior change.

4.2.2 Socio-demographic and commuting characteristics

The origin and destination models' results find median census tract income as an important

determinant of e-scooter demand in Chicago. A neighborhood with medium- and higher-income

households produce more e-scooter trips than that of a lower-income neighborhood. This result

contradicts the results of Jiao & Bai (2020), who find a negative relationship between income

and e-scooter usage in Austin, Texas. One possible reason for this contradictory finding is the

availability of e-scooters in low-income neighborhoods. None of the companies participating in

the Chicago pilot program consistently ensured 25 percent of their e-scooters were available in

low-income neighborhoods throughout the pilot (E-scooter pilot evaluation, 2020). This kind of

spatial disparity was also found in dockless bike-share systems in other cities. For example,

Mooney et al. (2019) investigated the spatial equity of access to dockless share bikes and found

that higher-income neighborhoods tended to have higher availability of dockless bikes in Seattle,

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[2]IRR=2.24, percentage change = (2.24-1) *100 = 124%

US. Another possible reason could be the presence of a higher percentage of unbanked households in Chicago compared to Austin (7.4% vs. 4.5%).

Moreover, 90 percent of these unbanked households in Chicago have an annual family income of less than $50,000 (FDIC, 2017). These unbanked or underbanked households are effectively excluded from new services like shared e-scooters, fare discounts for transit passes, and other transportation services that require access to credit cards (King and Saldarriaga, 2017). Indeed, the complaints received by the city of Chicago during the pilot suggested that some companies' programs were difficult to access for the people who do not have a bank account (E-scooter Share Pilot Program, 2019).

While the median age variable is not statistically significant in the origin model, it is significant in the destination model. The reason behind a different result in origin and destination models is hard to tease out due to the lack of disaggregated level user's demographic data. As expected, neighborhoods with a higher number of carless households produce more e-scooter trips. The variables related to commuting mode are significant and have positive signs in both origin and destination models. Results indicate that the higher demand for e-scooter trips is related to the higher percentage of workers who use public transport to get to and from work. This is expected as workers commuting by transit may prefer e-scooters to reach the transit stations instead of walking as there is evidence that e-scooter trips are replacing walking in some cases (E-scooter Share Pilot Program, 2019).

Although previous studies (e.g., Jiao and Bai, 2020) found a positive relationship between higher education attainment and e-scooter usage, we could not include this socio-demographic variable in the model because of the multi-collinearity issue.

4.2.3 Built-environment variables

The model shows that all the 'D' variables are statistically significant and have expected signs for both the origin and destination models. The population density variable reaffirms the findings of the previous studies (e.g., Jiao and Bai, 2020; Caspi et al., 2020) by showing a positive relationship with e-scooter usage. The land use mix variable appears to be an important determinant of e-scooter demand with a statistically significant positive sign. The IRR value of the origin model indicates that a one-unit increase in mixed land use (sd: 0.14) is associated with a 23% increase in e-scooter demand, whereas a 25% increase is observed in the destination model. This is possible because people living in a neighborhood with mixed land uses are more likely to make fewer car trips and use more alternative transportation (Moreau et al., 2020). This finding is consistent with the results of previous studies (Caspi et al., 2020).

The multimodal network density variable has a positive sign in both models, indicating that a neighborhood with more network density in terms of facility miles of multimodal links per square mile is associated with more e-scooter usage. But this variable is not statistically significant in the destination model.

The results of the transit supply features are mixed in both models. The coefficient of the number of CTA bus stops is only significant in the origin model. It indicates that the number of bus stops within an origin census tract is negatively associated with the demand for e-scooter trips. Conversely, a census tract with at least one rail station (sd: 0.35) is associated with 13% more e-scooter usage than a census tract with no rail station in the origin model. This variable is not statistically significant in the destination model.

There are many possible explanations for these mixed results. One possible reason behind this result is that travelers can use buses instead of shared e-scooter to make short-distance trips for which e-scooters are mostly popular (Lee et al., 2019). While it is expected that e-scooter

trips might complement the bus network for the first- and last-mile trips, the distance to the bus stops from residence may be short enough (due to the ubiquitous presence of bus stops in Chicago) that people would prefer walking to the bus stops rather than using an e-scooter. Because e-scooters cover the travel demand gap between walking and biking in cases where a trip is both too long to walk and too short to ride a bike (Jiao and Bai, 2020). On the other hand, the possible reason for the findings that origin tracts with no train station are associated with fewer e-scooter trips is that e-scooters are less likely to substitute an entire trip from origin to destination. Instead, it is more likely to replace an access/egress trip to public transportation (Lee et al., 2019). By the same token, travelers of an origin census tract with at least one train station might use e-scooters as a last-mile trip mode to a train station as the distance from a train station to their residences would be too long for a walking trip. One possible explanation for the insignificant transit variable in the destination model is that users may not be able to use shared e-scooters to reach a station (first-mile) because e-scooters in Chicago are more likely to be available near transit than in places away from transit (E-scooter Share Pilot Program, 2019). The result is also supported by Espinoza et al.'s (2019) findings that e-scooters in Atlanta were not commonly used to reach a transit station.

The parking feature variable is significant and positive in both origin and destination models. The IRR values of the parking cost in both models indicate that a one-dollar increase in per hour parking price (sd: 0.34) is associated with around a 10% increase in e-scooter demand. One potential explanation of this finding is that travelers significantly reduce their car use when parking is more expensive (Shoup, 2005; Yan et al., 2019), and modal responses are highly sensitive to local conditions such as the availability and convenience of competing travel modes (Gimenez and Molina, 2019). Since e-scooters are generally cheaper and environment-friendly

alternatives, many travelers may ride e-scooters instead of personal cars where the parking cost is comparatively higher.

We found an interesting association between the binary variable for the presence of a Divvy bike-share station and e-scooter usage. The origin and destination models show that a census tract with at least one Divvy bike-share station (sd: 0.50) generates 51% more shared e-scooter trips (52% in the destination model) than a census tract with no bike-share station. While this result seems counterintuitive, it echoes the results of Younes et al. (2020). They found a complementary relationship between dockless scooter trip activity and member station-based bike-share trip activity. Moreover, the result is consistent with the user survey findings, where respondents indicated they were more likely to use e-scooters to replace rideshare trips than to replace Divvy trips (E-scooter Share Pilot Program, 2019). There are many possible explanations for this complementary relationship between two seemingly competitive modes. First, following the explanation of Younes et al. (2020), Divvy is a station-based and member-based system where bikes may not be readily available at popular Divvy bike-share stations during the time of high demand of the limited bike capacity infrastructure. This forced bike-share users (members of the system) to use an alternative available similar transportation mode such as e-scooters. This is also supported by the e-scooter pilot evaluation findings, which reported that e-scooter ridership was geographically concentrated in areas with a high density of other options such as Divvy, bus, and rail rather than in areas with fewer options (E-scooter Share Pilot Program, 2019). Second, e-scooter unavailability in areas with fewer other transportation options may lead to this result. The pilot program serves neighborhoods that are not served well by other transportation services as well as covers areas that have a diverse set of additional transportation options (such as Divvy bikesharing). Moreover, e-scooters were not equitably distributed in the

former neighborhoods (E-scooter Share Pilot Program, 2019). Third, an important difference between the Divvy system and e-scooters is that Divvy bikes can only be picked up and dropped off at docked station locations. Divvy bikeshare members may use e-scooters for short-distance trips from or to the divvy stations. Finally, the pilot e-scooter program was new, and many divvy members may want to try it for the first time as survey respondents' motivations for trying e-scooters for the first time is very high (E-scooter Share Pilot Program, 2019).

4.2.3 Neighborhood characteristics

The coefficients of the two neighborhood variables are significant in both the origin and destination model. The positive coefficient for the number of parks and open spaces in a census tract is consistent with prior expectations and in line with previous studies (Caspi et al., 2020; Jiao and Bai, 2020). Finally, model results show that the census tract with more crimes has a negative impact on e-scooter demand. Both models' IRR values indicate that an increase in crime by one hundred (sd: 3.80) (between 2015 and 2019) reduces shared e-scooter usage by 4%. This finding echoes the relationship between crimes and public bikeshare station usage, as Hyland et al. (2018) found a negative association between crime and bike-share station usage in Chicago.

Chapter 5. Conclusion

5.1 Summary

The objective of this thesis is to model the determinants of shared e-scooter usage. To fulfill this objective, we analyze the data from the e-scooter pilot program (2019) in Chicago, containing the shared e-scooter trip data from the ten permitted e-scooter companies. The model acquires the e-scooter trip data for 123 days (from 15 June 2019 to 15 October 2019) on the census tract level within the pilot program's boundary. The variables included in the model are time-variant

variables (weather data, weekday/weekend, and gasoline prices) and time-invariant variables (socio-demographic, built environment, and neighborhood characteristics). As the overdispersion and serial correlation exist in the dataset, the study employs a random-effect negative binomial (RENB) model for the daily trip origin and destination counts at the census tract level.

Results of the RENB model reveal that the important determinants (significant in both origin and destination models) that contribute to increases in shared e-scooter demand in Chicago due to a unit change in the respective variable are: i) income, ii) gasoline prices, iii) presence of a Divvy bike-share station, iv) number of zero-car households, v) land use mix, vi) parking cost, vii) number of parks and open spaces in a census tract, viii) average temperature, and ix) weekend. On the other hand, the significant determinants that are found to decrease the shared e-scooter usage are: i) precipitation (rain), ii) the number of crimes, and iii) average wind speed.

5.2 Policy Implications

The findings of this study provide valuable insights for city planners and policymakers, which have implications for the regulations, planning, and management of shared e-scooters. Results indicate that areas with higher population density and mixed land use with a medium- to higher-income are more involved in e-scooter usage. This result contradicts previous studies which found a negative association between income and shared e-scooter use (Bai and Jiao, 2020; Jiao and Bai, 2020). The lower availability of shared e-scooter in the low-income neighborhood in Chicago may be one of the reasons for these contradicting results. To ensure equity and higher usage among lower-income communities, planners and policymakers should impose requirements and regulations that e-scooter operators ensure a certain percentage of e-scooter availability in low-income neighborhoods throughout the day. Another possible reason could be

the fact that many of Chicago's low-income households do not have access to mainstream bank accounts or credit cards (FDIC, 2017), which are required to access shared e-scooters or any other smartphone-based-shared transportation services. To ensure equity and provide services to underserved communities, policymakers and shared e-scooter companies need to create a system that is easily accessible to the users with no credit cards as well as considering access to mainstream financial products as part of their equity analyses (King and Saldarriaga, 2017; Golub et al., 2019). Besides, the City government can regulate the availability of dockless e-scooters in low-income areas to ensure equity.

The findings related to the parking cost suggest that a higher parking cost is associated with higher usage of e-scooters. The city authority could provide more e-scooters in areas where they want to increase the parking cost. This would minimize the negative impact of increased parking costs on car users and help reduce the use of personal vehicles. Results of transit supply feature variables reveal a mixed relationship between e-scooters and public transportation stations. On the other hand, while the origin census tracts with at least one train station generate higher e-scooter demand than census tracts with no station, this variable is not statistically significant in the destination model. These results indicate that shared e-scooter trips are more likely to start near a transit station than end near a transit station, i.e., they are more likely to be "the last-mile" than "the first-mile." These findings provide insights into the e-scooter companies and transit authorities that e-scooters may act as a complement mode to transit for "the last-mile" in areas with rail stations. It may also work as a "the first-mile" trip to transit station if the availability of these services can be increased throughout the city.

Usage of shared e-scooters is also associated with census tracts with at least one public Divvy bikeshare station. The findings can be helpful for shared e-scooter companies as they can

increase the usage of shared e-scooters by expanding the availability of e-scooters in areas with existing Divvy stations.

The result related to the weekly gasoline price is positively associated with e-scooter usage, which reinforces the importance of gasoline prices (and taxes) on the use of energy-friendly modes (Gimenez-Nadal and Molina, 2019). However, more research is needed to determine if the relationship established here holds and test whether these shifts are temporary adjustments or long-term behavior changes towards adopting "green" modes. Because this study, like most previous studies (e.g., Lane, 2010; Goetzke and Vance, 2018; He et al., 2020; Younes et al., 2020), considered changes in gas price over a relatively short period of time. As gas prices can fluctuate by large margins over a short period, we expect any modal shift response to be somewhat subdued, especially for non-discretionary travel. Previous research demonstrates that cutting discretionary auto travel is a popular response to higher gasoline prices (Trent and Pollard, 1983). If the higher prices are temporary, travelers are probably more likely to make personal budget adjustments in the short-term rather than switch modes due to higher prices (Lane, 2010).

Results of weather variables indicate that higher temperature is positively associated with e-scooter usage, while rain and higher wind speed negatively affect the e-scooter demand, suggested that inclement weather conditions are significant detractors for e-scooter trips. This information can help e-scooter companies and transportation planners to plan for and manage e-scooters under various weather conditions. In addition, e-scooters are found to be more popular during weekends than on weekdays. These findings can also benefit shared e-scooter companies as they can introduce different fare programs for weekdays to attract more trips.

5.3 Limitations and Future Research

Although the study only uses data from Chicago, which has unique characteristics like any other city, the findings of this study not only provide valuable insights for city planners and policymakers, they can also help future shared micromobility research identify important factors that appear to vary (or to be similar) across cities. However, careful consideration needs to be taken to generalize the findings since the model was developed based on specific time-period data from a pilot program. A similar model can be applied using year-long shared e-scooter data from other cities for the better generalizability of the results. For example, since the E-scooter pilot program in Chicago was conducted mainly in the warm weather period, the study could not capture the impact of winter weather on e-scooter usage. Future studies should use year-long data to estimate the effects of other weather events such as snowfall on e-scooter usage.

Another limitation of this study is that the pilot program data only covers a specific region in Chicago. As a result, some findings could be context-specific and inconclusive. For example, while previous bikesharing studies found several points of interest variables such as restaurants and museums are significant determinants of bikesharing demand (e.g., Hyland et al., 2018), these variables are not statistically significant in any of the models. It is not clear from this study whether this is due to the dissimilarity between e-scooter usage and traditional bikeshare usage or the limitation of the data's spatial coverage (pilot area only). Likewise, while the origin model's transit supply variables indicate that people link e-scooters to transit trips, it does not capture the substitute effect. That is, whether e-scooter trips replace bus or rail trips. A more in-depth investigation of these matters is needed using city-wide data.

While the usage of shared e-scooters is positively associated with the presence of Divvy bikeshare stations, it is not clear from the analysis whether shared e-scooters would have complementary or substitute relationships with station-based bike-share programs. A more in-

depth study using data from other cities beyond pilot programs is needed. The reliability of data related to crime variables used in this study, such as assaults, robberies, and battery counts, is not satisfactory. The relationship between crime variables and e-scooter usage needs to be investigated further using a more reliable data source. In addition, the findings of the relationship between users' socio-demographic characteristics and shared e-scooter demand are inconclusive. Future research using data from whole Chicago or other cities may provide more insights on this relationship. Moreover, future studies using disaggregate level users' demographic data can also shed light on this issue.

The model also did not consider the pilot program's design and operational principles (e.g., geofencing, rebalancing requirements, etc.). This design endogeneity issue (Wang and Chen, 2020) might influence the e-scooter demand. For example, the pilot program has a rebalancing requirement of 25 percent in the two priority areas in order to ensure accessibility to underserved community areas. While the availability of e-scooters throughout the day in a neighborhood will impact its usage, the study could not include this variable as a covariate due to data limitations. This is left for future works. While the result indicates that people use e-scooters in the same places where people use Divvy bikes, it does not ensure that the e-scooter riders and Divvy riders are the same customers. This study also does not show whether e-scooters replace rides on Divvy or increase the demand for Divvy. Future studies should focus on these research questions.

Access to the "smart mobility ecosystem," including bank accounts and credit cards, is a key to the use of smart mobility services like e-scooters, which could impact the usage of these services by lower-income communities. Because they rely more heavily on paying cash for transportation services, have lower access to the internet at home and work, and are more likely

to reduce data use or cancel cell plans because of cost or data restrictions (Golub et al., 2019).

Future research should estimate the impact of the accessibility to smart mobility ecosystems such as unbanked and underbanked rates and smartphone ownership rates on shared e-scooter usage among lower-income communities. Another future research avenue includes clustering the census tracts (based on land use, income, or car ownership) to investigate how determinants vary across different clusters. While the model addressed the heterogeneity caused by temporal autocorrelation, we did not test the heterogeneity of significant variables. Future research should estimate a random parameter model to capture the heterogeneity of variables. Another possible model improvement involves modeling origin-destination pair flows rather than modeling origin and destination trips separately. Besides, the relationship between the price and e-scooter demand can be an important future study. Finally, this study is performed using data from the pre-COVID-19 period, and the e-scooter usage pattern may change during COVID-19 (Heineke et al., 2020). Therefore, a study concerning the e-scooter usage pattern before, during, and after COVID should be of future interest.

Funding

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Appendix

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