Understand usage patterns of e-scooter sharing and policy implications

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by
Yu Zhang
Yujie Guo

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16. Abstract

Shared e-scooter is a fairly new transportation mode that emerged in late 2017. Since then, it has gained popularity around the world; however, it also has spiraled into disarray in many cities due to the lack of e scooter regulations and improper parking and riding behaviors. Limited understanding of shared e-scooters restrains policymakers from developing more effective regulations and promoting this sustainable transportation mode. This study takes a step towards understanding e-scooter user behaviors by investigating factors that influence e-scooter sharing usage and auto mode substitution. Survey data were collected from shared e-scooter users, and random parameter models were applied to explore the factors influencing e-scooter sharing usage and mode substitution. Factors considered in models include sociodemographic information, user behaviors, trip purposes, and health indicators. Model results identify several factors that significantly influence shared e-scooter usage, factors include user gender, helmet use, exposure to shared e-scooters, ownership of an e-scooter, where they ride, opinions on speed limits, and trip purposes. The findings for auto substitution suggest that shared e-scooters are potentially competing with TNC/taxi, lower costs and social/entertainment trip purposes are the contribution factors. We also find that user household with multiple vehicles contributes to private vehicle substitution. Research outcomes suggest shared e-scooters could play a significant role in urban transportation sustainability. The insights toward better practices of e-scooter regulations and planning are discussed at the end of paper to help cities improve the performance of shared e-scooter programs and make it a more sustainable transportation mode.

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1. Introduction

Micromobility has gained much attention in past years, from station-based bike sharing to dockless bike sharing and, recently, shared e-scooters (unless specified, "e-scooter" in this research refers to "kicked e-scooter"). These transportation modes provide users with a convenient option for short-distance travel. Similar to dockless bike sharing, shared e-scooters can be picked up wherever available and returned to any locations within the service area. Because of its convenience, fun riding experience, and flexibility, e-scooter sharing has reenergized the micromobility trend pioneered by Lime and Bird in the United States. Since its debut in late 2017 in Santa Monica, California, shared e-scooters have been adopted quickly compared with other shared mobility modes (e.g. bike sharing, car sharing) (Populus, 2018); by the end of 2018, the number of e-scooter sharing trips exceeded station-based bike sharing trips (NACTO, 2019), making it the most popular shared micromobility mode in the U.S.

Many cities have embraced shared e-scooters; as the National Household Travel Survey (NHTS) suggests, 45.6% of vehicle trips in the U.S. are less than 3 miles, making those journeys open to alternative micromobility modes (NHTS, 2019). Indeed, many published e-scooter sharing evaluation reports suggest that shared e-scooter has promise for replacing vehicle trips (City of Santa Monica, 2019; Mobility Lab, 2019) and are addressing first/last mile problems (City of Chicago,2020). However, e-scooter sharing is a new mode to the general public, and cities do not have regulations for this new mode. The boom of shared e-scooters has caused considerable complaints from the public regarding aggressive rider behaviors, safety concerns, abuse of street space, etc. Gössling (2020) surveyed 173 news items across the U.S., Europe, New Zealand, and Australia and found that shared e-scooter-related problems are different among cities. Irresponsible riding, safety/injuries, and cluttering of e-scooters are the top negative discussion points in many cities. To address these issues, Gössling (2020) suggests that urban planners need to introduce policies regarding speed limit, dedicated parking, etc.

Given the popularity of e-scooter sharing demand and related issues, there is a need to understand user behaviors of shared e-scooters. U.S. cities such as Chicago (IL), Portland (OR), and Arlington (VA) have implemented pilot programs, and survey responses and operational data have been collected to characterize user profiles and travel behaviors (motivations, mode substitution, etc.). Table 1 summarizes some key findings from these pilot program reports. Outside the U.S., Bieliński and Ważna (2020) conducted a survey of shared micromobility users in Poland, and results suggest that shared e-scooter users tend to be younger than e-bike users and that shared e-scooters are mainly used for leisure trip purposes, whereas e-bikes are popular for commuting. Similar findings on travel purposes also were found in Washington, D.C. with regards to shared bikes and e-scooters (McKenzie, 2019).

Table 1: User characteristics and behaviors of riding shared e-scooters

Metrics	Findings from Different Cities
User sociodemographics	Majority of users are male, white, have higher income and higher education degree (Mobility Lab, 2019; PBOT, 2018)
Average trip duration/length	12 min/1.5 mi (City of Chicago, 2020); 1.15 mi in Portland (PBOT, 2018)
Trip purpose (top 3)	Social/entertainment, connect to/from bus, connect to/from Metrorail (Mobility Lab, 2019); for fun, to/from work, social/entertainment (PBOT, 2018)
Motivations factors (top 3)	Get around faster, convenient, fun to ride (Mobility Lab, 2019); looked fun/curiosity, get around faster/easier, save money (PBOT, 2018)

In addition to analyzing survey data, McKenzie (2019) and Zhu et al.,(2020) explored the spatial-temporal travel patterns of shared e-scooters, and comparisons were made with bike sharing. To further understand shared e-scooters, Bai and Jiao (2020), Caspi et al. (2020), and Jiao and Bai (2020) built econometric models to explore how environmental, land use and demographic factors contribute to e-scooter usage based on shared e-scooter trip data. These studies identify several influential factors that include population density, student population, residents with higher education, employment rates, presence of transit stations, street connectivity, mixed land use, etc. To provide a better riding environment for shared e-scooters, Feng et al. (2020) and Zou et al. (2020) estimated trip trajectories of e-scooter routes and identified street segments with most e-scooter trips; several unsafe spots were identified, and suggestions were made to the city with regard to bike lane planning.

Previous studies have depicted user profiles and explored user travel behaviors/patterns of shared e-scooters. However, there is a lack of studies that explore how user characteristics and travel behaviors affect the usage of shared e-scooters. To better promote its sustainability, there is also a need to understand what factors encourage users to substitute vehicles with shared e-scooters. A better understanding of such topics will allow policymakers to better promote and regulate shared e-scooters. Similar studies have been explored by bike sharing (Guo et al., 2017; Barbour et al., 2019) and moped scooter sharing (Aguilera-García et al., 2020). To fill this research gap, this study applied econometric models to investigate the factors that influence the usage and auto mode substitution of shared e-scooters. Specifically, a survey questionnaire was developed that incorporated detailed questions about e-scooter user sociodemographic information, riding experiences and behaviors, accident experiences, and mode substitutions. The survey was disseminated to the public five months after an e-scooter sharing program was launched in Tampa, Florida. The collected survey data were used for econometric modeling, and modeling results provide insights into better understanding of user behaviors.

The contributions of this study are the following:

- Previous studies that explore factors that influence shared e-scooter usage rely on ridership data. This study took another approach, based on user characteristics, and provides another angle of understanding shared e-scooters usage.
- Shared e-scooters are promising for reducing auto use. Little is known about the underlying factors that motivate auto substitution. This study provides insights into understanding factors that lead to auto substitution.
- Findings from models and surveys shed light on the understanding of user behaviors of riding shared e-scooters. The outcomes are compared with other shared micromobility modes.

The rest of this paper is organized as follows. Section 2 summarizes the literature that explores micromobility usage and auto mode substitution. Section 3 describes the methodological framework of this study that includes study area, survey design, and model specifications. Section 4 presents and discusses modeling results. Finally, Section 5 concludes the paper, discusses limitations and future study directions, and offers policy implications.

2. Literature review

This section reviews the literature related to factors that influence usage and auto mode substitution of shared micromobility. As e-scooter sharing is a relatively new transportation mode, research is still limited compared with bike sharing; therefore relevant bike sharing and moped scooter sharing literature is summarized to enrich the discussion.

2.1 Influential factors on shared micromobility usage

Previous studies that capture the determinants of affecting e-scooter sharing usage are based on trip data. For details of these studies, refer to Bai and Jiao (2020), Caspi et al. (2020), and Jiao and Bai (2020). These studies explored how the built environment, land use, and socio-demographics in an area affect the use of shared e-scooters. These studies were undertaken at an aggregate level and do not provide much information about underlying factors of shared e-scooter users that contribute to shared e-scooter usage. Studies on other shared micromobility modes have provided considerable insights into the relationship between individual characteristics and shared micromobility usage; examples of individual characteristics include socioeconomic characteristics, travel behavior and history, personal attitude, and health indicators.

Socioeconomic characteristics are closely related with shared micromobility usage. From a gender perspective, 67–78% of bike sharing trips are made by men in countries such as the U.S., the UK, and Australia, where biking is not the primary mode of transportation (Pucher et al., 2011). Males also tend to ride shared bikes more frequently (Guo et al., 2017; Barbour et al., 2019). In terms of age, users of shared e-scooters tend to be younger in Portland (PBOT, 2018) and Arlington (Mobility Lab, 2019), and studies suggest younger users are more likely to use moped scooters frequently (Aguilera-García et al., 2020). Regarding ethnicity, studies found that Caucasians are generally overrepresented in bike sharing programs (Buck et al., 2013; Fishman, 2016), and Caucasians also ride shared bikes more frequently compared with other ethnicities (Barbour et al., 2019). Regarding income, users of bike sharing are mostly wealthier populations (Fishman et al., 2015), and higher-income users ride shared bikes more frequently (Barbour et al., 2019).

With regard to travel behaviors and travel history, vehicle ownership or use of private vehicles are related to micromobility usage. User households with three or more vehicles tend to ride bike share less frequently, similar to low parking time (Barbour et al., 2019). Users who never use private vehicles are more likely to use moped scooters (Aguilera-García et al., 2020). Use of other modes also have influence on shared micromobility usage; individuals who are frequent bike sharing users are significantly more likely to use moped scooter sharing, and individuals who never travel on foot are significantly less likely to ride moped scooters (Aguilera-García et al., 2020). Travel time is also an influential factor; users with a short trip (<30 min) or a daily travel time greater than 90 minutes were more likely to be frequent bike sharing users) (Guo et al., 2017). Trip purpose is another indicator that influences shared micromobility usage; users who frequently ride shared moped scooters for commuting purposes are more likely to be frequent users (Aguilera-García et al., 2020); lack of commuting, however, lessens the likelihood of being a frequent bike sharing user (Barbour et al., 2019). Helmet use is also related with the use of shared micromobility. Helmet use among shared bike users are significantly lower than private bike users (Kraemer et al.,2012; Zanotto and Winters,2017) and a lack of access to helmets are critical barriers to bike sharing programs in countries in which wearing helmets are mandatory(Fishman et al.,2012).

Personal attitude also significantly influences use of shared micromobility. Users with positive attitudes (e.g., familiarity, satisfaction, green travel) towards bike sharing use ride shared bikes more frequently, whereas negative attitudes (e.g., wastes travel time) present the opposite effects (Guo et al., 2017). Eccarius and Lu (2020) explored the usage intention of university students. Lack of perceived compatibilities with personal mobility needs, lifestyle, and personal values contribute to low intention of using shared e-scooters, and awareness/knowledge of a shared system and environmental values indirectly influence usage intention.

Active transportation and public health are closely linked. For example, riding shared bikes increases the physical activities of users and brings health benefits (Otero et al., 2018). The health indicator is also found to be related to the frequency of bike sharing usage. Barbour et al. (2019) found that users who are overweight are more likely to ride shared bikes frequently, suggesting the potential of bike sharing for improving public health.

2.2 Influential factors on auto mode substitution

Shared e-scooters can travel up to 15 mph, which makes them competitive with other transportation modes. It disproportionately replaces walking and bicycling for all trip types(Sanders et al.,2020). Survey results from different cities also show that shared e-scooters have great promise for replacing auto trips (private vehicle driving, TNC/taxi); for example, 48.6% of shared e-scooter trips could have been completed by vehicles if shared e-scooters were unavailable in Portland (PBOT, 2018); this value is 42.6% in Chicago (City of Chicago, 2020). Reduced auto use is not only good for alleviating traffic congestion and mitigating air pollutant emissions but also leads to increased physical activities. However, it is still unclear what factors encourage such mode substitution. For bike sharing, a few studies have explored this topic. Auto substitution ratios for bike sharing vary across areas, from 20% in Melbourne, Brisbane, and Minnesota to 7% in Washington, D.C. and 2% in London. Considering vehicles miles traveled for bike sharing rebalancing, Melbourne, Brisbane, Minnesota, and Washington, D.C. show reduced vehicle mileage travel, whereas London shows more vehicle mileage travel mainly due to a low car mode substitution ratio (Fishman et al., 2014).

In terms of factors that motivate users to substitute driving with bike sharing, Yang et al., (2016) conducted a survey in Nanjing to investigate factors motivating people to replace driving with metro (with bike share as feeder mode). Several factors identified include long drive, inconvenience of parking, traffic congestion, and high commuting expenses. Ma et al. (2019) conducted a survey about the willingness to shift from driving to bike sharing from a psychological perspective and found that perceived health benefits, ease of use, and usefulness have positive effects on people's attitudes on dockless bike sharing, and positive attitudes can be converted to higher willingness of mode shift from driving to dockless bike sharing. From a sociodemographic perspective, Barbour et al., (2019) found that users under age 30 are more likely to substitute bike sharing for driving, and respondents with high annual household income (more than $200,000) present the opposite results. Also, they found that respondents who commute by driving alone, who are obese (BMI above 30) are also more likely to substitute bike share for driving.

The literature review provides an overview of factors that affect shared micromobility usage and auto substitution from a person perspective. As the literature review shows, a rich array of influential factors has been discovered for shared micromobility usage. Influential variables for auto substitution are less discussed. These variables can potentially also influence shared e-scooter usage and mode substation and provides insightful information for survey design, model specification, and results comparison.

3. Methodological framework

To investigate the factors that influence e-scooter sharing usage and auto substitution, a survey was designed and disseminated to the public that incorporated questions about user riding behaviors, experiences, and sociodemographic information. The survey data were used to estimate econometric models, and model results were interpreted to help better understand user behaviors. This section describes the study area, survey design, and model specifications.

3.1 Study area and e-scooter sharing program

Tampa is the economic hub of west central Florida and is the third most populous city in the state. Its economy is founded on a diverse base that includes tourism, health care, finance, insurance, higher education, and technology, among others. According to DATA USA, in 2018 Tampa had a population of 393,000, ranking it the 49th most populous city in the U.S. Travel in Tampa heavily relies on private vehicles—76.1% of workers drive alone for daily commuting, 9.97% choose carpool, and only 2.47% use public transit. Private vehicle dependence causes significant traffic congestion. According to TOMTOM (2019), Tampa ranked as the 2nd most congested city in Florida and 25th nationally in 2018.

An e-scooter sharing program was introduced in Downtown Tampa in May 2019, with four vendors—Bird, Jump, Lime, and Spin. Each vendor could distribute up to 450 e-scooters on the street. The objective of the program was to introduce a new, low-cost transportation method to enhance the mobility and address first/last mile needs in the Downtown area. To better understand the performance of the program, the City of Tampa partnered with the University of South Florida to conduct a comprehensive evaluation of the program. As part of the evaluation process, a survey was disseminated to the public five months after the program was launched to collect public opinion. The study team also collected shared e-scooter operational data and accident data. Evaluation results suggest that the program has made Downtown areas better connected and has positive impacts on the local economy, especially entertainment and restaurants. However, a low shared e-scooter supply and use are observed in areas with higher poverty ratios. The City also received complaints from the public regarding to parking issues, high-speed sidewalk riding, usage violations in "no ride" zones, and violation of traffic rules. A majority of the public still hope shared e-scooters can be continued in the city, but adjustments are expected to address the complainant issues.

3.2 Survey design and data collection

The e-scooter sharing survey was disseminated to the public, including users and non-users. Design of survey questions was based on extensive review of survey questionnaires from other cities and shared micromobility literature. The survey asked non-users about sociodemographic information, e-scooter collision experiences (type of collision, cause, level of injury, etc.), safety perceptions, and opinions on the program. Safety perceptions asked for opinions on speed limits and right-of-way of e-scooters. Users were asked additional questions related to their riding behaviors and experiences and mode substitution. For riding behaviors, users were asked about the frequency of riding shared e-scooters, helmet use, where they ride shared e-scooters (sidewalk, bike lane, street lane, etc.), motivations for riding shared e-scooters, and trip purposes. For mode substitution, users were asked to recall their latest e-scooter sharing trip, trip purpose, motivation factors, and what other transportation modes they would have used for that trip if the e-scooter sharing program were unavailable. As Barbour et al. (2019) found that the health indicator "BMI" also influences user bike sharing usage and mode substitution, questions about user height and weight were also included in the survey to enable computation of BMI value for each survey respondent. The survey was coded in Qualtrics, which is a web-based survey. To ensure that the survey could reach a wide range of demographics, various channels were used to distribute it, including through the Hillsborough County Metropolitan Planning Organization (MPO), local homeowner associations, and e-scooter sharing operators. The City of Tampa also posted the survey through social media multiple times, and the link was added to the City's official webpage for the shared e-scooter program. In addition, the research team also distributed flyers in Downtown Tampa that contained the survey link and explained the purpose of the survey to pedestrians who accepted the flyers. The survey was disseminated from October 29–December 3, 2019, and a total of 698 user responses were collected. After data cleaning, 585 responses were kept for model estimation.

3.3 Sustainability of shared e-scooter program

The sustainability of shared e-scooter program was confirmed. In Tampa, survey statistics suggest that 45.4% of trips would have been made by vehicles if the program did not exist. After one year from when program was started, around 1 million trips were taken by shared e-scooters and 1.18 million miles were traveled by shared e-scooters. If it is assumed that the travel distance of vehicles and shared e-scooters are equivalent, shared e-scooters reduced 0.54 million vehicle miles traveled. Given that the average vehicle miles traveled per driver is 13,476 miles (FHWA, 2018), shared e-scooters in Tampa reduced 40 vehicle drivers annually. Given average gasoline consumption and carbon dioxide emission per mile (EPA, 2018), shared e-scooters reduced 53,566 gallon gas and 476.7 tons of carbon dioxide. The reduced vehicle miles traveled and traffic emissions due to vehicle substitution bring significant environmental benefits.

3.4 Model specification

To explores factors influencing e-scooter sharing usage and auto mode substitution, an econometric modeling approach was adopted. This section discusses the methodology of the econometrics models applied in this study.

3.4.1 E-scooter sharing usage model

To encode the user frequency of riding shared e-scooters, users were asked "How often did you ride shared e-scooters?" The choice set included "Once a while," "Occasionally, but less than once per week," "1 to 3 times per week," "4 to 6 times per week," "7 or more times per week," and "I don't know, just started using shared e-scooters." For users who ride shared e-scooters more than once a week, it showed the regularity of using this mode; thus, these users were grouped and termed "regular/ frequent users." Users who rode shared e-scooters "occasionally, but less than once a week" were termed "occasional users," and users who rode shared e-scooters once a while were termed "infrequent users." Users who just started riding shared e-scooters were filtered from the dataset, which resulted in 544 observations in total, including 193 infrequent users, 184 occasional users, and 167 regular users.

Since the dependent variable (e-scooter sharing usage) has discrete values, and these values are ordered from low to high, an ordered probability model was suitable for model estimation. According to Washington et al. (2020), an ordered probability model is derived by introducing a latent variable z as a basis for modeling the ordinal rank of e-scooter sharing usage. This unobserved variable is typically specified in a linear form as follows:

$$z = \boldsymbol{\beta X} + \varepsilon \tag{1}$$

Where $\boldsymbol{\beta}$ is a vector of estimable parameters, $\boldsymbol{X}$ is a vector of independent variables and ε is a random disturbance term. Using Equation 1, for each observation, the observed ordinal data y can be defined as:

$$\begin{aligned} y &= 1 \quad \text{If } z \leq \mu_0 \quad \text{(Infrequent user)} \\ y &= 2 \quad \text{If } \mu_0 \leq z \leq \mu_1 \quad \text{(Occasional user)} \\ y &= 3 \quad \text{If } z \geq \mu_1 \quad \text{(Regular user)} \end{aligned} \tag{2}$$

Where μ_0 and μ_1 are thresholds that define y and are jointly estimated with β parameters. The estimation of probability of specific ordered responses for each observation can be accomplished by assuming ε is normally distributed with mean 0 and variance 1, then the ordered probit model with the probability of each usage category can be derived as follows:

$$\begin{aligned} P(y = 1) &= \Phi(\mu_0 - \boldsymbol{\beta X}) \\ P(y = 2) &= \Phi(\mu_1 - \boldsymbol{\beta X}) - \Phi(\mu_0 - \boldsymbol{\beta X}) \\ P(y = 3) &= 1 - \Phi(-\boldsymbol{\beta X}) \end{aligned} \tag{3}$$

Where $\Phi(\cdot)$ is a cumulative normal distribution function and μ_0 is set as 0 without loss of generality. This standard form treats parameters $\boldsymbol{\beta}$ as constant across observations, which restricts each variable to having same impact on each observation. Such fixed parameter assumption may not be correct. In the model estimation, it is important to consider the possibility of unobserved heterogeneity across observations. To handle unobserved heterogeneity, a random parameter ordered probit model was introduced and simulated maximum likelihood estimation been developed by adding a randomly distributed error term φ (e.g. normal distribution) (Greene 2007):

$$\beta^* = \beta + \varphi \tag{4}$$

3.4.2 Mode substitution model

To sample mode substitution, users were asked "For your last ride on a shared e-scooter, if the e-scooters was not available, what other transportation mode would you have used instead? (most preferred)." The choices and counts (percentage) of selecting that choice included "Walking" 202 (38.4%), "Public transit (HART, etc.)" 3 (0.6%), "Lyft, Uber or taxi" 141 (26.8)%, "Coast Bike Share" 15 (2.9%), "Private bike/e-scooter" 17 (3.2%), "Drive the car" 99 (18.8)%, "Car share (e.g., Zipcar)" 1 (0.2%), "As a passenger in friend, family member, or another person's car" 8 (1.5%), "I wouldn't have made the trip" 30 (5.7%), and "Other" 12 (2.3%). Among these options, "Drive the car," "Walking," and "Lyft, Uber or taxi" were selected most often. This study was interested in understanding the contributing factors for substituting auto modes (e.g., private vehicle driving, TNC/taxi). As the substituted mode choices are discrete outcomes, to model discrete outcomes, multinomial logit (MNL) model is appropriate. For modeling purposes, this study reduced the choice set to 4 options, including "Walking," "Driving," "TNC/taxi," and "Other." "Other" includes all choices in the choice set except "Walking," "Driving," and "TNC/taxi" as those choices (e.g. 'Car share', 'Public transit') had a rather low choice count.

The definition of an MNL model follows (Washington et al., 2020). Given a set of discrete outcomes (e.g., substituted mode choices), the function determining the choice outcome probabilities can be defined as

$$T_{in} = \boldsymbol{\beta_i} \boldsymbol{x}_{in} + \boldsymbol{\varepsilon_{in}} \tag{5}$$

Where $\boldsymbol{\beta_i}$ is a vector of estimable parameters for discrete outcome i. Assuming the disturbances follow extreme value Type I distribution, a standard multinomial logit model has the form:

$$P_n(i) = \frac{\text{EXP}\,(-\boldsymbol{\beta}_i \boldsymbol{x}_{in})}{\sum_{\forall I} \text{EXP}\,(-\boldsymbol{\beta}_i \boldsymbol{x}_{in})} \tag{6}$$

In this research, $P_n(i)$ can be referred as the probability of respondent n used shared e-scooters to substitute mode i, I denotes all mode choices that users can substitute. Similarly, it is necessary for logit model to account for the unobserved heterogeneity across the populations, then Equation 6 can be rewritten as:

$$P_n{}^m(i) = \int P_n(i)\ f(\boldsymbol{\beta}|\boldsymbol{\varphi})d\boldsymbol{\beta} \tag{7}$$

Where $f(\boldsymbol{\beta}|\boldsymbol{\varphi})$ is the probability density function (e.g. normal distribution) of $\boldsymbol{\beta}$, $\boldsymbol{\varphi}$ refers to a vector of parameters that describe the densify function (mean and variance). This function allows some of $\boldsymbol{\beta}$ to be fixed and some of $\boldsymbol{\beta}$ to account for the variational effects of $\boldsymbol{x}$ on outcome probabilities across observations. The resulting model is called mixed logit model.

3.4.3 Model estimation

The estimation of the random parameter ordered probit model and the mixed logit model was undertaken by a simulated maximum likelihood approach because the integrations of probability functions are not in a closed form. There has been considerable research on how to best draw $\boldsymbol{\beta}$ from $f(\boldsymbol{\beta}|\varphi)$ so that accurate approximation of probability can be derived with as few draws as possible (Washington et al.,2020). Drawing sample values randomly is one of the start points, and the most popular alternative to random draw is the Halton draw, which is found to be much more efficient compared to random draw (McFadden and Ruud, 1994; Bhat, 2003). In this study, 1000 Halton draws were used, which has been shown to be more than enough for model estimation (Bhat, 2003; Milton et al., 2008; Anastasopoulos and Mannering, 2009; Behnood and Mannering, 2016). To confirm the significance of random parameters, in addition to significant t-statistics of the random parameter error term, this study also conducted a likelihood ratio test that compared models between fixed parameter and random parameter. The model estimation process was conducted in NLOGIT version 6 (Greene, 2016). The marginal effects of models were obtained in NLOGIT for variable interpretation. Marginal effects reflect the probability change on y if a variable x changes by one unit.

4. Results and discussion

This section presents survey observations, model estimation results, and variable interpretations for shared micromobility usage and mode substitution.

4.1 Survey statistics in the model

Tables 2 and 3 present independent variables included in the model; all variables are categorical indicators. The count and percentage of these indicators in total observations is also presented, and each indicator has at least 20 observations.

Table 2: Summary statistics for variables included in e-scooter usage model

Variable Description	Counts	Percentage
Socioeconomic factors		
Male indicator (1 if respondent is a male, 0 otherwise)	326	0.60
Live in Downtown Tampa (1 if respondent lives in downtown Tampa, 0 otherwise)	201	0.37
Own an e-scooter (1 if respondent owns a private usable e-scooter, 0 otherwise)	27	0.05
E-scooter riding behavior		

Ride e-scooters on bike lane (1 if respondent mostly rides shared e-scooter on bike lanes, 0 otherwise)	131	0.24
Wear a helmet (1 if respondent wears a helmet at least once while riding an e-scooter, 0 otherwise)	60	0.11
Low speed limit (1 if respondent thinks the speed limit of e-scooter should be lower than 10 mph, 0 otherwise)	82	0.15
Motivation factor of riding shared e-scooters		
Easy to use (1 if respondent thinks shared e-scooter is easy to use, 0 otherwise)	392	0.72
General trip purposes of riding shared e-scooters		
Dining (1 if respondent rides shared e-scooter for dining, 0 otherwise)	305	0.56
Sightseeing (1 if respondent rides shared e-scooter for sightseeing, 0 otherwise)	218	0.40
Recreation (1 if respondent rides shared e-scooter for recreation, 0 otherwise)	386	0.71
Commuting (1 if respondent rides shared e-scooter for commuting, 0 otherwise)	234	0.43

Table 3: Summary statistics for variables included in mode substitution models

Variable Description	**Counts**	**Percentage**
Socioeconomic factors		
Male indicator (1 if respondent is a male, 0 otherwise)	311	0.59
Medium-high income indicator (1 if respondent's annual household income is more than $99,999 and less than $199,999, 0 otherwise)	157	0.30
High income indicator (1 if respondent's annual household income is more than $200k, 0 otherwise)	114	0.22
College degree indicator (1 if respondent's highest completed level of education is college degree, 0 otherwise)	246	0.47
Household with more than one vehicle (1 if respondent's household has more than one vehicle, 0 otherwise)	372	0.70
Live in Downtown Tampa (1 if respondent lives in downtown Tampa, 0 otherwise)	348	0.66
E-scooter riding behavior		
Infrequent user (1 if respondent rides shared e-scooter once a while, 0 otherwise)	171	0.33
Motivation factor of riding shared e-scooter for last trip		
Lower cost (1 if respondent thought the cost of riding shared e-scooter is lower than other transportation modes, 0 otherwise)	147	0.28
It was just for fun (1 if respondent rode shared e-scooter for fun, 0 otherwise)	287	0.55

Fast and flexible (1 if respondent thought riding shared e-scooter is fast and flexible, 0 otherwise)	312	0.59
Difficult vehicle parking (1 if respondent thought parking was difficult at that time, 0 otherwise)	125	0.24
Trip purpose for last shared e-scooter ride		
Social/ entertainment purpose (1 if respondent's last shared e-scooter trip was for social/ entertainment purpose, 0 otherwise)	306	0.58
Health indicator		
Overweight (1 if respondent has BMI over 25, 0 otherwise)	287	0.55

4.2 E-scooter sharing usage frequency

Table 4 shows the modeling results of shared e-scooter usage in Tampa. "Commuting" was the only random parameter in the model. This significance was confirmed by conducting a likelihood ratio test, and test statistics rejected the null hypothesis (fixed and random parameter models are the same) with over 95% confidence. The parameter estimates in Table 4 provide a general sense of direction of variable impacts on model outcomes. Table 5 shows marginal effects that quantify variable impacts on each discrete outcome; the marginal effect values are statistically significant for infrequent users and regular users. Interpretation mainly focuses on the outcomes of regular users.

Table 4 Random parameter ordered probit model estimation results for usage frequency of shared e-scooters

Variable Description	**Estimated Parameter**	***t* Statistic**
Constant	-1.09	-7.21
Sociodemographic factors		
Male indicator (1 if respondent is a male, 0 otherwise)	0.34	3.06
Live in Downtown Tampa (1 if respondent lives in downtown Tampa, 0 otherwise)	0.45	3.76
Own an e-scooter (1 if respondent owns a private usable e-scooter, 0 otherwise)	0.50	2.32
Behavior and opinions		
Ride e-scooters on bike lane (1 if respondent mostly rides e-scooters on bike lane, 0 otherwise)	0.34	2.63
Wear a helmet (1 if respondent wore a helmet at least once while riding an e-scooter, 0 otherwise)	0.40	2.51
Easy to use (1 if respondent feels shared e-scooter is easy to use, 0 otherwise)	0.53	4.62
Low speed limit (1 if respondent thinks the speed limit of e-scooters shall be lower than 10 mph, 0 otherwise)	-0.65	-3.60
General trip purposes of riding e-scooters		
Dining (1 if respondent rides shared e-scooters for dining, 0 otherwise)	0.69	5.91
Sightseeing (1 if respondent rides shared e-scooters for sightseeing, 0 otherwise)	0.29	2.29

Recreation (1 if respondent rides shared e-scooters for recreation, 0 otherwise)	0.30	2.40
Commuting (1 if respondent rides shared e-scooters for commuting, 0 otherwise) (Standard deviation of parameter estimate, normally distributed. In parentheses)	0.75 (1.00)	6.46 (9.67)
Threshold 1	1.34	15.45
Number of observations	544	
Log-likelihood at convergence	–481.3	

Table 5: Average marginal effects for parameter estimates shown in Table 4 (y = 1 [infrequent user], y = 2 [occasional user], y = 3 [regular user])

Indicators	Marginal Effects		
	[y = 1]	[y = 2]	[y = 3]
Male indicator	-0.11	0.01	0.10
Live in Downtown Tampa	-0.14	0.00	0.14
Own an e-scooter	-0.14	-0.04	0.17
Ride e-scooters on bike lane	-0.11	-0.01	0.11
Wear a helmet while riding an e-scooter	-0.12	-0.02	0.14
Easy to use	-0.17	0.01	0.16
Low speed limit	0.24	-0.07	-0.16
Dining	-0.23	0.03	0.20
Sightseeing	-0.09	0.00	0.09
Recreation	-0.10	0.01	0.09
Commuting	-0.23	0.00	0.24

With regard to sociodemographic variables, male respondents had, on average, 0.1 higher probability of riding e-scooters regularly comparing with female. This aligns with the bikesharing literature, that male users are more likely to ride shared bikes in general (Pucher et al., 2011; Akar et al., 2013; Goodman and Cheshire, 2014; Barbour et al., 2019). Respondents who lived in Downtown had, on average, a 0.14 higher probability of riding e-scooters regularly than people who lived outside of Downtown Tampa. Since shared e-scooters are deployed only in the Downtown area, people living there had higher exposure to shared e-scooters and, consequently, used it more frequently. It is interesting to find that respondents who personally owned an e-scooter had, on average, a 0.17 higher probability of riding e-scooters regularly compared with non e-scooter owners, most likely because e-scooter owners are more familiar with riding e-scooters. Compared with the privately-owned e-scooters, shared e-scooters are free from charging and stealing issues. These might have motivated e-scooter owners to use shared e-scooters more frequently. Similar findings were also discovered for bike sharing (Guo et al., 2017).

In terms of shared e-scooter riding behaviors, users who had worn a helmet at least once had, on average, a 0.14 higher probability of riding shared e-scooters regularly. In the survey comments, some users also mentioned that lack of a helmet discouraged them from riding e-scooters because of safety concerns. Thus, available helmets could motivate users to ride shared e-scooters more frequently. It was also found that users riding shared e-scooters in bike lanes had, on average, a 0.11 higher probability of riding it regularly. Some survey comments mentioned that sidewalks in Tampa are uneven, which may cause riders to fall off an e-scooter; they believe that bike lanes provide a better riding experience that facilitate higher e-scooter usage. Furthermore, users who thought the speed limit should be slower than 10 mph had, on average, a 0.16 lower probability of being regular users and, on average, a 0.24 higher probability of being infrequent users. The imposed speed limit of riding an e-scooter is 15 mph in Tampa. Users preferring a lower speed used shared e-scooters less often due to safety concerns. If safety concerns are caused by unfamiliarity with riding e-scooters, a face-to-face training program might help. Finally, respondents who thought an e-scooter was easy to use had, on average, a 0.16 higher probability of riding one regularly; this finding is also consistent with bike sharing (Guo et al., 2017) and suggests that a better design of shared e-scooters (e.g., more stability) would encourage people to use them more frequently. In terms of trip purpose, it was found that dining, sightseeing, recreation, and commuting purposes all increased the likelihood of riding e-scooters regularly. Specifically, users who rode shared e-scooters for dining and commuting purposes had a higher probability (on average, 0.2 and 0.24, respectively) of being regular users than recreation (0.09) and sightseeing (0.09) purposes. This finding is interesting, as previous shared e-scooter literature suggests that shared e-scooters are mainly used for leisure trip purposes and commuting is not the main trip purpose (Hardt and Bogenberger, 2019; Caspi et al., 2020); it coincides with survey statistics. However, if users rode shared e-scooters for commuting, they tended to use it frequently, suggesting that some users adopted shared e-scooters as a regular mode for commuting. Moped scooter sharing literature also suggests that users riding moped scooters for commuting tend to be frequent users (Aguilera-García et al., 2020). In terms of dining, shared e-scooters provided a convenient way to access restaurants in the Downtown area without worrying about vehicle parking. Whereas recreation and sightseeing are leisure trip purposes, which do not occur as often as commuting or dining purposes in daily life, they also contribute to higher usage frequency. Other trip purposes that were insignificant in the model included shopping, connecting to public transit, and others. The commuting indicator was the only random parameter in the model, with a mean of 0.75 and a variance of 1, indicating a mixed impact on e-scooter sharing usage. Specifically, 77.3% of users who used shared e-scooters for commuting were more likely to ride it regularly.

4.3 E-scooter sharing mode substitution

Table 6 presents the model outcomes of auto mode substitution. In this mixed logit model, household with more than one vehicle was the only random parameter, and the significance of this random parameter was confirmed by conducting a likelihood ratio test; test statistics rejected the null hypothesis (fixed and random parameter models are the same) with over 90% confidence. To interpret model outcomes, marginal effects of variables were computed and are listed in Table 7. Interpretation of the variables mainly focused on vehicle driving and TNC/taxi.

Table 6: Mixed logit model estimation results for mode substitution

Variable Description	**Estimated Parameter**	***t*-Statistic**
Walk constant (defined for the walk substitution utility function)	1.29	6.09
Socioeconomic factors		
Male indicator (1 if respondent is a male, 0 otherwise; defined for driving substitution utility function)	0.87	2.31
College degree indicator (1 if respondent's highest completed level of education is college degree, 0 otherwise; defined for walk substitution utility function)	-0.35	-1.81
Medium-high income indicator (1 if respondent's annual household income is more than $99,999 and less than $199,999, 0 otherwise; defined for other modes substitution utility function)	0.48	1.99

High income indicator (1 if respondent's annual household income is more than $200k, 0 otherwise; defined for TNC/taxi substitution utility function)	0.83	3.33
Household with more than one vehicle (1 if respondent's household has more than one vehicle, 0 otherwise; defined for driving substitution utility function) (Standard deviation of parameter estimate, normally distributed. In parentheses)	-2.17 (4.25)	-1.2 (1.81)
Live in Downtown Tampa (1 if respondent lives in Downtown Tampa, 0 otherwise; defined for TNC/taxi substitution utility)	0.43	2.01
Live in Downtown Tampa (1 if respondent lives in downtown Tampa, 0 otherwise; defined for driving substitution utility function)	-1.24	-2.68
E-scooter riding behavior		
Once a while user (1 if respondent rides shared e-scooter once a while, 0 otherwise; defined for TNC/taxi substitution utility function)	-0.61	-2.53
Motivation factors of riding shared e-scooter for last trip		
It was just for fun (1 if respondent rode shared e-scooters for fun, 0 otherwise; defined for other modes substitution utility function)	0.36	1.6
Fast and flexible (1 if respondent thought shared e-scooter is fast and flexible, 0 otherwise; defined for other modes substitution utility function)	-0.56	-2.37
Lower cost (1 if respondent thought the cost of riding shared e-scooter is lower, 0 otherwise; defined for TNC/taxi substitution utility function)	0.67	2.99
Difficult vehicle parking (1 if respondent thought parking was difficult at that time, 0 otherwise; defined for driving substitution utility function)	1.46	3.22
Trip purpose		
Social/ entertainment purpose (1 if respondent's last shared e-scooter trip was for social/ entertainment purpose, 0 otherwise; defined for TNC/taxi substitution utility function)	0.64	3.13
Health indicator		
Overweight (1 if respondent's BMI is above 25, 0 otherwise; defined for driving substitution utility function)	-0.76	-1.73
Number of observations	546	
Log likelihood at zero [$LL(0)$]	–729.2	
Log likelihood at convergence [$LL(\beta)$]	-658.9	
ρ^2 [1- ($LL(\beta)$/ $LL(0)$]	0.096	
Corrected ρ^2 [1- ($LL(\beta)$-number of estimated parameters, K)/ $LL(0)$]	0.087	

Table 7: Marginal for parameter estimates shown in Table 6

	Average marginal effects			
Variable	**Walk**	**TNC/taxi**	**Drive**	**Other**
Constant (defined for walk substitution utility function)	0.26	-0.13	-0.05	-0.08

Variable	Average marginal effects			
	Walk	TNC/taxi	Drive	Other
Socioeconomic factors				
Male indicator (defined for driving mode substitution)	-0.02	-0.01	0.04	-0.008
College degree indicator (defined for walk mode substitution utility function)	-0.03	0.02	0.006	0.01
Medium-high income indicator (defined for other modes substitution utility function)	-0.01	-0.007	-0.003	0.02
High income indicator (defined for TNC/taxi substitution utility function)	-0.02	0.03	-0.004	-0.006
Household with more than one vehicle (defined for driving substitution utility function)	-0.02	-0.02	0.05	-0.009
Live in downtown Tampa (defined for TNC/taxi substitution utility function)	-0.02	0.03	-0.003	-0.006
Live in downtown Tampa (defined for driving substitution utility function)	0.01	0.01	-0.03	0.004
Riding behaviors				
Infrequent user (defined for TNC/taxi substitution utility function)	0.02	-0.03	0.004	0.008
Motivation factor of riding shared e-scooter for last trip				
It was just for fun (defined for other modes substitution utility function)	-0.02	-0.01	-0.004	0.03
Fast and flexible (defined for other modes substitution utility function)	0.02	0.01	0.004	-0.03
Lower cost (defined for TNC/taxi substitution utility function)	-0.02	0.04	-0.007	-0.007
Difficult vehicle parking (defined for driving substitution function)	-0.02	-0.01	0.04	-0.006
Trip purpose				
Social/ entertainment purpose defined for TNC/taxi substitution utility function)	-0.04	0.07	-0.01	-0.02
Health indicator				
Overweight (defined for driving substitution utility function)	0.01	0.01	-0.03	0.006

For socioeconomic variables, in terms of driving mode substitution, being a male user had, on average, a 0.04 higher probability of substituting shared e-scooters for driving. This suggests that shared e-scooters were more attractive to male users than driving. Users that lived in Downtown Tampa were, on average, 0.03 less likely to substitute private vehicle driving with shared e-scooters, possibly because respondents living in Downtown did not use private vehicles a lot in the Downtown area—expensive parking and congested traffic motivates them using other modes such TNC, bike sharing, etc. User households with more than one vehicle had, on average, a 0.05 higher probability of driving substitution. This is opposite to previous bike sharing literature, that users tend to use shared bikes less when they have access to vehicles (Barbour et al., 2019). Compared with bike sharing, shared e-scooter is more effective for auto substitution. Households with more than one vehicle is the random parameter in this model, with a mean of -2.17 and a variance of 4.64. This suggests that 68% of shared e-scooter users (with multiple household vehicles) were less likely to substitute driving with shared e-scooters. With regards to TNC/taxi substitution, users who had a high income or who lived in Downtown Tampa had, on average, a 0.03 higher probability of substituting TCN/taxi. Studies suggest that ridesourcing users also tend to be higher income groups and live in urban areas (Clewlow and Mishra, 2017). Given that users who are substituting

TNC/taxi tend to be the main users of TNC/taxi, this implies competition between TNC/taxi and shared e-scooters.

In terms of riding behavior and opinions, for users who substituted vehicle driving with shared e-scooters, parking was the main motivation factor. Users who had vehicle parking issues had, on average, a 0.04 higher probability of substituting driving. Thus, in areas with stressful parking issues, especially during big events, shared e-scooters can be deployed to encourage people to use the non-motorized mode. For users who substituted TNC/taxi, users who rode shared e-scooters infrequently had, on average, a 0.03 lower probability to substitute TNC/taxi, suggesting that frequent users or occasional users tends to use shared e-scooters to replace TNC/taxi. This finding also suggests the potential competition between shared e-scooters and TNC/taxi. Users who thought the cost of shared e-scooter was lower lead to, on average, a 0.04 higher probability of substituting shared e-scooters for TNC/taxi. Thus, the lower cost of shared e-scooters attracts TNC/taxi users.

With regards to trip purposes, for users who substituted TNC/taxi with shared e-scooters, users with social/ entertainment trips had, on average, a 0.07 higher probability of substituting TNC/taxi. Shared e-scooters provide a fun way to travel and can be very attractive for leisure trips compared with TNC/taxi.

From a health perspective, for users who substituted private vehicle driving with shared e-scooters, it was found that overweight users were, on average, 0.03 less likely to substitute driving, opposite the bike sharing mode (Barbour et al., 2019). Overweight users may use bike sharing to replace vehicle driving as a means of physical exercise; shared e-scooter does not require as much physical effort as bike sharing, so overweight users might be less likely to use it to replace vehicle driving.

5. Conclusions and policy implications

Shared e-scooters are surging in the United States and bring numerous benefits to society, both positive (e.g., reduced vehicle trips) and negative (e.g., high-speed riding on sidewalks). Previous studies on shared e-scooters have characterized user profiles and travel patterns; however, few investigated how user profiles and travel behaviors factors could affect the use and auto mode substation of shared e-scooters. Understanding these factors can help policymakers better regulate and promote shared e-scooters as a sustainable transportation mode. This study contributes to the existing literature by performing econometric modeling analysis to identify factors that influence e-scooter sharing usage and auto mode substitution.

This study identified several factors that affect e-scooter sharing usage, findings that are generally aligned with other shared micromobility literature—users who are male, ride shared e-scooters for commuting, and have positive attitudes towards e-scooters (e.g., easy to use) tend to ride shared e-scooters more frequently. Our estimated model also suggests that users who have higher exposure to shared e-scooters, own private e-scooters, ride shared e-scooters in bike lanes, and ride shared e-scooters for dining and leisure trip purposes are more likely to be regular users. Users who prefer lower speed limits ride shared e-scooters less frequently.

With regards to factors that affect TNC/taxi substitution, modeling results suggest that shared e-scooters potentially are competing with TNC/taxi. A contribution factor is lower traveling cost offered by shared e-scooters. Users who take social and entertainment trips are more likely to substitute shared e-scooters for TNC/taxi. For private vehicle driving substitution, users who are male, households that have more than one vehicle, and difficult vehicle parking are the contribution factors for driving substitution, although such mode substitution is less for users who are overweight. It is interesting that households that have more than one vehicle presents the opposite outcome with bike sharing, which suggests that shared e-scooters could be more effective for reducing auto use than bike sharing.

Based on research outcomes, shared e-scooters could play a significant role in urban transportation sustainability. Compared with bike sharing, shared e-scooters add potential to reduce auto trips in cities, not only because of a higher auto substitution ratio but because shared e-scooters are also attractive to user households with multiple vehicles. Their environmental benefits are huge considering reduced traffic congestion, traffic noise, and emissions. Based on research outcomes, we propose three implications for shared e-scooter operators and policymakers to better regulate and promote shared e-scooters and achieve the goal of sustainability:

1. **Encourage frequent use**: To encourage users to ride shared e-scooters more frequently, our model suggests that making shared e-scooters easy to use and having users wear a helmet increase the probability of being regular users. Thus, operators could provide users with e-scooters that have good user experience (e.g., are more stable), provide free helmets for new users, or a reward users who have ridden e-scooters for a certain number of times. In survey comments, some users mentioned they feel unsafe riding e-scooters due to the unavailability of helmets and are afraid of falling from e-scooters. The increased usage of e-scooters generates higher revenues for shared e-scooter companies that can offset helmet and device improvement expenditures. Also, helmets provide safer riding for users and create a positive image for the company. For policymakers, cities may consider building a well-connected bike lane network; our modeling results suggest that users who ride e-scooters in bike lanes have a higher probability of being frequent users. A well-connected and protected bike lane will help users feel safer and encourage more users become frequent users.
2. **Ride e-scooters on bike lanes or sidewalks**: Whether e-scooters should be allowed to be ridden on sidewalks is constantly debated in many cities. Pedestrians complain about high e-scooter speeds on sidewalks, while users feel safer doing so. Our survey statistics show that 63% of users rode shared e-scooters on sidewalks and 24% rode in bike lanes; for users who rode shared e-scooters on sidewalks, 58% thought it was safer. Another survey question statistics show that a total of 46% of riders would prefer bike lanes, and 43% would prefer sidewalks. One of the reasons that users prefer using a bike lane could be the pleasant riding experience offered by bike lanes; as survey comments suggested, users complained about uneven sidewalks that lead to falling from e-scooters. Understanding the reasons behind riding shared e-scooters on bike lanes and sidewalks is important. The City of Tampa could encourage users to use bike lanes to address complaints about high-speed riding on sidewalks, and other actions are needed to make it successful—build more connected and protected bike lanes to improve the safety of bike lane riding, which will also increase shared e-scooter usage, as our model suggests; for unskillful users who are concerned about safety of bike lane riding, regular in-person training sessions or online tutorial videos could be provided to help new riders to use the vehicles on bike lanes; and if riding on sidewalks and bike lanes are both allowed, the imposed speed limit on sidewalks could be lower than that on bike lane to make other street users more comfortable.
3. **Encourage auto substitution**: There are several ways to encourage auto substitution based on model results. First, study results suggest difficult parking is a motivation factor. Shared e-scooters could be deployed to areas with limited parking spaces but high demand from activities to help people move around. Also, cities could increase parking fees and/or reduce parking spots to stimulate the mode shift from driving to e-scooter and encourage the use of micromobility. Second, shared e-scooters and TNC/taxi are potential competitors. Promoting shared e-scooters could reduce TNC/taxi trips. To compete with TNC/taxi, e-scooter sharing companies may consider reducing the cost of using shared e-scooters to attract TNC/taxi users, which could further reduce vehicle use in a city.

This study had some limitations. First, the survey data were collected only five months after the program began, so the analysis results are applicable to that ramp-up period. If similar studies are conducted again, modeling results could change. Second, an online survey may not be accessible to people who have no access to internet and computer or are unfamiliar with this technology; a paper or phone survey could be added to get a more representative sample.

There are several avenues to which this research could be refined and extended. First, the study could be expanded and refined by including a few travel-pattern related questions in the survey, such as daily travel time and use frequency of other transportation modes and considering the variables in the modeling. Second, from methodological perspective, the analysis could adopt more complex econometric modeling techniques (e.g., heterogeneity in means and variance, latent variable model) and combining different indicator variables. Third, many cities have surveyed shared e-scooter users such as Portland, Santa Monica, etc. Similar studies could be conducted in different cities, and it would be interesting to discover the similarities and differences of factors between cities. Lastly, if membership programs are available for shared e-scooters in other cities, it would be interesting to investigate behavior differences between members and non-members.

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