Evaluating shared e-scooters' potential to enhance public transit and reduce driving

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Abstract

This study evaluates if and to what extent shared e-scooters can enhance public transit and reduce driving. Survey results obtained from Washington D.C. and Los Angeles show that many users have ridden shared e-scooters to connect with transit and to replace car trips. Mode choice models further suggest that males, non-Whites, and people without a college degree are more inclined to choose shared e-scooters. The stated preference for combined use of shared e-scooters and transit ("scoot-N-ride") is stronger among non-Whites, but it does not differ by gender, age, income, or education level. Moreover, we find that "e-scooter + transit" bundled pricing can effectively promote scoot-N-ride. Finally, while survey respondents intend to use shared e-scooters for short trips only, they are willing to use scoot-N-ride for medium-to-long trips. We call for coordination between transit agencies and e-scooter operators to maximize the potential for shared micromobility to enhance transit and reduce driving.

Keywords: Public transit, micromobility, mode choice, stated preference, bundled pricing

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1. Introduction

Shared micromobility options, including docked bikesharing, dockless e-scooters, and dockless e-bikes, have become increasingly popular in recent years. Most impressive is the

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growth of shared e-scooter trips: just two years after shared e-scooters first appeared in North America, the number of e-scooter trips (86 million) was more than double that of station-based bikesharing trips (40 million) in 2019 (NACTO, 2020). When the COVID-19 pandemic began in March 2020, e-scooter ridership plummeted but has quickly rebounded. According to the 2021 Shared Micromobility State of the Industry Report, the number of shared micromobility systems and vehicles in 2021 has surpassed 2019 levels in North America (NABSA, 2020). As shared micromobility systems continue to grow in the post-COVID era, it is important to understand whether and how they can contribute to long-term transportation goals such as accessibility, equity, and environmental sustainability.

Micromobility proponents have suggested that shared e-scooters can deliver two essential transportation benefits. One is the potential for shared e-scooters to substitute short car trips, which can reduce greenhouse gas emissions associated with driving. The importance of this benefit is supported by the fact that almost half of the personal trips made by U.S. travelers are three miles or less and that more than 70% of these short trips are currently made by cars. If these short car trips were to be replaced by e-scooters, enormous environmental benefits could be achieved (Gebhardt et al., 2022; Meroux et al., 2022). The other benefit of shared e-scooters is to serve as a last-mile solution to public transit. The "first- and last-mile" problem, referring to the difficulty of buses and trains to transport people to and from the doorsteps of their trip origins and destinations, has been an enduring challenge for U.S. transit systems (Chen et al., 2021). When functioning as a last-mile feeder mode, affordable and accessible shared e-scooters can significantly enhance multimodal travel experience and promote transit use. Moreover, by allowing people to gain access to a much wider geographic area than they could reach with either mode, combined transit and shared e-scooter use may make some travelers give up driving for longer trips.

Recent research, largely based on questionnaire surveys, has indeed generated empirical evidence suggesting that shared e-scooters replaced some car trips and that many travelers used e-scooters to connect with transit (NABSA, 2022). These studies suggest that driving is one of the most replaced modes by shared e-scooters and that a substantial percentage (5% to 70% depending on study context) of riders have used shared e-scooters to access transit (Wang et al., 2022; Ziedan et al., 2021). Nevertheless, there is limited understanding of how people make mode choice decisions between shared e-scooters (and their use in conjunction with transit) and competing alternatives such as driving or riding with a for-hire vehicle (FHV), including taxi and Uber/Lyft. In other words, we know little about how utility trade-offs between travel attributes such as cost and time were made in the process by various groups of travelers. So far, only several studies have conducted mode choice analysis on shared e-scooters to examine the modal competition and substitution patterns systematically (e.g., Lee et al., 2021; Reck and Axhausen, 2021; Reck et al., 2021). Notably, to our best knowledge, no published work has examined traveler preferences for combined use of shared e-scooter and transit, i.e., "e-scooter + transit" use (to be termed as scoot-N-ride for the rest of the paper) and the potential of scoot-N-ride to reduce driving.

This study aims to advance travel behavior understanding regarding the potential of shared e-scooters to enhance public transit and reduce driving with a mode choice analysis. The analysis is based on stated choice experiments (SCEs) included in a travel survey conducted in Washington D.C. (DC) and Los Angeles (LA), two U.S. cities with a mature shared e-scooter market and a large transit network. Our work makes two major contributions to the literature. First, the mode choice models developed here generate novel insights into how preferences for shared e-scooters, scoot-N-ride, and competing alternatives (especially driving modes) differ across population groups and how travelers make utility trade-offs between trip attributes such as travel cost and time in their mode choice decisions. Notably, by shedding light on the factors that influence the use of scoot-N-ride, this study fills a major research gap discussed above. Second, we further apply the choice models to reveal mode substitution patterns and to estimate modal split under a variety of scoot-N-ride bundle pricing scenarios. The results provide valuable empirical evidence that can inform policies and strategies to promote transit and shared micromobility integration with the goals of increasing transit use and reducing driving.

2. Literature Review

The topic of shared e-scooters has attracted significant research attention since 2019. Existing studies have generated rich insights regarding the user profile of shared e-scooters and factors associated with e-scooter adoption and usage, the characteristics of e-scooter trips and their spatiotemporal patterns, e-scooters' modal substitution effects, and shared e-scooters' relationship with public transit. Here we summarize the main findings.

2.1. *Shared e-scooter user profiles*

Compared to the populations of the cities where shared e-scooters operate, e-scooter riders are disproportionately young (particularly age below 40), White, male, have higher household income levels, and have a college degree (Mobility Lab, 2019; NABSA, 2020; Portland Bureau of Transportation (PBOT), 2019; Reck and Axhausen, 2021; San Francisco Municipal Transportation Agency (SFMTA), 2019). Interestingly, however, the North American Bikeshare Association found that people in the lowest-income bracket were proportionately represented in the e-scooter rider profile (NABSA, 2020). This may be because the equity programs implemented in some cities have promoted e-scooter use among low-income travelers; these programs may require e-scooter operators to place a certain percentage of e-scooters in predefined equity zones or to provide discount fares for low-income individuals (Stowell, 2020). In addition to demographic and socioeconomic characteristics, studies have shown that attitudinal factors such as safety perceptions of e-scooters and perceived reliability have a major impact on e-scooter adoption and use (Blazanin et al., 2022; Javadinasr et al., 2022). Finally, some authors have examined preference heterogeneity in e-scooter use through advanced modeling techniques such as latent class models and Structural equation modeling (Baek et al., 2021; Guo and Zhang, 2021; Javadinasr et al., 2022; Lee et al., 2021).

2.2. *Shared e-scooter trip characteristics*

On e-scooter trip characteristics, analysts have mostly focused on trip purpose, trip distance, trip duration, trip costs, and the current mode replaced by e-scooters. Studies showed that travelers used e-scooters both for leisure and recreation and for utilitarian purposes such as commuting, shopping, running errands, and attending social activities (NABSA, 2020). The land-use contexts (e.g., college campus, downtown, or tourist attractions) where most e-scooters were placed can be a main factor shaping trip purposes. E-scooter trips were quite short in general, and most studies found that the average trip length was between 1-1.5 miles and the average duration was 12-20 minutes (NABSA, 2020; NACTO, 2020). The average e-scooter trip cost was between \$2.8 and \$4.5 in 2019, but the price has increased over time (Lazo, October 18,2019). Existing research on spatiotemporal patterns of shared e-scooter services often compares shared e-scooters with station-based bikesharing and examines their relationship with public transit. Empirical results have shown that despite some level of similarity between the two, e-scooter trips and bikeshare trips have quite different spatial and temporal patterns (McKenzie, 2019; Younes et al., 2020; Zhu et al., 2020). For instance, Zhu et al. (2020) showed that e-scooter trips were more spatially concentrated than bikesharing trips in Singapore.

2.3. *Modal substitution effects and relationship with public transit*

Regarding modal substitution effects, e-scooters were found to mostly replace walking, followed by either driving modes (including personal driving, taxi, and ridehail) or public transit (Laa and Leth, 2020; NABSA, 2020, 2022; NACTO, 2020; Portland Bureau of Transportation (PBOT), 2019; San Francisco Municipal Transportation Agency (SFMTA), 2019). For each mode, the exact percentage of trips replaced by shared e-scooters varies significantly across study areas; in general, the car substitution rates tend to be higher in North America, whereas the transit substitution rates are higher in European cities (Reck et al., 2022; Wang et al., 2022). Several studies have further examined e-scooters' environmental impacts (e.g., reductions in greenhouse gas emissions) if travelers use them to replace personal car travel (Gebhardt et al., 2022; Meroux et al., 2022). An important finding from these studies is that e-scooters can have a more significant positive impact if their life cycle becomes longer and if they replace gasoline (not electric) car trips.

Preliminary results are available from existing research regarding how shared e-scooters can be integrated with public transit. Surveys conducted across cities around the world showed that many users have ridden shared e-scooter to connect with transit public transit (NABSA, 2020, 2022; NACTO, 2020; San Francisco Municipal Transportation Agency (SFMTA), 2019; Ziedan et al., 2021). A recent report by NABSA (2022) suggests that 63% of riders have used shared micromobility to connect with transit at least once and that 19% of them do this on a weekly basis. Even though the frequency of such combined e-scooter and transit use is less known, these results indicate a general willingness toward combined transit and e-scooter use. In addition, some studies that analyzed e-scooter trips have found a strong correlation between transit stops and e-scooter trips (Merlin et al., 2021; Tuli et al., 2021; Ziedan et al., 2021; Zuniga-Garcia et al., 2022), which may indicate the use of e-scooters for first- or last-mile transit connections. Some authors have further attempted to estimate the potential first- and last-mile e-scooter trips that happened at each transit stop and to understand their patterns (Ma et al., 2022; Yan et al., 2021). Overall, empirical studies of how shared e-scooters interact with public transit appear to share many common findings with studies of bikeshare (Romm et al., 2022).

2.4. Gaps in the literature

So far, limited research has been conducted on the mode choice modeling of shared e-scooters. Mode choice models allow the transportation community to understand modal competition and substitution patterns between shared e-scooters and competing modes such as personal cars, public transit, and bike. Also, mode choice analysis can reveal which factors influence choice behavior and can shed light on the relative influence of important factors in different choice situations. Nevertheless, only a handful of studies have fit mode choice models on shared e-scooters (Baek et al., 2021; Cao et al., 2021; Guo and Zhang, 2021; Reck et al., 2021, 2022). Though generating rich behavioral insights, these studies have not fully addressed who are more likely to integrate the use of shared e-scooters with transit and under what circumstances are driving trips (especially FHV trips) more likely to be replaced by e-scooter or scoot-N-ride trips. Several studies have started to explore these questions (Baek et al., 2021; Guo and Zhang, 2021; Reck et al., 2022) but not in a comprehensive fashion; moreover, little work has been conducted to examine the potential of scoot-N-ride trips to reduce car trips.

In sum, despite some early findings, our overall knowledge regarding the potential for shared e-scooters to serve as a last-mile complement to public transit and their potential to reduce driving is limited (Oeschger et al., 2020). Specifically, much is unknown regarding mode choice, the underlying traveler preferences for integrating shared e-scooters with transit trips, and the potential of these trips to reduce car use. This study addresses these research gaps by conducting a travel behavior survey in Washington D.C. and Los Angeles.

3. Data

3.1. Study area

Our study area includes Washington D.C. and Los Angeles, California, two large U.S. cities that are both early adopters of dockless micromobility. During the study period (2021-2022), over 10,000 shared e-scooters were permitted in a geofenced operating area of DC and about 37,000 in LA's operating area. The e-scooters in DC were operated by six private companies (Bird, Lime, Lyft, Razor, Skip, and Spin), and those in LA were operated by five companies (Bird, Lime, Lyft, Spin, and Wheels). Both cities' Department of Transportation has established permit requirements for operating dockless micromobility, with detailed terms and conditions for fleet management, parking, data reporting, payment options, and low-income customer programs. Unlike the publicly subsidized station-based bikeshare systems (Capital Bikeshare in DC and Metro Bike Share in LA), however, no formal public-private partnerships exist to promote the integration between shared e-scooters and public transit.

Both cities have a large transit system consisting of rail and bus services. Specifically, the transit network in DC includes a Metrorail system (six lines) and a Metrobus system (about 335 routes) which serve the DC metropolitan area, as well as the DC Circulator (six bus routes) and the DC Streetcar which mainly serve central areas of DC. The LA transit network consists of a metro rail system (six lines) and a metro bus system (nearly 200 routes) that serves the Greater Los Angeles area, as well as the DASH bus service that serves downtown LA and 27 neighborhoods within the City of LA. The two cities have distinctive travel patterns. For instance, according to the American Community Survey 2016-2020 5-year estimates, the mode share for commuting trips in DC is drive alone (32.1%), carpool (4.9%), public transit (31.5%), bike (4.2%), walk (12.5%), and work-from-home (12.3%); by contrast, the commute mode share in Los Angeles is drive alone (67.7%), carpool (8.9%), public transit (8.2%), bike (0.8%), walk (3.3%), and work-from-home (9.2%). Being much more car-dependent, LA travelers use public transit and non-motorized modes much less than DC travelers. These differences can ensure that our study findings regarding travel preferences for shared e-scooters and scoot-N-ride are transferable across a wider range of transportation contexts.

3.2. Survey description and participant recruitment

We developed a web-based survey that contains three sets of questions. First, we asked whether and how frequently people have used different travel modes (personal vehicle, walking, public transit, biking, e-scooter, scooter or moped, FHV, and carsharing) in the last 30 days, followed by some questions on their travel attitudes and preferences related to public transit and e-scooters. Transit users were asked additional questions related to the last-mile access problem, and e-scooter users were asked additional questions regarding trip purpose, use of e-scooters to connect with transit, and barriers to scoot-N-ride trips. Second, we developed some SCEs to elicit traveler responses to bundled "transit + e-scooter" pricing schemes, that is, to evaluate how lower pricing can make individuals shift from using other travel modes to scoot-N-ride. Additional details regarding the SCEs are provided in the next section. Finally, we collected information on individual demographic and socioeconomic characteristics.

The survey was piloted among a small group of individuals who are familiar with the transportation systems in DC and LA, whose feedback was incorporated into the final survey. We administered the survey to adults who live, work, or frequently visit the two cities through a variety of means, including personal social networks, email listservs, newsletters of several advisory neighborhood commissions (in DC only), and social media platforms (Facebook groups, Twitter, and Linkedin). In other words, while the study areas are the two cities where the shared e-scooter systems operate, respondents are recruited from their corresponding metropolitan regions. Moreover, the e-scooter company Spin helped distribute the survey to its users in the study regions. No cash incentive was offered to survey respondents, but they can get a promo code that can be used to redeem for $5 Spin rider credits. Respondents were offered an option to opt out the SCEs, in which case they will get a promo code worthy of $3 Spin rider credits (only 17 respondents did so). Finally, we paid Centiment.co, a survey firm, to collect 150 responses from the DC area (including Arlington, Virginia) and 200 responses from LA. Participants were recruited in April 2021 and May 2022 in DC and in May 2022 for LA. In the end, 430 individuals in the D.C. region and 377 individuals in the LA region, respectively, provided valid responses.[1]. After a data cleaning process, we kept a total of valid 336 responses in DC and 274 responses in LA, respectively, for mode-choice modeling. Some cases were removed either because the respondent did not answer some questions (e.g., the SCEs) or because the responses provided for the SCEs were deemed unreasonable.

3.3. Representativeness of survey sample

To evaluate the representativeness of the survey samples, we compare the socioeconomic profiles of the survey samples with those of the two cities (i.e., DC and LA). As shown in Table 1, in DC, 43.8% of survey respondents used an e-scooter at least once in the past 30 days and 45.2% of them used transit; in LA, these percentages were 43.1% and 29.2%, respectively. Both e-scooter and transit users are probably oversampled here. Given that the survey focuses on the two modes, it is natural for their users to be more willing to participate in the survey. Other contributing factors include the distribution of the survey to Spin e-scooter users and the offering of Spin rider credits as survey incentives, both of which are likely to draw disproportionate responses from shared e-scooter users.

A slightly higher proportion of males responded to the survey in both cities, even though their male populations were smaller. White populations were significantly overrepresented in DC but only slightly overrepresented in LA; both Hispanic and Black populations were significantly underrepresented in DC, but only Hispanic populations were underrepresented in LA. In terms of age, survey populations skewed younger than city populations in both cities. People aged between 25 and 40, who are significantly overrepresented, mostly attributed to this difference. In both cities, people from higher-income households were overrepresented. Regarding educational attainment, both surveys have an overrepresentation of people having a college degree. Most DC survey respondents had an annual household income over $75,000,

[1]People who did not finish the survey or who spent three minutes or less answering the survey were considered invalid responses.

Table 1: Socioeconomic profile of survey respondents

	Washington D.C.			Los Angeles		
	N	Sample %	City %	N	Sample %	City %
Sample size	336	100.0%		274	100.0%	
E-scooter user[1]	147	43.8%		118	43.1%	
Transit user[1]	152	45.2%		80	29.2%	
Neither e-scooter nor transit user	121	36.0%		121	44.2%	
Gender						
Female	161	47.9%	52.4%	134	48.9%	50.5%
Male	175	52.1%	47.6%	140	51.1%	49.5%
Race/ethnicity						
Hispanic	13	3.9%	11.1%	55	20.1%	48.1%
White	226	67.3%	41.1%	143	52.2%	48.9%
Black	46	13.7%	45.4%	22	8.0%	8.8%
Have a college degree	269	80.1%	55.2%	159	58.0%	32.9%
Age						
18-24	48	14.3%	10.5%	31	11.3%	10.0%
25-29	73	21.7%	11.8%	43	15.7%	9.4%
30-39	97	28.9%	20.3%	72	26.3%	16.4%
40-49	47	14.0%	11.8%	48	17.5%	13.5%
50-59	32	9.5%	10.5%	35	12.8%	12.3%
60-69	22	6.5%	8.9%	27	9.9%	9.5%
70 or over	17	5.1%	8.2%	18	6.6%	8.6%
Household income						
Less than $25,000	23	6.8%	17.7%	48	17.5%	20.6%
$25,000-$49,999	50	14.9%	12.8%	47	17.2%	19.3%
$50,000-$74,999	54	16.1%	12.4%	53	19.3%	15.4%
$75,000-$99,999	54	16.1%	10.6%	40	14.6%	11.4%
$100,000-$149,999	72	21.4%	16.4%	40	14.6%	14.9%
$150,000 or more	83	24.7%	30.1%	46	16.8%	18.3%
Student	39	11.6%	12.4%	40	14.6%	10.9%
Own a vehicle	240	71.4%	64.6%	238	86.9%	88.1%
Have no smartphone	3	0.9%		8	2.9%	
Have no mobile data plan	3	0.9%		2	0.7%	
Have no bank account	2	0.6%		9	3.3%	
Have disability	10	3%		18	6.6%	

Note: 1. E-scooter and transit users are defined as individuals who have used the corresponding mode at least once in the past 30 days.

with less than 7% below $25,000, suggesting an underrepresentation of the low-income population. However, the income distribution of the LA sample appears to be quite close to that of the city population. As existing research generally found that shared e-scooter users are disproportionately White, male, younger, having higher income and better education (NABSA, 2022; NACTO, 2020), the overrepresentation of these population groups in our survey samples is not surprising. On the other hand, the percentages of survey respondents who were students and owned a car were not very different from the city percentages.

The survey also asked questions about the potential barriers to using e-scooters. Among the survey participants, roughly 5-13% of users face one or more technological barriers (no smartphone, data plan, or inter) or a physical barrier (having a disability), with higher proportions in LA compared to DC. Since the same access barriers may also impact one's ability or likelihood to participate in the survey, we believe that these proportions are underestimated. Future work may consider reducing this sampling bias by conducting a paper-based survey and distributing the survey through other channels (e.g., mailing and in-person recruitment).

4. Stated choice experiments

SCEs are used in this study to understand how individuals make utility trade-offs between travel attributes such as cost and time when they choose among various travel modes. We use the stated-preference data generated from SCEs rather than reveal-preference data due to several reasons. First, scoot-N-ride is not a commonly used travel option, which means collecting revealed-preference data on it will be challenging. Also, when someone took a trip with a travel mode that does not involve a shared e-scooter, it is difficult to distinguish if it is because e-scooters were unavailable or because e-scooters were not chosen. Accordingly, using revealed preference data could lead to more biased coefficient estimates. Finally, an important focus of this project is to evaluate the potential of scoot-N-ride to replace driving under various bundled "transit + e-scooter" pricing schemes. Since bundled pricing of transit and e-scooters is not implemented in practice yet, stated-preference methods such as SCEs are ideal for this purpose (Louviere et al., 2000).

That respondents fully understand the SCEs and make reasonable selections is critical to the successful implementation of this research approach. To improve the realism of the

SCEs, each respondent was presented with individual-specific choice scenarios tailored to their prior trip experiences. Specifically, we asked respondents to report a one-way trip that they regularly made before COVID-19 and then constructed the SCEs based on the attributes of this self-reported trip. The trip attributes that we asked for include trip purpose, travel mode used, trip length, trip cost, and components of travel time (e.g., for a transit trip, individuals were asked to estimate the walking to and from transit stops, wait time, and riding time). Prior to data entry, we asked respondents to only consider a trip longer than 0.5 miles but no longer than 10 miles, which is a range appropriate for riding a shared e-scooter or using the scoot-N-ride option. Moreover, we limited the choice of travel modes used for this trip to four options: personal vehicle, walking, transit with walking as the access/egress mode, and FHV (taxi or Uber/Lyft). These are the travel modes most replaced by shared e-scooters according to recent empirical research (NABSA, 2022; Wang et al., 2022).

The focus of the SCEs was to evaluate whether and to what extent bundled pricing schemes can make travelers shift from the mode they currently use to scoot-N-ride under a variety of trip scenarios shaped by e-scooter speed, e-scooter baseline price, and the type of transit system to be integrated with. To design realistic SCEs that can effectively elicit traveler responses, we applied orthogonal main-effects experimental design to obtain nine SCEs (shown in Table 2) based on the following trip attributes and attribute levels: e-scooter travel speed (6 mph, 9 mph, 12 mph), e-scooter price (one dollar to unlock and 32 cents per minute use, and one dollar to unlock and 40 cents per minute use),[2] transit type (bus and rail), and bundled "transit + e-scooter" pricing discount (waive of e-scooter unlock fee, 25% off e-scooter trip costs, and 50% off e-scooter trip costs). The attribute levels were determined based on empirical values derived from the study area. In each SCE,

[2]These are the prices used for DC. The e-scooter pricing in LA differed from DC when we conducted the survey. Hence, we set the price levels in LA as follows: one dollar to unlock and 39 cents per minute use, and one dollar to unlock and 45 cents per minute use.

respondents were asked which of the three travel options they would choose for the one-way trip that they described: the travel mode currently used, a shared e-scooter, or the scoot-N-ride option. Across the SCEs, the attribute values for the currently used mode do not change, whereas the attribute values for the shared e-scooter and scoot-N-ride options vary in accordance with the attribute levels shown in Table 2.

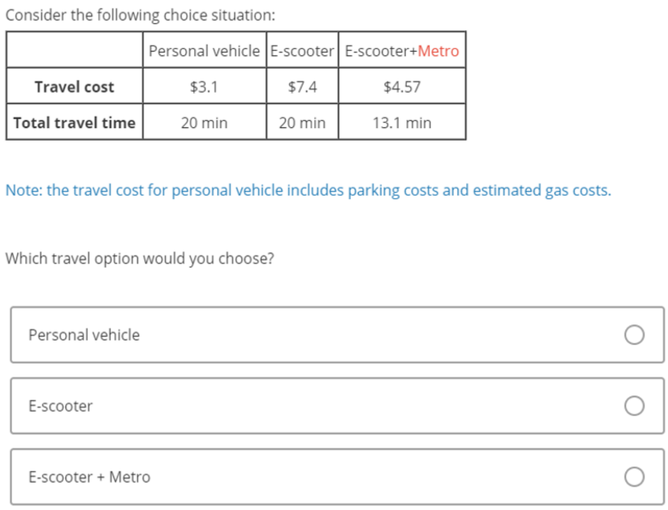
Table 2: Profiles of the nine stated choice experiments

Experiment	E-scooter speed	E-scooter pricing[1]	Transit type[2]	incentive
1	12 mph	\$1 to unlock, ¢32 per min	Metro	Waiver of unlock fee
2	6 mph	\$1 to unlock, ¢32 per min	Bus	Waiver of unlock fee
3	9 mph	\$1 to unlock, ¢32 per min	Metro	50% off e-scooter fare
4	12 mph	\$1 to unlock, ¢32 per min	Bus	25% off e-scooter fare
5	9 mph	\$1 to unlock, ¢32 per min	Bus	25% off e-scooter fare
6	9 mph	\$1 to unlock, ¢40 per min	Bus	Waiver of unlock fee
7	6 mph	\$1 to unlock, ¢32 per min	Bus	50% off e-scooter fare
8	12 mph	\$1 to unlock, ¢40 per min	Bus	50% off e-scooter fare
9	6 mph	\$1 to unlock, ¢40 per min	Metro	25% off e-scooter fare

Notes: 1. The prices shown in the table are for DC. In LA, the pricing levels were "\$1 to unlock, ¢39 per min" and "\$1 to unlock, ¢45 per min."
2. In DC, the bus travel speed was set as 10 mph and rail travel speed 35 mph, and the bus fare was \$2 (one-way regular fare), and the rail fare is set as \$3 (DC's Metrorail system has a distance-based fare system that ranges from \$2-\$3.85 during non-peak hours and \$2.25-\$6 during peak hours). In LA, the bus travel speed was set as 10 mph and rail speed 30 mph, and the bus and rail fares were both \$1.75 (one-way regular fare). These values were empirical values derived from local conditions.

Figure 1 is an illustration of an SCE presented to a respondent who reported a driving trip. We used the self-reported trip length, as well as the attribute levels as shown in Table 2, to estimate the attribute values for the shared e-scooter option. In addition, we assumed the wait time for the bus or train to be three minutes when estimating the attribute values for scoot-N-ride. Finally, to reduce the cognitive burden for each survey respondent, we presented a random subset (five) of the nine SCEs to each respondent. Previous research has shown that the validity of responses to SCEs decreases if respondents are overburdened (Louviere et al., 2000).

A total of 336 DC respondents and 274 LA respondents, respectively, participated in the SCEs. As shown in Table 3, For the revealed preference trips reported by DC respondents,



Consider the following choice situation:

	Personal vehicle	E-scooter	E-scooter+Metro
Travel cost	$3.1	$7.4	$4.57
Total travel time	20 min	20 min	13.1 min

Note: the travel cost for personal vehicle includes parking costs and estimated gas costs.

Which travel option would you choose?

Personal vehicle

E-scooter

E-scooter + Metro

Figure 1: A stated choice experiment presented to a respondent who reported a driving trip

119 (35%) were made by public transit, 113 (34%) by personal vehicle, 70 (21%) by walking, and 34 (10%) by FHV. By contrast, most LA respondents (58%) reported a personal vehicle trip, followed by FHV, transit, and walking. In DC, the median and mean distance of trips made by personal vehicle is the longest, followed by FHV, transit, and walking. However, on average, the travel time is the longest for transit trips, and the travel cost is the highest for FHV trips. On average, the revealed preference trips reported by LA respondents were longer than those reported by DC respondents, which may be because DC has a more compact built environment. Another key difference is that the FHV trips reported by LA respondents were shorter than those reported by DC respondents, but their costs were quite similar. Finally, transit fare was generally lower in LA than in DC, but the cost of driving in LA also appears to be lower (mainly due to the greater availability of free parking). These differences allow us to capture traveler's modal preferences in a broader set of land-use and transportation contexts, which can enhance the generalizability of our study findings.

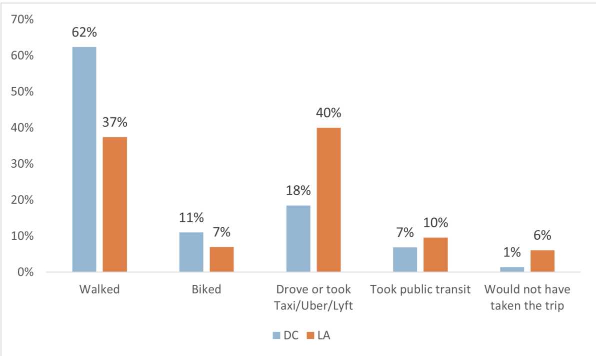
Table 3: Characteristics of revealed preference trips reported by survey respondents

	N	Distance (mile)		Time (min)		Cost ($)	
		Median	Mean	Median	Mean	Median	Mean
Washington D.C.							
All	336	3.00	5.13	25	26	2.00	3.73
For-hire vehicle	113	5.00	8.40	20	24	1.63	4.25
FHV	34	4.00	5.17	20	21	12.00	14.16
Transit	119	3.00	4.13	30	32	2.25	2.54
Walk	70	1.20	1.52	20	24	0.00	0.00
Los Angeles							
All	274	3.75	6.44	20	22	1.20	3.93
Personal vehicle	158	4.70	8.21	17	20	1.00	3.15
For-hire vehicle	40	2.55	3.47	15	17	12.16	14.15
Transit	43	5.00	6.22	30	33	1.55	1.37
Walk	33	1.50	1.86	25	25	0.00	0.00

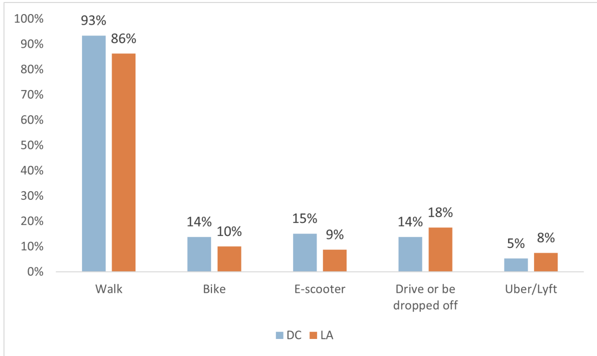
5. Results

5.1. Descriptive analysis

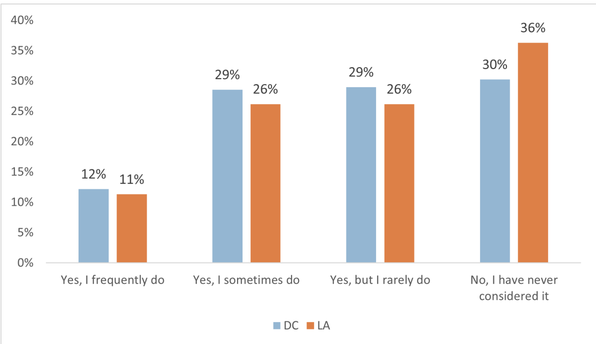
In the survey, we asked some questions to investigate to what extent shared e-scooters have replaced car use and have been used as a last-mile feeder mode to transit. Figure 2 shows the survey responses for these questions. Specifically, Figure 2a sheds light on the modal substitution effects of shared e-scooters. The question asks shared e-scooter users: "Think about your last shared e-scooter trip in [City]. If a shared e-scooter had not been available, how would you have traveled around?" Consistent with previous findings from North America (Wang et al., 2022), the results suggest that waking and driving (including FHV options) were the most replaced modes in both DC and LA. The substitution effect of shared e-scooters on driving appears much stronger in LA than in DC, but it can be due to sampling bias. Figure 2b reveals how transit riders usually get to bus or rail stops. Note that a respondent was allowed to select up to two travel modes for this question. Unsurprisingly, we found that walking is the dominant option, followed by driving or being dropped off, riding e-scooters or bikes, and taking Uber/Lyft. Considering that shared e-scooters were oversampled, the actual percentage of DC/LA population who rode e-scooters for transit connections is probably lower. Regardless, these results offer preliminary evidence on the use of shared micromobility (including e-scooters) as a last-mile feeder mode to transit.



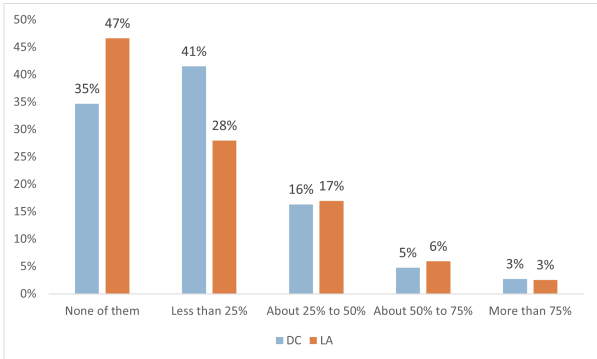
(a) How would one have traveled if shared e-scooters were unavailable for last trip (N=146 in DC, N=115 in LA)



(b) How people usually travel to transit stops (N=152 in DC, N=80 in LA)



(c) Have one considered using e-scooters to reach transit stops at a distance (N=238 in DC, N=168 in LA)



(d) Proportion of shared e-scooter trips connecting with public transit (N=147 in DC, N=118 in LA)

Figure 2: Descriptive results on shared e-scooters' potential to replace car use and enhance transit

Figure 2c and 2d offer additional behavioral insights into the potential use of shared e-scooters for enhancing transit connectivity. For Figure 2c, the survey asks: "Have you considered using shared e-scooters to connect with transit stops when they are too far away to walk to?" This question was only displayed to survey participants who reported the "last-mile" transit connectivity issue as a major barrier to riding transit (79% of DC respondents and 78% of LA respondents, respectively). The results suggest that about 40% of respondents in both cities have frequently or sometimes considered shared e-scooters a last-mile feeder option. This percentage can grow over time if the penetration rate of shared e-scooters increases or if shared e-scooters become more available and affordable. Finally, Figure 2d presents results on the proportion of shared e-scooter trips made by current users to connect with public transit. We find that about two-thirds of users in DC and about half of the users in LA had used shared e-scooters for connecting with transit at least once. In addition, for about one-fourth of current shared e-scooter users in DC and LA, over a quarter of their trips were for the purpose of connecting with transit.

In sum, the survey results show that shared e-scooters are replacing some driving trips, including personal-vehicle and FHV trips. In addition, most existing users have used shared e-scooters as a last-mile feeder mode to public transit at least once. For some, e-scooters have become a main mode to access transit stops. Finally, we find a wide interest among DC and LA travelers in using shared e-scooters to connect with transit stops at a distance, suggesting the potential for shard micromobility to enhance transit operations and traveler experience.

5.2. Mode choice modeling and parameter specification

To further reveal modal competition and substitution patterns, we examine how travelers with different modal preferences and socioeconomic characteristics made trade-offs among various trip attributes such as travel time and cost in their travel mode choice. As discussed above, we constructed individual-specific SCEs based on attributes of a self-reported trip. The SCE responses, together with some socioeconomic and travel-related variables, were used for discrete choice modeling. Following a bottom-up model-building approach (i.e., gradually adding parameters to the model), we tested a variety of specifications before deciding on the final model. The final model is a mixed-logit (ML) model (i.e., a random parameter logit model) whose functional form is as follows.

$$
\begin{aligned}
&U_{Car} = \beta_{tt} * TT + \beta_{ovtt} * OVTTDistance + \beta_{cost} * CostHHIncome \\
&U_{FHV} = ASC_{FHV} + \beta_{tt} * TT + \beta_{ovtt} * OVTTDistance + \beta_{cost} * CostHHIncome \\
&U_{Transit} = ASC_{Transit} + \beta_{tt} * TT + \beta_{ovtt} * OVTTDistance + \beta_{cost} * CostHHIncome \\
&U_{Walk} = ASC_{Walk} + \beta_{tt} * TT + \beta_{ovtt} * OVTTDistance \\
&U_{\text{E-scooter}} = ASC_{Scooter} + \beta_{tt} * TT + \beta_{ovtt} * OVTTDistance + \beta_{cost} * CostHHIncome + \beta_{Safety} * EscooterSafety \\
&\quad + \beta_{ScooterUser,\text{E-scooter}} * ScooterUser + \beta_{Age,\text{E-scooter}} * AgeBelow40 + \beta_{White,\text{E-scooter}} * White \\
&\quad + \beta_{Male,\text{E-scooter}} * Male + \upsilon_{\text{E-scooter},\text{Scoot-N-ride}} \\
&U_{\text{Scoot-N-ride}} = ASC_{\text{Scoot-N-ride}} + \beta_{tt} * TT + \beta_{ovtt} * OVTTDistance + \beta_{Safety} * EscooterSafety + \beta_{cost} * CostHHIncome \\
&\quad + \beta_{ScooterUser,\text{Scoot-N-ride}} * ScooterUser + \beta_{TransitUser,\text{Scoot-N-ride}} * TransitUser + \beta_{Income,\text{Scoot-N-ride}} * LowIncome \\
&\quad + \beta_{Age,\text{Scoot-N-ride}} * AgeBelow40 + \beta_{White,\text{Scoot-N-ride}} * White + \upsilon_{\text{E-scooter},\text{Scoot-N-ride}},
\end{aligned}
\tag{1}
$$

where ASC refers to alternative-specific constant, TT refers to travel time (TT), OVTTDistance refers to out-of-vehicle time (OVTT) divided by trip distance, and CostHHIncome refers to trip cost divided by household income. TT includes in-vehicle travel time (IVTT) and OVTT. We defined IVTT as riding time on the bus and in the FHV and riding time on e-scooters as OVTT; OVTT also includes walking time and waiting time (for the FHV and the bus). The specification of OVTTDistance has two considerations: first, it ensures that travelers will be more sensitive to OVTT than IVTT, an expectation consistent with the literature (Abrantes and Wardman, 2011); second, dividing OVTT by trip distance makes the sensitivity of individuals to OVTT diminish with the trip distance. We divided trip costs by household income because higher-income people tend to be less sensitive to trip costs. Doing so also reduced the degree of correlation between trip cost and travel-time variables. The EscooterSafety variable was developed based on a survey question that asks respondents to what extent they agree riding e-scooters is a safe way to get around, with a higher value (which ranges from 1 to 5) indicating a more favorable safety perception toward e-scooters. All other variable codes and their corresponding coefficients should be self-explanatory. By omitting the ASC for the driving alternative, we have set driving as the reference alternative. The coefficients of time and cost variables were generic, and all other coefficients were alternative specific; the subscripts indicate the alternative that each coefficient is associated with. Moreover, two ASCs (for e-scooter and scoot-N-ride) and three level-of-service coefficients (i.e., β_{tt}, β_{ovtt}, and β_{cost}) were specified as random parameters. The two ASCs were assessed with a normal distribution whereas the level-of-service variables were assessed with a constrained triangular distribution (i.e., equal mean and standard deviation). The assumption of triangular distributions can ensure non-negative estimates of individual willingness-to-pay measures. Finally, $\upsilon_{E\text{-}scooter,Scoot\text{-}N\text{-}ride}$ is an error component used to capture the unobserved heterogeneity associated the shared e-scooter and scoot-N-ride options. Prior to finalizing the model specification, we tested additional random parameters and error components (e.g., between transit and scoot-N-ride) but found them to be statistically insignificant.

Since the sample size for each city was relatively small, we decided to pool the data from DC and LA together to fit the final model. We also fitted separate models for the sample data in each city and observed minor differences in the results (the significance level of coefficients was largely the same across models). We computed the variance inflation factor value for all independent variables and found that all the variables had a value smaller than 5, which indicates little concern for multicollinearity. Finally, following common practice, we fitted a multinomial logit (MNL) model with an identical set of variables and displayed its outputs alongside those of the ML model as a reference.

5.3. Model results

As shown in Table 4, the adjusted McFadden pseudo R-square for the MNL model was 0.19, which is neither very high nor too low. McFadden (1979) noted that the McFadden pseudo R-square in a choice model should not be judged by the standards for a "good fit" in ordinary regression analysis and that values of 0.2 to 0.4 represent an excellent fit. Except for the ASC of transit, all ASCs were negative and statistically significant at the 0.05 level. This means that, on average, respondents prefer driving over other travel options. This could result from the fact that most survey respondents own a personal vehicle. As expected, all level-of-service variables (i.e., time and cost variables) were negative and highly significant (at the 0.01 level). Moreover, respondents appear to value OVTT much more than IVTT. For instance, for a 1-mile trip, the MNL model estimated that the travelers valued one min of OVTT 1.48 times as much as they valued IVTT. We save the discussions of the socioeconomic and demographic variables for the ML model because the MNL model is not the focus here. The main weakness of the MNL model is that it does not account for serial correlation, which means that the coefficient estimates could be biased. We hence turn out attention to the ML model, which not only addresses this issue but also allows one to examine individual preference heterogeneity.

The outputs of the ML model are also presented in Table 4. When estimating the ML model, we used 3000 Halton draws from the mixing distribution to perform the integration. The adjusted McFadden's pseudo R-square value for this model was 0.36, a significant improvement compared to the MNL model, which indicates excellent model fit as McFadden (1979) suggested. Compared to the MNL model, the coefficient estimates of the ML model were largely similar except for a few differences. First, due to the addition of random effects, the significant level of most coefficients dropped to some degree. Second, while the coefficient of OVTTDistance (OVTT divided by trip distance) was not significant at the 0.05 level in the MNL model, it became highly significant in the ML model. Since

Table 4: Outputs of the final mixed logit model and the reference multinomial logit model

Variable	**Alternatives**	**Multinomial logit**		**Mixed logit**	
		Coeff.	z value	Coeff.	z value
Constants					
Walk	Walk	-0.526*	-2.50	-0.050	-0.08
Transit	Transit	-0.176	-1.14	-0.150	-0.28
FHV	FHV	-1.096**	-6.14	-1.608*	-2.21
E-scooter	E-scooter	-3.286**	-13.22	-6.130**	-7.16
Scoot-N-ride	Scoot-N-ride	-4.275**	-14.43	-8.024**	-8.37
level of service variables					
Travel time	All modes	-0.045**	-9.88	-0.106**	-8.12
Out-of-vehicle travel time (divided by trips distance)	All modes	-0.021	-1.77	-0.110**	-3.26
Trip cost (divided by income)	All modes	-0.176**	-8.21	-0.550**	-6.10
Random parameter standard deviations					
$ASC_{\text{E-scooter}}$	E-scooter			1.779**	4.69
$ASC_{\text{Scoot-N-ride}}$	Scoot-N-ride			1.908**	4.78
Travel time	All modes			0.106**	8.12
Out-of-vehicle travel time (divided by trips distance)	All modes			0.110**	3.26
Trip cost (divided by income)	All modes			0.550**	6.10
Sociodemographic and behavioral variables					
Male	E-scooter	0.266*	2.17	0.404	0.95
	Scoot-N-ride	0.134	0.84	0.154	0.34
Age below 40	E-scooter	0.205	1.68	0.507	1.18
	Scoot-N-ride	-0.047	-0.28	-0.065	-0.14
White	E-scooter	-0.461**	-3.74	-0.966*	-2.15
	Scoot-N-ride	-0.642**	-4.02	-1.197**	-2.58
Household income <$25,000	Scoot-N-ride	-0.061	-0.32	-0.064	-0.14
College Graduate	E-scooter	-0.331*	-2.34	-0.996*	-2.09
	Scoot-N-ride	0.048	0.25	-0.332	-0.64
E-scooter safety perception	E-scooter, Scoot-N-ride	0.424**	8.16	0.902**	4.97
E-scooter user	E-scooter	1.135**	8.70	2.418**	5.24
	Scoot-N-ride	0.539**	3.25	1.431**	2.83
Transit user	Scoot-N-ride	0.417**	2.68	0.782	1.85
Error component	E-scooter, Scoot-N-ride			2.683**	8.74
Number of individuals		610		610	
Number of observations		2854		610	
Log likelihood at convergence		-1529.69		-1192.17	
Log likelihood (Null model)		-1880.74		-1880.74	
McFadden Pseudo R2		0.19		0.36	

** Significance at %1, * Significance at %5 level.

existing studies have commonly shown that people are more sensitive to out-of-vehicle travel time more than in-vehicle travel time (Abrantes and Wardman, 2011), the coefficient was expected to be negative and statistically significant; in other words, the ML model result is more consistent with the literature. Finally, several previously significant variables in the MNL model, including $\beta_{Male,E\text{-}scooter}$, and $\beta_{TransitUser,Scoot\text{-}N\text{-}ride}$, became insignificant in the ML model. These results indicate that once preference heterogeneity is accounted for, there is no group difference between males and females regarding their stated preference for e-scooters or between transit users and non-users regarding their stated preference for Scoot-N-ride. Overall, these results imply that the coefficient estimates of the MNL are likely biased, and an ML model that accounts for preference heterogeneity can reduce these biases.

The mean estimates of all ASCs in the ML model had a negative sign. However, unlike the MNL model, the ASC of walking was not significantly different from zero, suggesting that the average respondent prefers walking as much as driving after individual preference heterogeneity is accounted for. Unsurprisingly, all level-of-service variables were negative and highly significant. The results on their standard deviations indicate significant response heterogeneity among the survey participants, which is consistent with prior mode choice studies on e-scooters (Baek et al., 2021; Lee et al., 2021; Reck et al., 2022). Compared to the MNL model, the travel time importance ratio between OVTT and IVTT estimated by the ML model is closer to the commonly assumed value of two. According to the ML model, the mean estimate of OVTT is 2.04 times that of IVTT for a 1-mile trip. Based on the coefficients of travel time and cost, we can further compute willingness-to-pay measures. For instance, based on the mean estimates of the ML model, for a 3-mile trip, the willingness-to-pay measure for travelers whose household income was between \$50,000 and \$75,000 was \$23.17 per hour of in-vehicle travel time and \$31.19 per hour of out-of-vehicle travel time.

We found that the socioeconomic and demographic groups that indicate a stronger preference for shared e-scooters differ from those who currently use them. The ML model suggests that males, non-Whites, and people without a college degree had a stronger preference for using shared e-scooters. Preference for shared e-scooters did not differ between respondents aged 40 or below and those aged above 40 or between low-income respondents (household income below ¡$25,000) and higher-income ones. These findings stand in contrast to existing research which shows that shared e-scooter users are disproportionately young, White, male, better educated, and have higher income (NABSA, 2020, 2022; NACTO, 2020). Though somewhat surprising, these results are largely consistent with recent studies that examine behavioral intentions or modal preferences as related to shared e-scooters. For instance, Sanders et al. (2020) surveyed over a thousand university staff in Tempe and found that non-White travelers had a stronger intention to try e-scooters. Baek et al. (2021) found that travelers' stated preferences for using shared e-scooters as a last-mile travel mode did not vary by age or income. Mode choice analysis conducted by Reck et al. (2022) based on revealed preference data also showed that individual preferences for shared e-scooters did not differ across age groups or between college graduates and those without a university education. Overall, these results suggest that stated intentions or preferences often differ from actual behavior (Buehler et al., 2021; Louviere et al., 2000), which can be explained by two reasons. First, individuals sometimes do not translate their intentions or preferences into action. Second, there exists a variety of barriers (e.g., pricing, technology access, or safety) that prevent people from using shared e-scooters even if they wanted to (Sanders et al., 2020).

Unsurprisingly, e-scooter users, transit users, and individuals who have a more favorable perception of e-scooters as a safe way to get around have a stronger preference for the shared e-scooter and scoot-N-ride options. The fact that e-scooter and transit users are generally onboard with the scoot-N-ride option corroborates the descriptive finding that there exists a broad interest in using shared e-scooters as a last-mile feeder mode to public transit.

Moreover, non-White respondents showed a stronger inclination to use scoot-N-ride than White respondents, and respondents' preference for scoot-N-ride does not differ by gender, age, income, or education level. The stronger preference for scoot-N-ride among non-White travelers, who tend to be more reliant on public transit than other population groups (Clark, 2017), may indicate a strong desire to find solutions to the last-mile transit connectivity issue commonly faced by them. This finding suggests the need for service coordination between public transit and shared micromobility systems to enhance public transportation options for traditionally underserved populations.

6. Simulating market shares under various pricing scenarios

To further shed light on modal substitution patterns, we applied the ML model results to estimate market shares among the six travel options: personal car, FHV, walk, transit (with walking as the access mode), shared e-scooters, and scoot-N-ride. Specifically, we simulated market shares of each travel mode under different scoot-N-ride bundled pricing schemes. We focus on bundled pricing schemes here because it is the most selected option when DC and LA survey participants were asked about changes that can increase their use of shared e-scooters to connect with transit. Moreover, both shared micromobility companies (e.g., Spin) and some transit agencies have an interest in implementing this strategy. We used the revealed-preference data (i.e., the one-way trips reported by the survey respondents) as the input data for these simulations. Note that the main purpose here is to evaluate the relative effectiveness of plausible scoot-N-ride bundled pricing schemes rather than to have a precise prediction of future modal split. The latter is unrealistic considering that the sample size was relatively small, that the sample was not representative of the general population, and that the one-way trips reported by respondents were not representative of the trips taken by all travelers. One could also argue that as travel trends constantly shift during COVID-19, performing travel demand forecasting based on existing data is extremely challenging, if not impossible.

We tested the following scoot-N-ride bundled pricing incentives: 25% off e-scooter fare, 50% off e-scooter fare, \$1 off e-scooter fare (i.e., waiver of e-scooter unlock fee), and \$3 off e-scooter fare. Informed by our discussions with several transit agencies and the e-scooter company Spin, these options are what we believe to be plausible discounts that future public-private partnerships between transit agencies and micromobility operators can lead to. There have been ongoing conversations on developing such partnerships to our knowledge, and time-limited, small-scale partnerships have already happened in some places (e.g., the 2020 Miami-Dade County multimodal rewards program). When estimating the market share among the six travel modes that we modeled, we made the following assumptions: 1) for the travel modes that people currently use (i.e., personal vehicle, walking, transit, and FHV), their trip attributes were respondents' own estimates. 2) for e-scooters, the e-scooter fare was assumed to be "one dollar to unlock, and 32 cents per min use" in DC and "one dollar to unlock, and 39 cents per min use" in LA, and the e-scooter speed was set at 9 mph; 3) for scoot-N-ride, we assume the e-scooter speed to be 9 mph and applied the same e-scooter baseline pricing. Also, we assumed the e-scooter leg of the scoot-N-ride trip to be one mile. Travelers may take an e-scooter to either connect with the bus or the Metro (the two transit types were randomly assigned to trip scenarios), which will result in different trip estimates. Considering that the impacts of the bundled pricing schemes may differ between the two cities, we initially performed the simulations for each city separately. However, we found that the findings from the two cities were consistent. Hence, for simplicity, we performed the simulations based on the pooled sample data.

Figure 3 shows the simulation results grouped by current travel mode, which can shed light on the relative effectiveness of each bundled pricing scheme on promoting scoot-N-ride as well as the underlying modal substitution patterns. The results suggested that offering a \$3 e-scooter credit would be the most effective pricing strategy, followed by a half-price

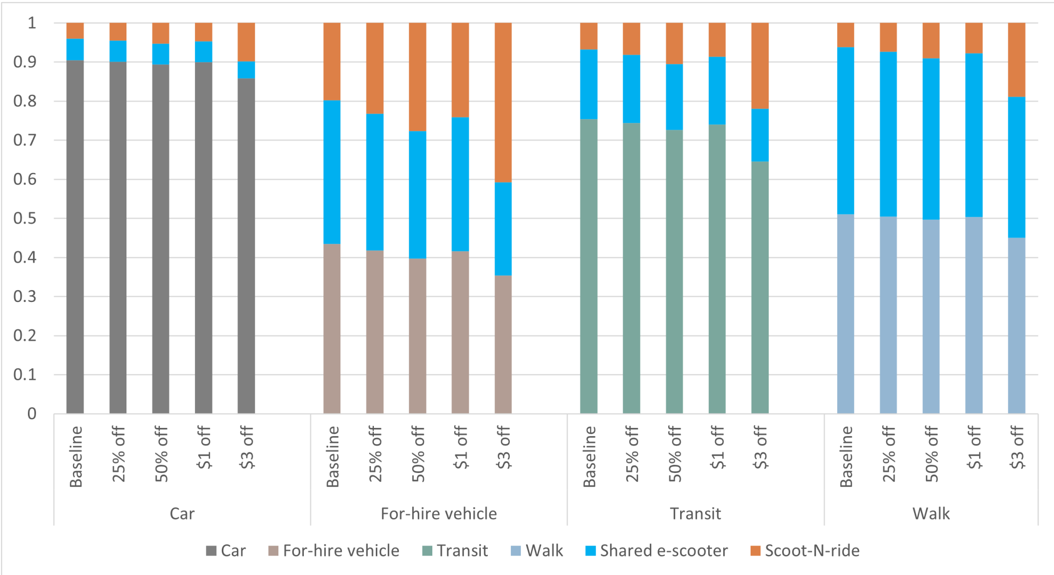


Figure 3: Market share under various pricing scenarios by current travel mode

discount. In the case of a feeder trip to public transit, a $3 discount is usually great than a half-price discount. A 25%-off or a "unlock for free" (i.e., one-dollar off) fare discount would have a small impact on the overall market share. Regarding modal substitution effects, we find that the market-share gains of scoot-N-ride mostly likely come from FHV trips, followed by existing transit trips with walking as the access/egress mode, and walking trips. Only a very small proportion (less than 1% under all scenarios) of personal vehicle trips are expected to switch to scoot-N-ride trips. Considering the large volume of driving trips happening in DC and LA, however, the growth in the absolute number of scoot-N-ride trips can still be substantial. In addition to transit improvements, road and parking pricing are needed to promote the switch from personal driving to scoot-N-ride. Only a "carrot and stick" strategy can make more drivers who enjoy free parking in most places consider switching modes (Small, 2005).

Figure 4 presents the simulation results grouped by trip distance, which visualizes modal split and modal substitution effects at different ranges of trip distance. We observe that survey respondents generally perceive shared e-scooters as a travel mode that serves short

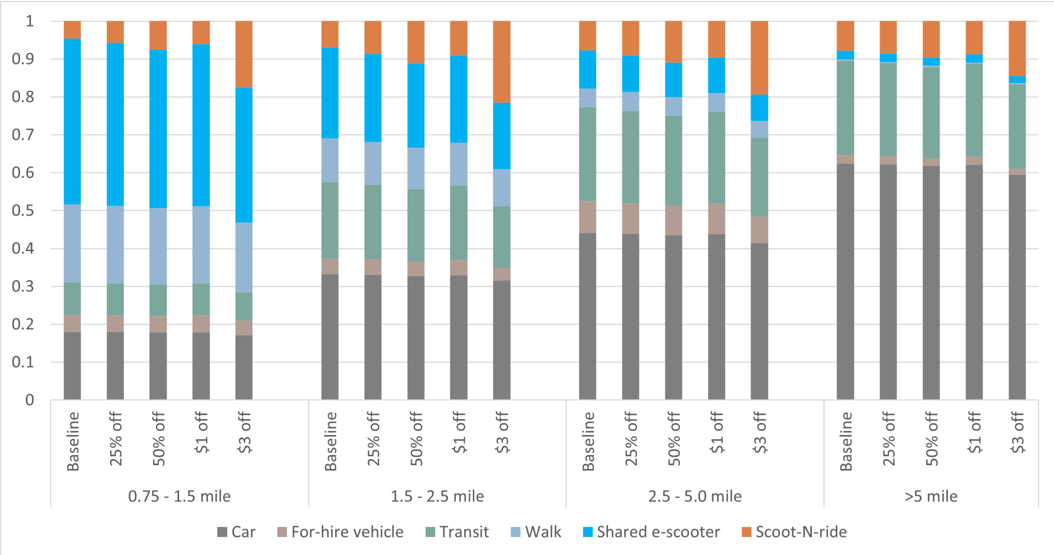


Figure 4: Market share under various pricing scenarios by trip distance

trips. A very small proportion of individuals would choose to use an e-scooter when the trip distance is longer than 2.5 miles. By contrast, the proportion of individuals choosing scoot-N-ride does not differ significantly across distance ranges, which implies that the scoot-N-ride option can serve a broader range of travel needs. By serving as a last-mile complement to transit and hence expanding the geographic area that people can reach with transit, shared e-scooters can broaden the appeal of public transit in many trip scenarios.

7. Conclusion

With shared e-scooter programs continuing to expand to more cities, e-scooters are becoming an increasingly visible and indispensable component of urban transportation systems. This study evaluates the potential for shared e-scooters to complement public transit and to reduce driving either by itself or by its combined use with buses or trains. We conducted a survey in Washington D.C. and Los Angeles to understand travel behavior as related to using shared e-scooters (including using them to connect with transit) and the underlying traveler preferences, as well as modal competition and substitution patterns. Descriptive analysis of the survey data has shown some substitution effects of shared e-scooters on driving trips, including personal-vehicle and for-hire vehicle trips. In addition, a wide interest exists among survey participants to use shared e-scooters as a solution when they face the last-mile problem. A majority of current users have already been using shared e-scooters as a last-mile feeder mode to transit; for some, e-scooters are the main mode to access transit stops.

Discrete choice models further show that both travel time and cost are significant factors shaping travelers' choice of travel modes and that significant preference heterogeneity exists among DC and LA travelers with regard to shared e-scooters and scoot-N-ride. The mixed-logit model estimates that travelers value out-of-vehicle time more than in-vehicle travel time, about two times as much for short trips. Interestingly, the socioeconomic and demographic groups who indicate a stronger preference for shared e-scooters differ from those who currently use them. We find that males, non-Whites, and people without a college degree have a stronger tendency to choose shared e-scooters and that stated preference for shared e-scooters did not differ by age or household income. Considering that the current e-scooter users are found to be disproportionately young, White, male, better educated, and have higher income (NABSA, 2022), we interpret these results as suggesting that barriers such as higher cost or safety concerns have impeded many population groups from using shared e-scooters. Moreover, we find that non-White respondents are more inclined to use scoot-N-ride than White respondents, which may arise from a desire to seek last-mile transit solutions. These results imply that understanding and addressing the barriers faced by various population groups, especially those who are traditionally underserved by the transportation systems, to use shared e-scooters (especially their combined use with public transit) should be a key future research agenda.

Market share simulations based on the ML model outputs further generate insights into modal substitution patterns between shared e-scooters, scoot-N-ride, and competing modes such as driving. By simulating the impacts of several "e-scooter + transit" bundled pricing scenarios, we confirmed that fare discounts can incentivize a shift from some driving trips (mostly for-hire vehicle trips) to scoot-N-ride trips. The impacts of scoot-N-ride on personal vehicle trips are estimated to be small, suggesting that improving multimodal travel options alone is not enough to make drivers switch modes. Additional measures such as road and parking pricing are probably needed to promote the switch from personal driving to riding e-scooters or scoot-N-ride. Moreover, survey respondents generally intend to use shared e-scooters only for short trips, but they are willing to use scoot-N-ride for medium to long trips. Promoting scoot-N-ride should be a key strategy if reducing vehicle miles traveled is the policy focus.

Overall, the study results provide empirical support for the idea of developing partnerships and coordinating services between transit agencies and e-scooter operators to enhance multimodal travel and reduce car use. However, some limitations should be noted. First, the study focuses on DC and LA, two large U.S. cities that offer wide and extensive transit services. More empirical studies in other cities, especially smaller ones with significantly different transportation contexts, should be conducted to verify and enrich our study findings. Also, the paper has two objectives: evaluating the potential of shared e-scooters to enhance transit, and evaluating to what extent shared e-scooters can reduce reducing. While both objectives were addressed here, more emphasis is placed on the first objective. Due to the significance of the second objective, future studies should conduct in-depth analyses of important topics not examined here, such as why and when people may choose shared e-scooters over driving. Moreover, information on trip origins and destinations was not collected from the stated preference survey, which prevented us from developing land-use variables to be included in the choice models. Considering that the built environment is expected to influence travel mode choice (Handy et al., 2005), our model results can have some omitted variable bias. Future research should investigate under what land-use and trip circumstances travelers are more likely to use shared micromobility or scoot-N-ride options and what strategies can effectively promote a switch from personal driving to these options.

Author contributions

Study conception and design: Yan, Zhao, Broaddus, and Johnson; data collection: Yan, Zhao, Johnson, and Broaddus; analysis and interpretation of results: Yan, Zhao, Broaddus, and Srinivasan; draft manuscript preparation: Yan, Zhao, Broaddus, and Srinivasan.

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