American Micromobility Panel (Part 2): Transit Connection, Mode Substitution, and VMT Reduction

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A Research Report from the National Center for Sustainable Transportation

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16. Abstract This study examined the sustainability of shared micromobility services using data from 48 cities in the US using a 21-day smartphone travel diary and survey data. Population-weighted analysis indicated a much smaller share of transit connection than in prior reported studies, with more reliable data. However methodological decisions could be a cause for such discrepancies suggesting a sensitivity analysis of this same data may be a good next research step. Results also indicated median VMT reduced per micromobility trip to be roughly 0.15 miles for e-scooter share trips and 0.25 miles for bike share (including e-bike) trips. Models of mode substitution confirm prior evidence of factors affecting car substitution including trip distance as the strongest factor. This study also proposed two frameworks for building a sketch planning tool for examining VMT reduction from future micromobility services. This tool could help cities and regions better plan for the micromobility services to achieve real VMT and GHG reduction goals. While more research is needed to employ this framework, it helps motivate a series of additional research topics to inform a decision support tool for shared micromobility planning.		
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Disclaimer

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EXECUTIVE SUMMARY

In this report we extend the research conducted in the American Micromobility Panel: Part 1 (Fitch-Polse et al., 2023). This report weights and models the preliminary findings from the first-of-its-kind examination of all mode travel behavior of micromobility users in the US. Specifically, we focused the analysis of that data on the transit connection, vehicle miles traveled (VMT) reduction, and mode substitution of shared micromobility services in the 48 US cities of the American Micromobility Panel.

Preliminary results reported in the American Micromobility Panel: Part 1 on the low share of micromobility trips connecting to transit among all micromobility trips in the data (compared to other studies) remain when the data is weighed to the population level. This suggests that either the results are heavily dependent on the definition of micromobility-transit connection, or that the results of past studies have been influenced by measurement error. Research results also suggest that even though the share of micromobility trips connecting to transit is small, and the car substitution of those transit trips is also small, the impact can still be significant. If that car substitution is attributable to micromobility services, the share of VMT reduced, when accounting for transit connections, could be substantial because of large transit trip distances (12% of total VMT reduced from micromobility).

When evaluating the potential causes of car substitution, and mode substitution more broadly, trip distance and drivers' licensure prove to be the strongest factors. Time of day is also a strong determinant of car substitution, with micromobility more likely to substitute ridehailing during nighttime hours, and personal car use during off-peak hours (bike-share only). Both results suggest the sustainability of micromobility services may be more for the non-commute portion of travel behavior given how micromobility services are deployed and operated in US cities today.

When accounting for the VMT reduced from direct mode substitution of micromobility trips, the population-weighted summaries suggest median VMT reduced per micromobility trip to be roughly 0.15 miles for e-scooter share trips and 0.25 miles for bike share (including e-bike) trips. These results are comparable to past estimates in the US; however, this estimation does not account for indirect VMT reduction such as that described by transit connections. Heavy users of micromobility travel less in general and trips make up a much smaller proportion of their trips compared to other micromobility users. This indicates a need for other car-light sustainability metrics beyond VMT reduction on a trip-by-trip basis as micromobility may be allowing people to travel without cars beyond simply allowing them to substitute car trips.

This report also leverages analysis to develop two potential frameworks for developing a decision support tool for VMT reduction from potential shared micromobility services that leverage this analysis. These frameworks helped to highlight the future research need of

understanding the relationship between pricing and micromobility demand. While this research and many past studies can be used to help predict VMT reduction from existing services, forecasting VMT reduction from future services will require research on the influences of pricing on demand since demand, closely linked to the extent of VMT reduction, varies significantly based on prices. This is also important for helping cities and regions compare alternative pricing and service options when planning micromobility services for VMT reduction benefits. Additionally, this framework could be extended beyond VMT reduction to many benefit categories.

Introduction

Micromobility services (e.g., bike share, e-bike share, e-scooter share) are often considered good options for reducing vehicle miles traveled (VMT) and related greenhouse emissions. The expected benefit of using micromobility services assumes that most users substitute bike and scooter trips for personal car and ride-hailing trips. If a major mode shift comes from other sustainable transportation options like walking and bicycling, the benefits of micromobility services may be more limited. Prior studies show that micromobility users substitute micromobility services for car use and occasionally use the services to connect to transit at the trip level (Kong et al., 2020; Fitch et al., 2020; Fukushige, et al., 2021; Guo and Zhang, 2021; Wang et al., 2023; Ju et al., 2024). These substitution and connection effects are important for estimating the overall environmental sustainability of micromobility services.

However, quantifying metrics to monitor the impact of micromobility services on travel behavior change and transportation emissions is a challenge. Data on transit connections either requires integrated payment systems or invasive travel behavior data collection (e.g., GPS travel diaries), and because travel mode substitution is inherently counterfactual, estimating sustainability metrics from counterfactual survey responses raises numerous validity concerns - how far can we trust data derived from what people think they would have otherwise done? Further, most studies of micromobility sustainability focus on one city, with either system trip data without information of users or survey data without information of travel patterns. These studies, while informative, have serious internal validity concerns and their results may not generalize to other cities.

Conceptually, the introduction of shared micromobility has the potential to change travelers' mode choice on a trip-by-trip basis. It also has the potential for people to restructure their travel in ways such as leaving and departing at new times, going to different destinations, even leaving a personal vehicle at home for the day and thus forgoing more driving than a trip-level substitution analysis would suggest. In fact, preliminary analysis of the data used in this report suggests that when evaluating trip chains, people may be altering their travel for entire chains or days as they use micromobility (Mohiuddin et al. 2024).

In this project we will quantify the magnitude of micromobility service effects on vehicle miles of travel (VMT) through population-weighted summary statistics from travel diary data. This quantification is an important first step for cities and regions to understand the scope of micromobility service effects in their current state. This project extends a prior NCST funded project (American Micromobility Panel, Fitch-Polse et al. (2023)) by leveraging the data from that panel (smartphone travel diary) to address the goal of quantifying VMT reduction. It also leverages past research at the trip level in one city (Fitch et al., 2020; Fukushige, et al., 2021).

In this project we will also explore the factors that lead to greater VMT reduction within micromobility services, what the barriers and accelerators exist for micromobility services (particularly as a car replacement), and what these factors mean for planning and policy as micromobility services continue to rapidly change in terms of vehicle form, app design, and monitoring technology. To address these goals, we focus on two groups of research questions that provide a deeper look at micromobility service sustainability. These questions help move our understanding beyond cross-sectional surveys of trip-based mode substitution, toward a clearer causal model of how micromobility services are changing travel behavior and in turn impacting the landscape of future sustainable mobility. The groups of questions are:

- Transit Connection: How are micromobility services used for first or last mile connection to transit? What are the barriers to and catalysts of connecting these modes? In what context do transit-connected micromobility trips replace vehicle trips? How much additional VMT reduction is achieved when considering transit connections?
- Mode substitution and VMT reduction: From what travel modes do people shift when they use micromobility services? How much VMT does this reduce? What variables (trip purpose, personal characteristics, trip context) are associated with a mode switch to micromobility? Do those mode shifts result in meaningful reductions in ride-hailing and personal car travel?

This project also outlines prototypes of a decision support tool for estimating VMT reduction from a proposed shared micromobility service. Using two simplified conceptual frameworks based on the results in this report, this report demonstrates what additional research is needed to build such a tool to support the planning of shared micromobility services.

Methods

Data Collection

This study uses data from the American Micromobility Panel (Fitch-Polse et al., 2023). The data includes smartphone travel diaries and surveys from micromobility users in 48 cities in the US (Figure 1). Recruitment of participants included study selection based on a variety of city-level characteristics and the presence and size of the micromobility market from partner operators: Bird, Lime, Lyft, Spin, and Superpedestrian. Partner operators recruited participants based on person-level trip weightings, where users with more frequent micromobility trips were most likely to be selected. In many cases, recruitment in a given market exhausted the entire userbase, and so recruitment was unbiased. However, in some markets the recruitment was biased toward frequent micromobility users (super users). Because of this bias, we calculated survey weights for descriptive statistics which provide estimates of the population of micromobility trip making in the selected cities for more generalizable results.

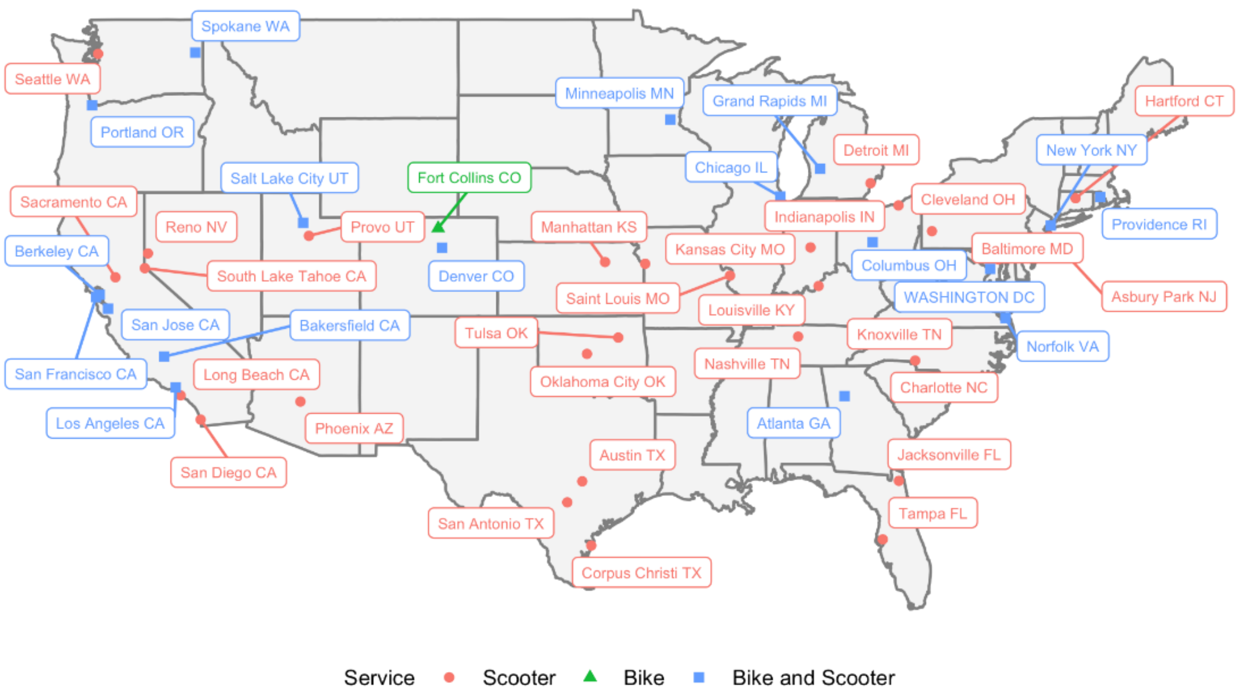

Figure 1. Location of selected cities and type of services

Travel Diary Survey

The American Micromobility Panel included a 21-day smartphone travel diary administered by the Resource System Group (RSG) using their app rMove during the summer of 2022. The travel diary was a form of prompted recall, where participants travel was recorded at the trip level by the app, and participants were asked to label their travel mode and travel purpose. When participants made micromobility trips, they responded to prompts about several other key questions including: type of micromobility, mode replacement, how they parked micromobility.

In addition to travel data, participants also reported person-level variables about their socio-demographics, household characteristics, and general travel behavior.

Trip Weighting

As samples collected through the survey have sampling error and non-response bias, it is important to weigh on the data to mitigate the issue for generalizing the outcome. We implemented poststratification using a R package, srvyr. Poststratification is one method to adjust the sampling weights by making strata based on population categories of an auxiliary dataset. We used a count of users by the number of person-specific trips by city and vehicle type for each micromobility service partner obtained from the five partners as a population data of micromobility users.

This analysis considered population characteristics including: frequency of micromobility use (Super user and regular user), what operator was used (Bird, Lime, Lyft, Spin, Superpedestrian, and other), types of cities (Big and dense cities and other cities), and micromobility vehicle types (Bike-share and e-scooter-share). For frequency of micromobility use, we used at least once a week as a threshold to determine whether participants are Super users. For types of cities, we defined two groups: "big and dense cities," which included New York City, Chicago, San Francisco and Washington D.C.; and "other cities," which included all other cities in the sample. We established such coarse categories to ensure that all strata had observations. We assumed that users who had similar frequency of micromobility use for an operator by mode type in cities with similar characteristics were likely to have similar individual characteristics. This is a strong assumption, but because there is no census of micromobility users, and trip frequency data is the only population level variable we had access to, it is the best way we could attempt to mitigate sampling errors and non-response bias to generalize the results to the population of micromobility users.

Some participants only participated in the travel diary for a few days making their data insufficient to calculate their frequency of micromobility use. To avoid mislabeling them in terms of frequency of micromobility use (super vs. regular users) given this uncertainty, we used validation data at the person level from the company partners (participants' trip information without any spatial characteristics in three months before and during the travel diary survey) to calibrate their frequency of micromobility use for any category. This approach may have introduced another bias as it is unlikely that participants use all micromobility operators with the same frequency. However, we assume this bias is less than the bias that would have been introduced by labeling people with very little diary data.

Because we only had five micromobility partners, and in some markets, we were missing micromobility trips from other operators, we assumed that the unknown population of non-partners' services was equivalent to the population of partners' service multiplied by the percentage of micromobility trips taken with non-partners in our diary dataset. All these steps resulted in population-scaled (expansion) weights for each micromobility trip (Table 1).

Table 1. Number of micromobility trips in the dataset

		Total micromobility use in study cities	
		Unweighted	Weighted
Big and Dense cities	Bike-share	10,336	179,626
	E-scooter-share	1,460	33,073
Other cities	Bike-share	1,376	10,904
	E-scooter-share	4,871	103,564

We also attempted to generate person-level weights (population weights scaled to the sample, not the population) to evaluate bias at the person level. Person-level analysis involves not only micromobility trip data but also other travel mode data, such as person travel miles and vehicle travel miles. Among 2092 participants, only 1606 participants (77%) took our travel diary survey for seven or more days. Among 1208 participants who made shared micromobility trips during the survey period, 487 participants (40%) used the services from multiple operators. These facts prevent us from making weights based on the company validation data. As the share of participants who use multiple services is substantial, we believe that the bias of ignoring trips across multiple operators may be stronger than the bias of unweighted results. As shown in Table 2 and Figure 2, the difference of individual characteristics between dataset for person-level analysis and for trip-level analysis was not large. Therefore, we determined to use our dataset without any weighting process when conducting person-level analysis.

Table 2. Summary statistics of participants

	Person level analysis	Trip level analysis	
	Unweighted (obs=1606)	Unweighted (obs=1208)	Weighted (obs=1208)
Age			
Under 35	51%	49%	53%
Age 33 - 55	28%	30%	32%
Over 55	20%	21%	16%
Woman	36%	33%	34%
Employed	84%	85%	86%
Race			
Asian	11%	12%	7%
Black	10%	8%	9%
White	60%	62%	66%
Other	19%	18%	17%
Income			
Less than $50k	33%	31%	35%
$50 - 100k	27%	27%	30%
$100k - $150k	16%	17%	16%
Over 150k	20%	21%	16%
Prefer not to answer	4%	4%	4%
Car license	76%	72%	71%
Own car	54%	45%	50%
Student	18%	15%	13%
Having children	12%	9%	10%

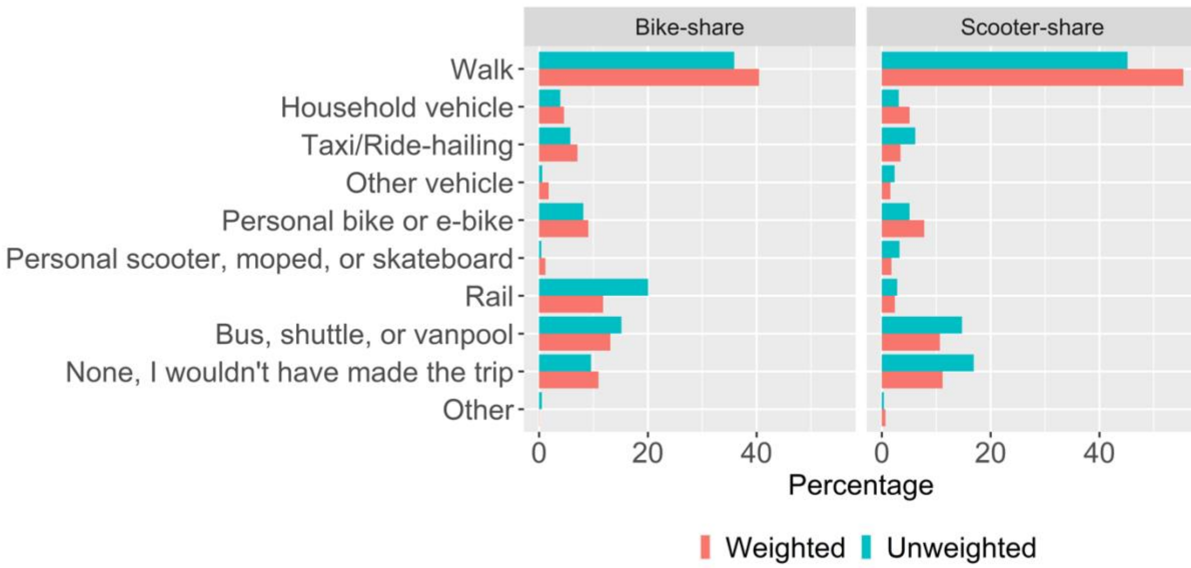

Figure 2. Impact of weighting on substituted mode share of micromobility trips by micromobility type

Analysis

To address the series of research questions we conducted a series of weighted descriptive statistics and statistical models. We separate the analysis into three primary analyses.

1. Analysis of transit connections and potential VMT reduction effects
2. Analysis of factors of mode substitution
3. Analysis of car use and VMT reduction

Transit connection

We analyzed behavior of micromobility use connecting to and from transit in three ways. First, we counted the number of micromobility trips used to access and egress from public transit. We define micromobility trips as transit connecting if the reported micromobility use either immediately preceded or succeeded a transit leg, or had a walk leg in between of no more than 0.4 miles. We determined the threshold based on the relationship between reported trip purpose and travel mode. To understand the scale of transit connections in our selected cities, we applied the population expanded weights.

Second, we explored mode substitution of transit when micromobility was a connecting mode. We used a response from participants to the question in the travel diary survey: *Imagine shared bike and scooter services did not exist in the city. What mode would you have used for most of the distance on this trip?* This question was asked of participants when they used micromobility services or public transit services connecting to and from micromobility use.

Third, we estimated VMT reduced for transit trips when micromobility was a connecting mode. This represents a potential VMT reduction from micromobility that to our knowledge has been ignored in past research. We conceptualize the VMT reduction as both an indirect effect of choosing transit instead of a car or ridehailing resulting from the introduction of micromobility services, in addition to the direct effect of mode substitution of the micromobility leg. By comparing the product of car substituting transit trip distance for micromobility connected transit trips, to the product of the direct car substituted micromobility trip distances, we derived an expected VMT reduction attributed to the multimodal use of shared micromobility and public transit.

Mode substitution of shared micromobility use

We examined factors influencing mode substitution of shared micromobility trips. The dependent variable in this analysis is mode substitution of shared micromobility trips, a categorical variable derived from the travel diary survey response to the question: *Imagine shared bike and scooter services did not exist in the city. What mode would you have used for most of the distance on this trip?*

We estimated statistical models to examine the factors that influence mode substitution including trip/tour attributes, land use characteristics, and individual characteristics, as shown in Table 3. Details of the modelling process are discussed in Appendix A.

This analysis is an extension of our prior study focused on mode substitution of dock-less e-bike-share trips in the Sacramento region, California (Fukushige et al., 2021). Our analysis in this study expands that analysis to include various types of shared services, more measures per participant, and encompasses a broader range of cities. Additionally, we incorporate tour-level information obtained through smartphone diary survey. These improvements enable more comprehensive and robust estimates, facilitating a deeper understanding of the mode substitution pattern among shared micromobility users.

Table 3. List of Predictor Variables

Variable	Description
Trip/Tour Attitudes	
Travel Distance (log)	Travel distance (mile)
Trip Purpose	1: Home, 2: Shopping/Errand, 3: Work/School, 4. Recreation/Social/Exercise, 5: Meal, 6: Change mode, 7: Other
Time of Day	1: Midnight (Midnight-7am), 2: AM peak (7-10am), 3: Off-peak (10am-4pm), 4: PM peak (4-7pm), 5: Night (7pm-midnight)
Weekday/Weekend (0/1)	1: Weekend/Holiday, 0: Else
Precipitation (0/1)	Presence of precipitation when any of trips in a day started
# Trips	Number of trips in a tour associated with a micromobility trip
Transit access	whether a micromobility trip was access to public transit
Transit egress	whether a micromobility trip was egress from public transit
Land Use Characteristics	Percent of land use category within 400-meter buffer of trip start or trip end location: 1: Civic use, 2: Commercial use, 3: Health use, 4: Industrial use, 5: Recreational/Park use, 6: Residential use, 7: Retail use, and 8: Other
Individual Characteristics	
Age	1: Age -34, 2: Age 35-54, 3: Age 55-
Race	1: Asian, 2: Black, 3: White, 4: Else
Gender	1: Woman, 0: Else
Work Status	1: Commute to at least one workplace, 0: Else
Student Status	1: Full or part-time student, 0: Else
Education	1: Bachelor's degree or higher, 0: Else
Children (Under 16)	1: One or more children, 0: Else
Household Income	1: Less than $50k, 2: $50k – 100k, 3: $100k – 150K, 4: $150k -, 5: Prefer not to answer
Vehicle Ownership	1: One or more car per person, 0: Else

VMT Reduction

We summarized VMT reduction from micromobility services by the population weighted product of car substitution and the distance traveled. We cross tabulated this estimate by micromobility vehicle type, and person-level travel and micromobility trip making. These summaries are the first multi-city estimates that include a smartphone travel diary.

Results and Discussion

Micromobility Use and VMT Reduction

Transit connection

In the weighted sample, only a small share (5-13%) of micromobility use connects to public transit (Figure 3). In big and dense cities, that share is greater, double in some cases compared to other cities. Both bike-share and scooter-share connect to transit at similar rates, with the exception of as an access mode in big and dense cities. There, scooter-share acts as a much more frequent connector for transit compared to bike-share. This may be because bike-share in big and dense cities acts more as a substitute, not complement for public transit. Also, in big and dense cities, bike-share acts as an egress mode at nearly double the rate as it acts as an access mode. This is only slightly the case in other cities, which bike-share is only slightly more likely to be an egress mode compared to access mode. More detailed analyses of these trip chains are needed to understand why bike-share varies in its use to access and egress from public transit. These results may be specific to the four big and dense cities in this study, and not generalizable to others.

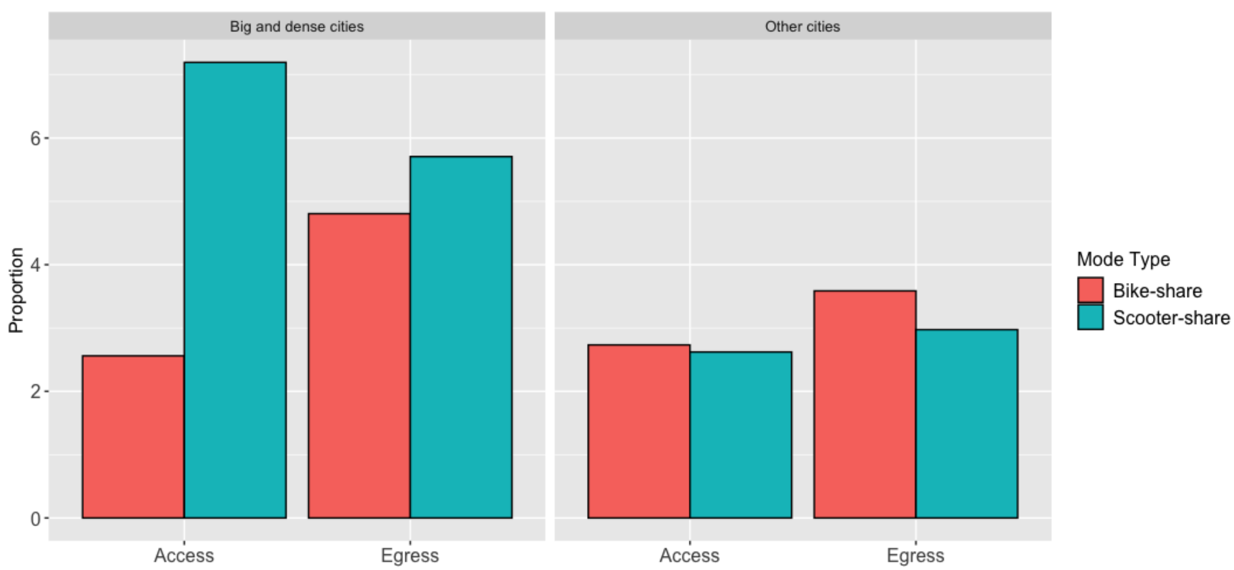

Figure 3. The share of micromobility uses connecting to/from public transit use by mode type and city type (Weighted)

Our finding that the share of micromobility connecting to transit in our dataset was small suggests micromobility in the US may still not be a great facilitator of public transit and thus has a limited VMT reduction capacity. This suggestion is further supported by the fact that when micromobility connects to transit, the share of those transit trips that are substituting for car trips (including personal, taxi/ridehailing, carpool, etc.) is also small (Figure 4). In addition, results suggest that even if micromobility was unavailable, the majority of people would continue to use public transit. These results taken together indicate that only a very small number of trips are multimodal micromobility with transit trips that are replacing car trips. Figure 5. also indicates that bus connections are less common than rail connections when using micromobility.

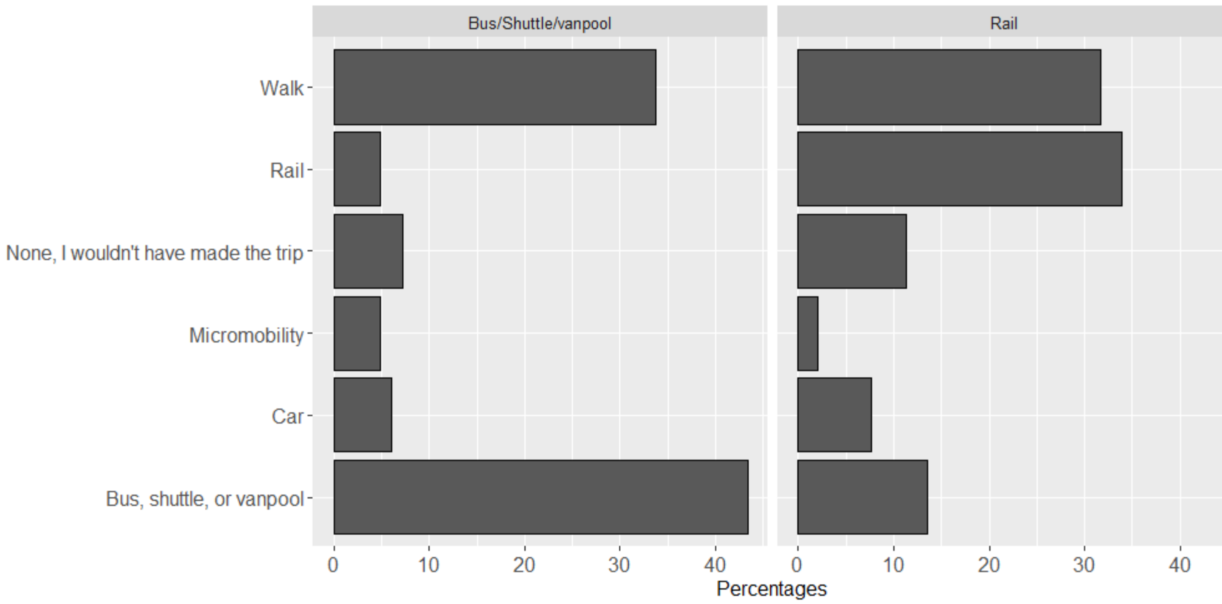

Figure 4. Mode substitution of transit trips connecting from/to shared micromobility use (n=83 for bus/shuttle/vanpool and 354 for rail)

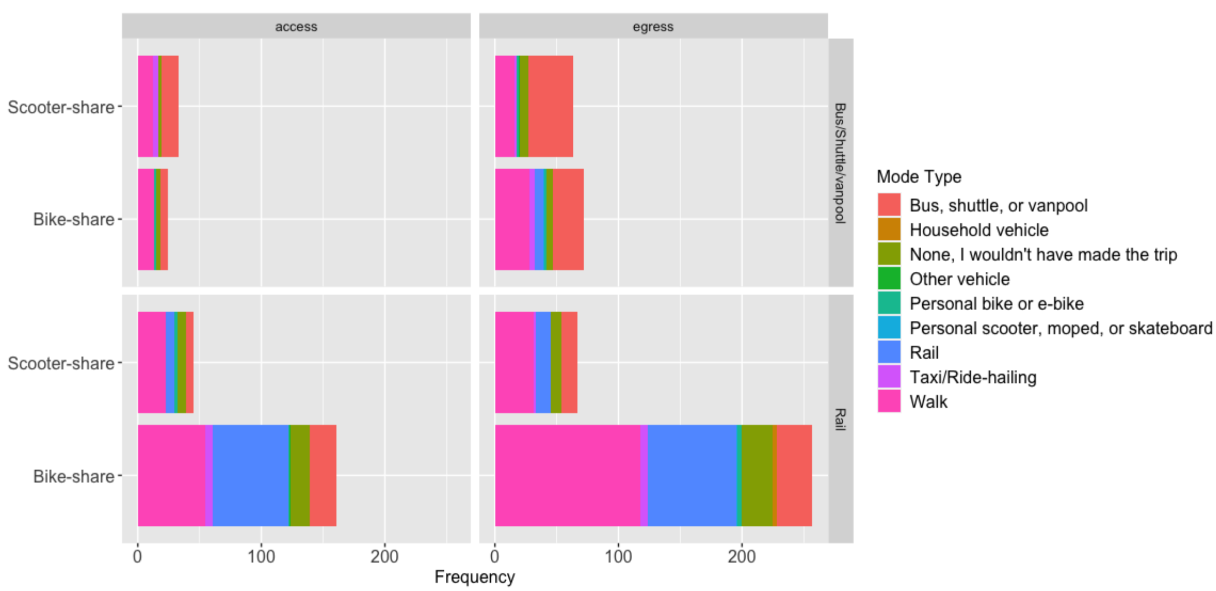

Figure 5. Mode substitution of micromobility uses connecting to/from public transit use by mode type and transit connection type (Unweighted)

While this evidence suggests the connection between micromobility services and public transit is small, some of this result may be due to our definition of transit connections. We define micromobility-transit connections as having to immediately precede or succeed each other. Yet, it is possible that activities near transit stations could occur in between the two modes (e.g., getting a coffee in between riding a bike and getting on the train). This could arguably still be seen as a micromobility-transit connection, yet our analysis does not consider it. At least one study in the US that examines the broader micromobility-connection by allowing participants to indicate it after micromobility rides without being explicit about the definition of a micromobility-transit connection. That study suggests a much greater rate of micromobility-transit connection in the range 17-30% (unweighted) (Ahmad et al., 2023). The conflicting magnitude of micromobility and transit connections in US cities between that study and this one suggests that additional analyses where the definition of a "connection" could be relaxed to learn more about micromobility-transit connections from this data in the future.

Using the share of car substituting transit trips that were connected with micromobility trips in this study suggests that accounting for transit connections increases VMT reduction estimates by 12%. This estimate is obtained by comparing the product of car substituting transit trip distance for micromobility connected transit trips, to the product of the direct car substituted micromobility trip distances (see section VMT Reduction below). Because of the constrained definition of micromobility-transit connection, as mentioned above, it is possible that percent of VMT reduction from transit connections could be larger. Further, most of the micromobility services in the US are not operating in concert with public transit. If coordinated planning and operations were to occur, we might expect a much larger micromobility-transit connection, and subsequent VMT reduction.

Mode substitution

The most direct and easy to measure effect of VMT reduction from micromobility services is from direct mode substitution. Our prior study showed that trip distance is one of the strongest factors for mode substitution (Buehler, 2011; Fukushige et al., 2021). This result is consistent with this data analysis for both bike-share and e-scooter-share trips (Table 5 and Table 7 in Appendix B). Walking is the dominate substituted mode by micromobility for trips up to about 2.5 miles for bike-share and about 3-5 miles for e-scooters.

Car substitution varies widely by driver's licensure and distance combined (Figure 6 and Figure 7). Although estimates of trip distance show strong effects on car-related substitution at longer distance trips, the dominate substituted mode for long distance trips (3 miles or longer) was rail for bike-share trips and bus for e-scooter-share trips. This is not consistent with our prior study showing that car-related modes were the dominant substituted mode at long distances for any trip purpose except recreational purpose (Fukushige et al., 2021). This conflict comes from the lower car substitution rate in this dataset compared to other prior studies (Fukushige et al., 2022; Wang et al., 2023). Possible explanations require further study. For example, the prior studies are more likely to be subject to response bias due to their cross-sectional designs. On the other hand, the biased recruitment of this study for heavy micromobility users could have obtained a biased car-light population (meaning they own fewer cars, and use cars less such that their car substitution is necessarily less) that even survey weights could not overcome. Another possible explanation is that as shared micromobility becomes more prevalent, the individual characteristics and travel behaviors of users have also changed in the time since the prior data were collected.

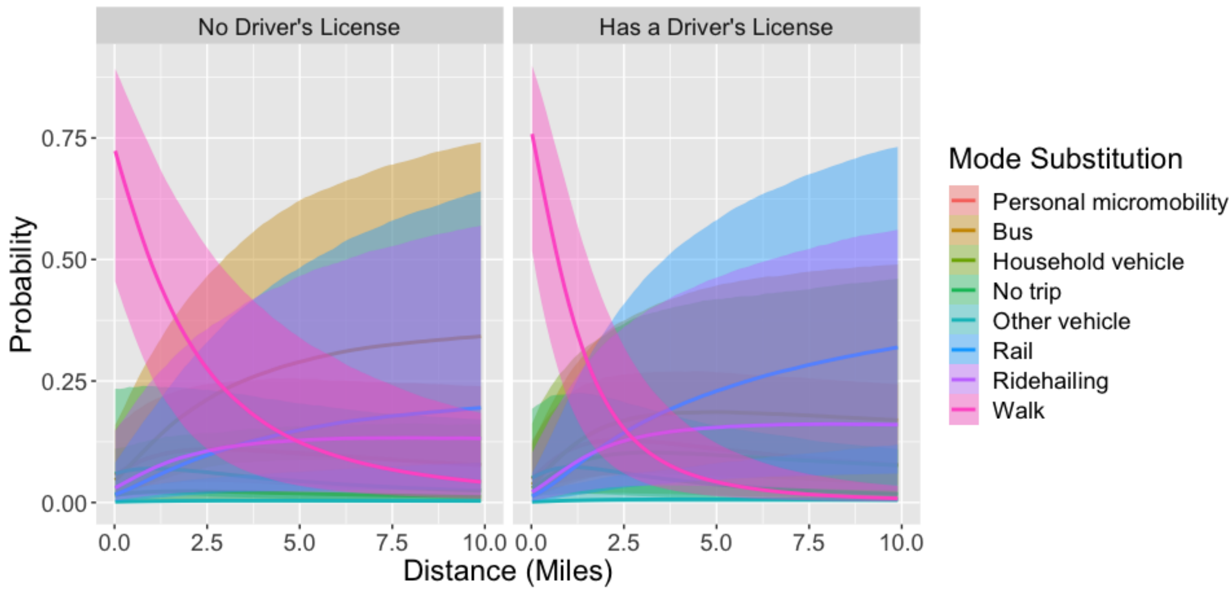

Figure 6. Conditional Combined Effects of Trip Distance and Driving License on Mode Substitution of Bike-Share Trips (Assuming the following: Off-peak trips; Under 35; Home purpose; Weekday; Non-student; No child; Employed; Male; mean values of other continuous predictors)

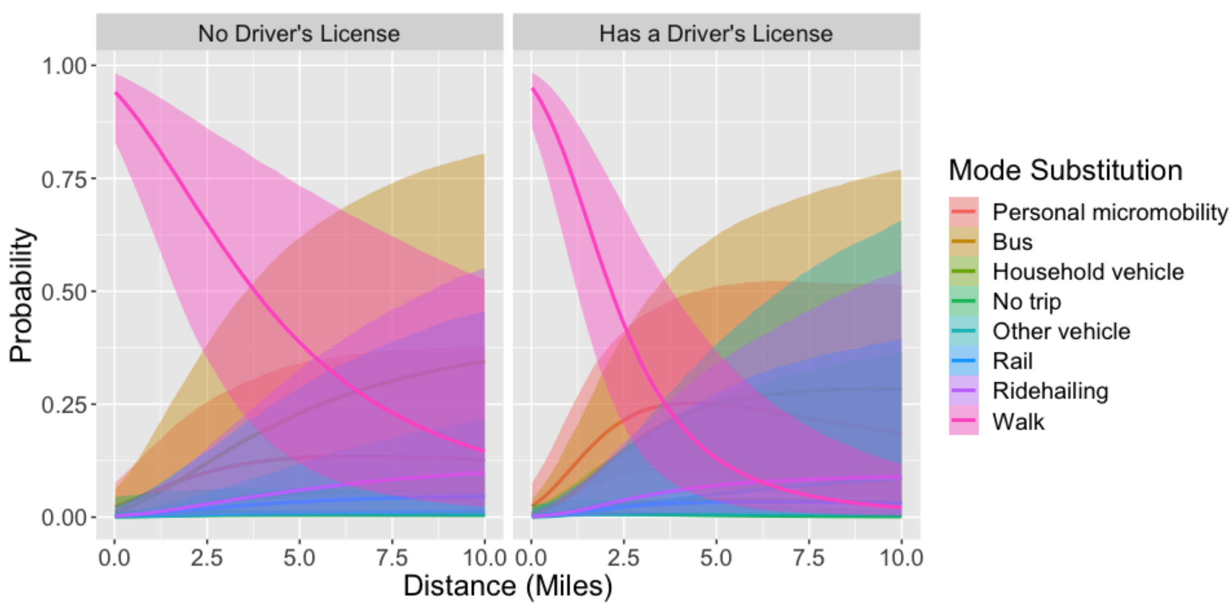

Figure 7. Conditional Combined Effects of Trip Distance and Driving License on Mode Substitution of E-Scooter-Share (Assuming the following: Off-peak trips; Under 35; Home purpose; Weekday; Non-student; No child; Employed; Male; mean values of other continuous predictors)

Mode substitution also varies by time of day. People are more likely to use bike-share or e-scooter-share services at night and midnight than at the rest of day instead of ride-hailing if the service was available (Table 5 and Table 7). That bike-share is likely to replace household-vehicle trips in off-peak hours is consistent with our prior study (Fukushige et al., 2021). Figure 8 shows that ride-hailing is the dominate substituted mode in Midnight and Night at long bike-share trips (2.5 miles).

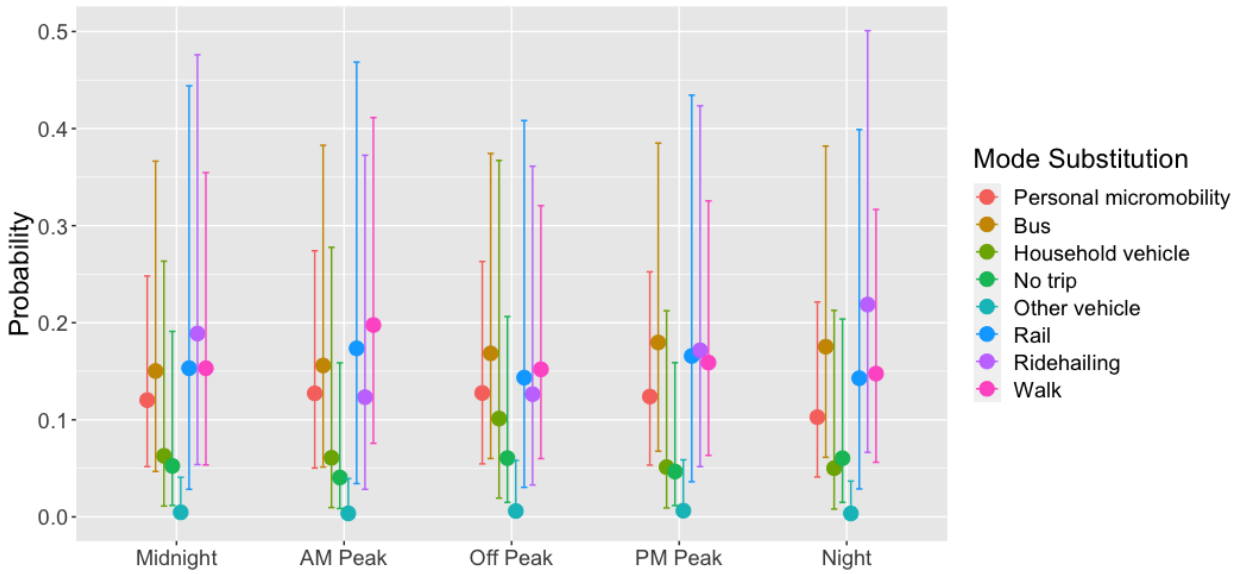

Figure 8. Conditional Combined Effects of Time of Day on Mode Substitution of Bike-Share Trips (Assuming the following: Under 35; Home purpose; Weekday; Non-student; No child; Employed; Male; Driving license; Trip Distance of 2.5 miles; mean values of other continuous predictors)

That bike-share is less likely to replace ridehailing trips for commuting purpose is consistent with our prior study (Fukushige et al., 2021), but interestingly e-scooter-share has an opposite tendency. E-scooter-share trips tend to replace household vehicle trips when users go to restaurants.

When people have more activities at different places, people are less likely to make household vehicle substitution than other modes. People may not give up using household vehicles when they need to visit many locations, or when many activities in a day often happen in the downtown area. Interestingly, land use did not help explain mode substitution of either bike-share trips or e-scooter-share trips. This may be due to a weak causal link or poor quality of the open-source data used (i.e. the noise of the data overwhelmed the signal).

Unlike our prior study (Fukushige et al., 2021), women did not show more car substitution than others when they used bike-share. On the other hand, for e-scooter-share trips, women were more likely to replace private vehicle trips than others. It is not clear why car substitution varied for women by micromobility vehicle type. Early evidence of shared micromobility (Clewlow,

2019) suggested women may be more comfortable e-scooting compared to biking, but subsequent results suggest a nearly equivalent gender gap in both modes. Yet, if women use e-scooters more to replace cars as our model suggests, more research is needed to understand why. Although the effects of race are small, Black micromobility users are predicted to substitute their private vehicle use with e-scooter-share use more compared to other race groups, and white micromobility users are predicted to substitute their ride-hailing use with bike-share use more than other race groups. Both results need more detailed follow up analysis to provide hypotheses as to why this is occurring, which may prove to be both market and even neighborhood specific.

VMT Reduction

Results from the product of reported mode substitutions and trip distances show that expected VMT reduction per trip in bike-share market area ranges between 0.03 miles and 0.55 miles (median 0.25 miles) (Figure 9). Markets of e-scooter-share services had even lower number of expected VMT reduction per trip a maximum of 0.29 miles (median 0.15 miles). These findings are consistent with early findings that docked bike-share service reduced 0.14 mile and 0.42 miles per trip in Washington, D.C. and Minneapolis (Fishman et al., 2014), but slightly lower than our prior finding that dock-less e-bike-share service in Sacramento reduced 0.58 to 0.85 miles per trip on weekdays (Fukushige et al., 2023).

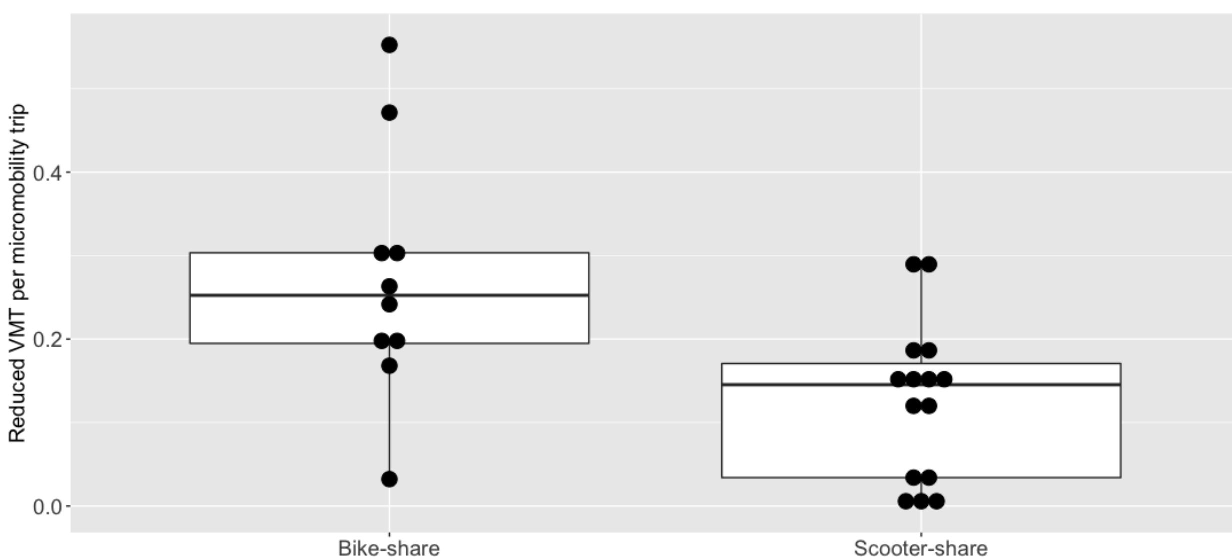

Figure 9. Reduced VMT per micromobility trip by market area for each mode type (Weighted)[1]

[1] Market area with less than 20 micromobility trips and less than 10 participants are excluded from this plot because of high uncertainty of the output.

Cities aspire for residents to increasingly use shared micromobility and reduce their dependence on cars in daily life. While VMT reduction from direct car substitution is an obvious performance metric, it may miss other ways micromobility reduced VMT. For example, our findings indicate that frequent micromobility users tend to generate fewer VMT compared to infrequent users (Figure 10). Additionally, frequent users rely less on cars for their total person-miles traveled than their less frequent users (Figure 11). One possible explanation is that micromobility services are substituting for car trips, leading to decreased car dependence among frequent users. Another plausible explanation is that individuals who frequently use micromobility services tend to live in environments or follow travel patterns with inherently lower car dependency. While we confirmed that some micromobility trips replace car trips, the difference in VMT among users with varying frequencies of micromobility use cannot be explained solely by car substitution. Further investigation is required to understand the directionality between micromobility use and car use. In addition, if micromobility is facilitated car-light and car-free travel, how should that be accounted for in terms of VMT reduction? This is an important question for performance metric development and policy evaluation.

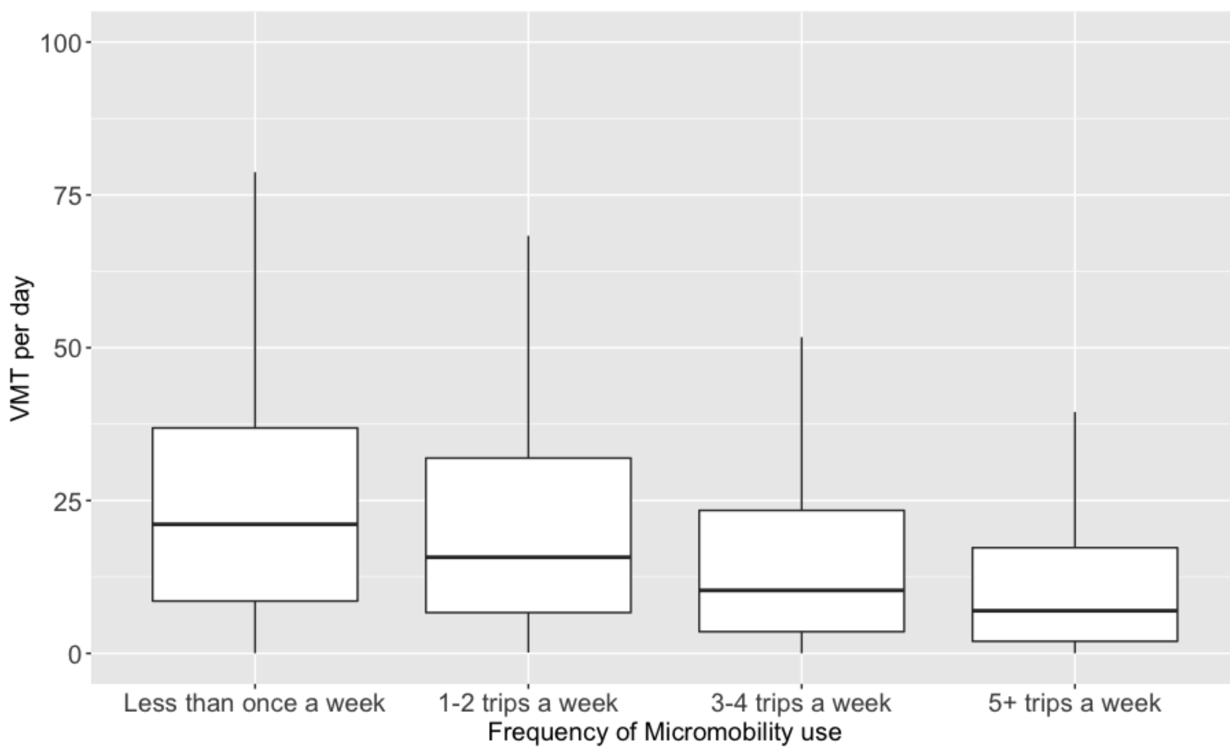

Figure 10. Average daily VMT by frequency of micromobility use (Unweighted) [2]

[2] We used data of participants involved in our travel diary survey in 7 or more days. PMT includes travel distance of any mode, except air trips, participants made.

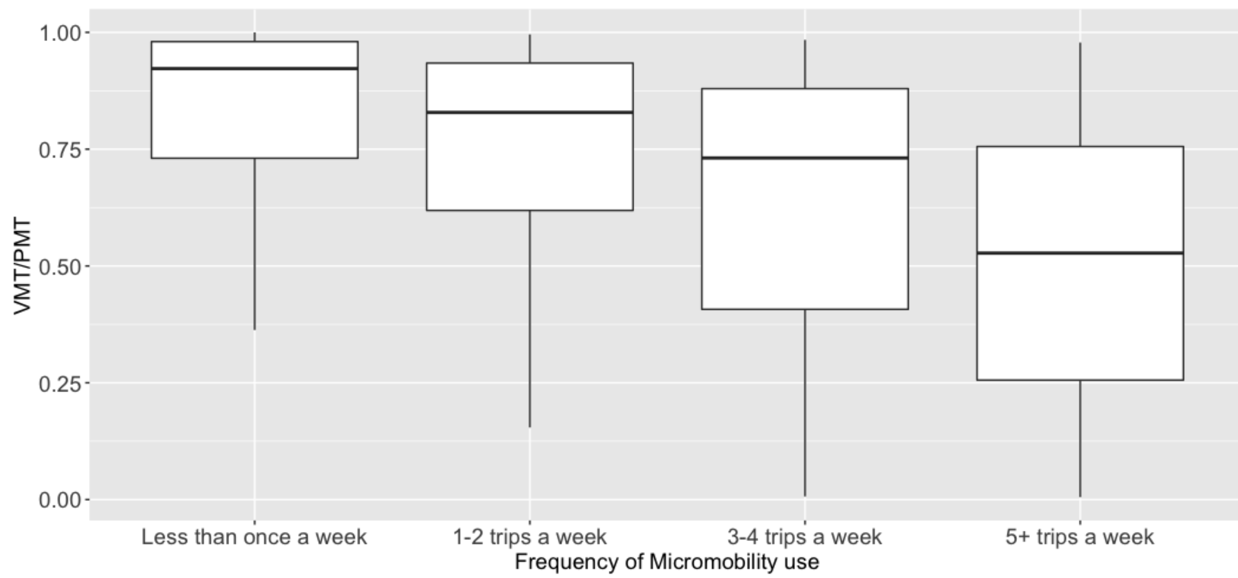

Figure 11. Share of average daily VMT to PMT by frequency of micromobility use (Unweighted)

Prototype VMT Reduction Tool

One of the goals of this research is to put the findings into practice. With many cities considering how to implement or modify shared micromobility programs, knowing the potential sustainability benefits can help in decision making. This can inform a variety of regulatory decisions, from whether or not to assess program fees or to instead provide subsidy, to whether shared micromobility should be included in more Travel Demand Management programs.

One way to help cities plan for micromobility is to provide a sketch planning tool that leverages the data and evidence from this study. Because the use of micromobility is very context sensitive, even results gathered from 48 cities in the US may not adequately address local conditions. This means that a generalized tool must account for local conditions to be accurate for new micromobility services.

The following are two proposed conceptual frameworks for how to integrate the findings into a tool for cities to use to estimate potential VMT reduction. We see this prototype as a first attempt to synthesize the findings into a decision support framework that can be explored and adjusted by practitioners as they consider the design and subsidy for shared micromobility programs.

Average Distance-Based Framework

The Average Distance-Based Framework is a simple framework that involves the multiplication of four estimates derived from separate models. This is an extension of a framework used in Fishmans' study (2014) by deriving key parameters from statistical models. The Reduced Vehicle Miles Traveled from micromobility can be formulated through a product of three terms, each with an equation derived from parameters and summaries from this and future research. This framework is defined as:

$$RVMT = NMT * CSR * ATD * TC - OW$$
$$NMT = f(\cdot)$$
$$CSR = g(\cdot)$$
$$ATD = h(\cdot) = X$$

where:

RVMT: Reduced vehicle-miles traveled
NMT: Number of micromobility trips derived from a prediction model, $f(\cdot)$
CSR: Car substitution rate (%) derived from a prediction model, $g(\cdot)$
ATD: Average trip distance of micromobility use (miles)
X: Unknown distribution of micromobility trip distance in a market
TC: Transit connection factor to adjust for transit segments connected to micromobility trips where car use was replaced
OW: Operational works by vans and truck
$f(\cdot)$: A function to predict number of micromobility trips in an area
$g(\cdot)$: A function to predict substituted mode
$h(\cdot)$: A function to predict average trip distance of micromobility use in an area

NMT represents the number of micromobility trips. This will be the most important parameter to have reliable estimations of potential VMT reduction. One key prerequisite for this method is a robust model to predict the demand of a future micromobility service. Variables in the model should include pricing, service area, and socio demographics at a minimum. Transportation cost is a critical factor influencing mode choice of residents and total demand of shared services. While existing studies have proposed demand models of shared micromobility services (Eren and Uz, 2020; Tuli et al., 2021), the price elasticity of demand is largely unknown in existing markets. Further study is required to examine the relationship between pricing and demand.

CSR represents the average car substitution rate. Prior studies and this study show large variation of that rate by city. Ideally, a local model from stated preferences or a model from a matched city (by population density, mode share, etc.) would function for forecasting car substitution. In leu of that, we propose to use the model from this work across 48 cities where one (or many averaged) city-level estimate can be chosen as a “match” for the city in question.

ATD represents average micromobility trip distance in the market. Our prior study (Fukushige et al., 2021) shows variation of mean trip distance by cities in the range between 0.5 miles and 3.6 miles, suggesting the need of a method to predict average trip distance in the market. The distribution will be likely to follow the gamma distribution or log-normal distribution. Identifying a type of distribution and its parameters by examining the relationship with various factors, including size of market area, availability of vehicle types and presence of tourists is required. Although not developed in this report, future model development of trip distance by city in this dataset could be used for cities to select a distance from one or an average of multiple “matched” cities.

TC represents transit connection factor to adjust for transit segments connected to micromobility trips where car use was replaced. Availability of the service has the potential for people to restructure their travel for partial or entire chains or days, we call as indirect effects. Transit segments connecting to micromobility trips are one example of this effect. In this study, we identified the factor with 12% to account for the transit segments, including bus and railway, from our dataset, but our sample to determine this factor is too small. Further data collection and analysis are required to determine this factor.

OW represents operational works by vans and trucks generating VMT. Operational VMT will be one negative effect of micromobility services. Depending on geographic characteristics, demand, and operational strategies, operational miles vary a lot (Fukushige et al., 2023). Though operational strategies are arbitrary for private businesses, all businesses pursue for optimum operational strategies. We believe that some factors would be strongly associated with operational miles, helping for estimating reasonable operational miles. Because this topic has not been explored well, modelling operational miles will be encouraged as a further.

We did not include other indirect VMT reduction factors (change in destination choice, differences in distance between micromobility and substituted models) in this framework. Future analysis may reveal this to be an important factor to add to the framework. We have ongoing research on other indirect VMT reduction factors. Until more is known about the magnitude of additional VMT reduction, we have suggested to ignore them in this framework.

Beyond VMT reduction, one additional broader car use reduction that micromobility services could provide is by allowing more people to live car-free or car-light. This is not the same as VMT reduction, if VMT was not occurring before. Yet it encompasses a real sustainability benefit that needs to be considered in the future in addition to VMT reduction.

Distance Effect Framework

The Distance Effect Framework is an extension of Average Distance-Based Framework by utilizing mode substitution models that considered the interaction between trip distance and mode substitution. While the multiplication of total demand, car substitution rate and average trip distance is simple and intuitive, the Average Distance-Based Framework assumes that all car substitution occurs at any trip distance, which this report shows is not accurate. This distance effect framework can be defined as:

$$RVMT = TC * \sum_{i=1}^{NMT} (TD_i * MS_i) - OW$$

$$NMT = f(\cdot)$$

$$\{TD_i\}_{i=1}^{NMT} \sim X = h(\cdot)$$

$$MS = g(\cdot)$$

$$MS_i = \begin{cases} 1 & if\ MS_i = \text{"Car substitution"} \\ 0 & else \end{cases}$$

where:

RVMT: Reduced vehicle-miles traveled
NMT: Number of micromobility trips derived from a prediction model, $f(\cdot)$
X: Unknown distribution of micromobility trip distance in a market
TD_i: Trip distance of a micromobility trip i generated from a prediction model X
MS_i: Substituted mode of micromobility trip i derived from a prediction model, $g(\cdot)$
TC: Transit connection factor to adjust for transit segments connected to micromobility trips where car use was replaced
OW: Operational works by vans and trucks
$f(\cdot)$: A function to predict number of micromobility trips in an area

$g(\cdot)$: A function to predict a substituted mode The Distance Effect Framework is an extension of Average Distance-Based Framework by utilizing mode substitution models that considered the interaction between trip distance and mode substitution. While the multiplication of total demand, car substitution rate and average trip distance is simple and intuitive, Average Distance-Based Framework assumes that all car substitution occurs at any trip distance. However, our prior study in Sacramento region, California (Fukushige et al, 2021) and this study found an important role of trip attributes, especially trip distance, in predicting a substituted mode. Instead of using a mean trip distance, in this framework we draw samples from an identified distribution of trip distance and predict a substituted mode with a mode substitution model encompassing trip attributes. This ensures the effect of trip distance on mode substitution varies in the estimation based on real variation in our data. As our findings also shows a large effect of time of day on ride-hailing substitution, this framework could be more robust if the demand model has a parameter for time of day, another potential extension.

In either framework, we envision this future tool to allow the user to explore potential VMT reduction from a planned shared micromobility services by defining a service area on a map and inputting a few key pieces of information about the potential service, including pricing of the service. Spatial match between a defined area and census data in the background of the tool will proceed to apply the model predictions to the study area to produce VMT reduction forecasts.

Conclusions

This study examined new facets of the sustainability of shared micromobility services using data from 48 cities in the US. Using this large novel data of reliable travel behavior matched with survey measures, results indicated that a smaller share of micromobility and transit connections may be common in US cities compared to prior reported studies. However methodological decisions could be a cause for such discrepancies suggesting a sensitivity analysis of this same data may be a good next research step. Results also indicated median VMT reduced per micromobility trip to be roughly 0.15 miles for e-scooter share trips and 0.25 miles for bike share (including e-bike) trips. When modeling mode substitution, this data confirms many prior conclusions of factors affecting car substitution including trip distance as the primary factor. However, in this data, the interaction of car licensure and trip distance was important for understanding car substitution. Finally, in this study we proposed two frameworks for building a sketch planning tool for examining VMT reduction from future micromobility services. Using one of these frameworks, a tool could be developed to help cities and regions better plan for the micromobility services to achieve VMT and GHG reduction goals. While more research is needed to employ this framework, it helps motivate a series of additional research topics to achieve a policy-focused result of a decision support tool for shared micromobility planning.

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Data Summary

Products of Research

In this project, we used a 21-day smartphone-based travel diary of shared micromobility users. The dataset was collected in Summer 2022, targeting bike-share or scooter-share users in 48 US cities to understand the current impacts of micromobility services on other mode use. We used a third-party vendor (RSG) to monitor the travel diary survey. Five micromobility service companies (Bird, Lime, Lyft, Spin, Superpedestrian) we partnered with recruited users in three waves to avoid oversampling and to balance the number of participants by city and vehicle types in our dataset. We also recruited those who have not experienced any shared micromobility service before to understand the difference of travel behavior and attitude toward transportation in general and micromobility service. We used a snowball sampling technique to recruit these participants. However, our recruitment failed as we were only able to collect 32 participants from this approach. The total number of valid responses for this survey was 2206 participants (2174 users and 32 non-users) with 183,483 trips data. This dataset consists of eight different .csv files and contains various types of information, including household characteristics, person-level characteristics, types of vehicle participants own, daily-level information, trip attributes, locations of trips, trip classifier, and code lookup to merge travel diary survey dataset with post-diary survey dataset.

Data Format and Content

There are nine .csv files for the database, and an .html file for the codebook and dataset guide.

Database: Each row represents a single survey participant, a collected trip, or a collected location with a unique ID number assigned, and each column corresponds to one variable.

Codebook and dataset guide: This file describes variables and attributes in the database, and a dataset guide with information about data privacy, data preparation, and notes on joining table.

Data Access and Sharing

The final data of this project is subject to the UC Davis Institutional Review Board (IRB) guidelines on the treatment of human subject data and is available upon request from the principal investigator.

Reuse and Redistribution

The final data of this project is subject to the UC Davis Institutional Review Board (IRB) guidelines on the treatment of human subject data and is available upon request from the principal investigator. For all purposes allowed by the IRB guidelines, there are no restrictions on the use of the data. Data can be reused with credit to this report and the authors of the research.

Appendix A: Extended Methods

Mode Substitution of Micromobility Trips

In this analysis, we used three different types of predictor variables for both bike-share models and e-scooter-share models. The first set includes trip/tour attributes such as travel distance, trip purpose, time of day, weekday/weekend, precipitation presence, transit access and egress, and the number of trips associated with a tour (see Table 4). We log-transformed the travel distance data, assuming that its effect diminishes with longer distances.

The second set of predictor variables represents the land-use mix around trip start and end locations, using data from OpenStreetMap. We reclassified the land use data into eight categories: Civic, Commercial, Health, Industrial, Recreational/Park, Residential, Retail, and Other. We calculated the percentage of each land use category within a 400-meter radius around the trip points, consistent with our previous study (Fukushige et al., 2021). We also included individual characteristics of the respondent as a final set of predictor variables. Exceptionally, we interacted the presence of driving license with travel distance based on our data exploration which indicated a negligible and uncertain effect of distance on car substitution without the interaction.

To analyze the effects of the predictor variables on mode substitution for bike-share and e-scooter-share trips, we used multi-level multinomial logistic regression. This approach allowed us to account for person-level and market-level variations by permitting the average probability of mode substitution to vary by person and by market area, considering factors such as unobserved person-level characteristics, infrastructure quality, mode availability, and temporal characteristics across different cities.

We developed our models using the R package brms, which interfaces with the probabilistic programming language "Stan" for Bayesian modeling. We applied the Markov Chain Monte Carlo (MCMC) simulation method, drawing random samples from the posterior distribution to ensure convergence (R-hat < 1.1). The parameters set included 4 chains, 4000 iterations, 2000 warmups, 0.95 adapt_delta, and 16 max_tree_depth.

Choosing appropriate priors is crucial in Bayesian modeling to balance under-fitting and over-fitting. Lacking sufficient prior information on bike-share and e-scooter-share mode substitution, we based our priors on prior predictive checks that ensured reasonable data simulation. We used Student's t priors (deg. of freedom = 5, mean = 0, std. dev = 2) for intercepts, Gaussian distribution priors (mean = 0, std. dev. = 0.75) for predictors, and Student's t priors (deg. of freedom = 3, mean = 0, std. dev = 1) for person-level varying intercepts. These priors are "weakly informative," reducing over-fitting while allowing data-driven parameter estimates.

We evaluated several models with increasing complexity (see Table 4). Model I is the baseline with only alternative-specific constants. Model II adds varying intercepts by person and by market area. Model III incorporates trip attributes, Model IV includes land use variables, and Model V includes individual characteristics.

Table 4. Model Specification

	Intercept	Varying Intercept (Person & Market)	Trip Attribute	Land Use	Individual Characteristics
Model I	x				
Model II	x	x			
Model III	x	x	x		
Model IV	x	x	x	x	
Model V	x	x	x	x	x

To assess model performance, we used out-of-sample prediction metrics, balancing under- and over-fitting through stratified 10-fold cross-validation. The metrics included expected log pointwise predictive density (elpd), overall accuracy, true positive rate, false positive rate, F1 score, and weighted F1 Score. Elpd is a log-likelihood metric based on held-out data, providing a natural relative assessment of model accuracy. Overall accuracy indicates the proportion of correctly classified samples (an absolute metric) but may be flawed for assessment of data with imbalanced data classes.

To evaluate class-specific predictions, we used the true positive rate and false positive rate. As there is a tradeoff between these rates, we also reported the F1 score by class and the weighted average F1 score. The latter combines class-specific F1 scores weighted by sample size, balancing true positives and negatives across classes. For each model, we reported the mean and standard error of each metric, reflecting the 2,000 posterior distribution samples from the MCMC iterations post warm-up.

Appendix B: Model Parameter Summaries

Mode Substitution Model for Bike-share Trips

Table 5. Summary of estimates of mode substitution model for bike-share trip (full model) including the posterior mean and standard deviation

n = 7258 (Base = Micromobility)	Bus	Household vehicle	No trip	Other vehicle	Rail	Ridehailing	Walk
Intercept	-0.01 (1.1)	-1.55 (1.4)	0.33 (1.17)	-3.76 (1.69)	-1.96 (1.23)	-1.61 (1.26)	2.89 (1)
Person-level Std. Dev.	0.24 (0.18)	0.44 (0.32)	0.46 (0.29)	0.42 (0.32)	0.38 (0.25)	0.21 (0.16)	0.22 (0.15)
Market-level Std. Dev.	0.30 (0.23)	0.61 (0.45)	0.87 (0.36)	0.58 (0.46)	1.37 (0.48)	0.39 (0.31)	0.58 (0.25)
Trip/Tour Attributes							
Distance (log mile)	0.68 (0.41)	-0.25 (0.58)	-0.51 (0.46)	0.2 (0.63)	0.89 (0.42)	0.46 (0.49)	-1.33 (0.4)
Time of day (Base: Midnight)							
AM Peak	-0.01 (0.46)	-0.08 (0.56)	-0.3 (0.5)	-0.3 (0.67)	0.07 (0.46)	-0.49 (0.53)	0.21 (0.42)
Night	0.31 (0.45)	-0.07 (0.57)	0.3 (0.47)	-0.13 (0.68)	0.09 (0.45)	0.29 (0.49)	0.12 (0.42)
Off Peak	0.06 (0.43)	0.4 (0.52)	0.09 (0.45)	0.2 (0.62)	-0.11 (0.43)	-0.47 (0.49)	-0.06 (0.39)
PM Peak	0.16 (0.43)	-0.23 (0.54)	-0.14 (0.46)	0.28 (0.63)	0.05 (0.43)	-0.12 (0.48)	0.01 (0.4)
Weekend	-0.1 (0.36)	-0.4 (0.5)	0.29 (0.38)	0.45 (0.6)	-0.15 (0.35)	0.03 (0.42)	0.23 (0.3)
Trip purpose							
Change mode	-0.04 (0.52)	0.06 (0.61)	0.28 (0.5)	-0.09 (0.71)	0.31 (0.48)	0.32 (0.58)	-0.44 (0.46)
Home	-0.07 (0.43)	0.07 (0.51)	-0.24 (0.46)	-0.32 (0.64)	-0.2 (0.43)	0.03 (0.47)	0.17 (0.39)
Meal	-0.11 (0.51)	-0.02 (0.6)	0.11 (0.5)	0.27 (0.67)	0 (0.48)	0.08 (0.54)	0.31 (0.44)
Shopping and errand	0.14 (0.44)	-0.06 (0.53)	-0.44 (0.48)	0.1 (0.63)	-0.16 (0.44)	-0.13 (0.5)	0.13 (0.41)
Social / Recreation	-0.09 (0.45)	-0.19 (0.56)	0.21 (0.46)	0.23 (0.63)	0.07 (0.43)	0.11 (0.49)	-0.05 (0.41)
Work / School	0.44 (0.49)	0.22 (0.58)	-0.29 (0.57)	-0.11 (0.69)	0.12 (0.49)	-0.45 (0.59)	-0.23 (0.47)
Precipitation	-0.08 (0.46)	-0.34 (0.61)	0.32 (0.47)	-0.09 (0.69)	-0.08 (0.43)	0 (0.54)	0.23 (0.38)
# Trip	0.13 (0.28)	-0.36 (0.43)	0.34 (0.3)	0 (0.55)	0.22 (0.27)	0.27 (0.35)	-0.28 (0.25)
Transit Access	0 (0.64)	-0.14 (0.7)	0 (0.64)	-0.04 (0.74)	0.35 (0.6)	-0.12 (0.7)	0.28 (0.58)
Transit Egress	0.28 (0.55)	-0.23 (0.68)	-0.06 (0.57)	-0.09 (0.72)	0.45 (0.52)	-0.22 (0.64)	0.34 (0.48)

n = 7258 (Base = Micromobility)	Bus	Household vehicle	No trip	Other vehicle	Rail	Ridehailing	Walk
Land Use (Origin)							
Civic	-0.02 (0.72)	-0.07 (0.72)	0.39 (0.71)	0.04 (0.74)	-0.12 (0.71)	-0.06 (0.73)	-0.09 (0.7)
Commercial	-0.29 (0.56)	-0.39 (0.67)	-0.13 (0.59)	0.1 (0.71)	0.52 (0.53)	0.22 (0.61)	0.23 (0.51)
Health	-0.14 (0.71)	0.42 (0.72)	-0.18 (0.71)	-0.03 (0.74)	0.12 (0.72)	-0.01 (0.72)	-0.32 (0.69)
Industrial	0.22 (0.64)	-0.04 (0.7)	0.21 (0.67)	0.05 (0.73)	-0.47 (0.67)	-0.22 (0.68)	-0.02 (0.64)
Recreation/ park	0.17 (0.56)	-0.01 (0.65)	0.07 (0.58)	-0.13 (0.71)	0.02 (0.54)	0.03 (0.6)	0.19 (0.52)
Residential	-0.21 (0.49)	-0.17 (0.6)	0.04 (0.54)	-0.06 (0.69)	-0.03 (0.48)	0.08 (0.55)	-0.04 (0.46)
Retail	0.29 (0.55)	0.34 (0.65)	-0.17 (0.63)	0.04 (0.72)	-0.22 (0.63)	0.01 (0.62)	-0.08 (0.53)
Land Use (Destination)							
Civic	-0.02 (0.74)	-0.05 (0.75)	-0.03 (0.73)	-0.01 (0.74)	0.01 (0.72)	0.03 (0.74)	0.17 (0.69)
Commercial	-0.02 (0.56)	-0.21 (0.66)	-0.26 (0.58)	0.03 (0.72)	0.39 (0.53)	-0.06 (0.63)	0.39 (0.51)
Health	0.01 (0.73)	0.03 (0.73)	-0.09 (0.73)	-0.01 (0.76)	0.17 (0.71)	-0.01 (0.74)	0 (0.72)
Industrial	0.21 (0.63)	0.06 (0.71)	0.42 (0.65)	0.21 (0.74)	-0.29 (0.65)	-0.2 (0.69)	-0.1 (0.6)
Recreation/ park	-0.11 (0.57)	0.05 (0.67)	-0.15 (0.58)	0.12 (0.71)	-0.06 (0.55)	0.25 (0.59)	0.3 (0.51)
Residential	-0.06 (0.5)	-0.13 (0.61)	-0.14 (0.54)	-0.16 (0.7)	0.1 (0.5)	-0.44 (0.57)	-0.04 (0.46)
Retail	0.11 (0.57)	0.35 (0.65)	0 (0.65)	-0.13 (0.72)	-0.14 (0.63)	0.27 (0.63)	-0.38 (0.55)
Individual Characteristics							
Driving license	-0.07 (0.46)	0.78 (0.61)	-0.01 (0.48)	0.14 (0.67)	-0.07 (0.47)	-0.18 (0.54)	0.22 (0.4)
Woman	0.03 (0.35)	0 (0.49)	0.16 (0.4)	-0.35 (0.62)	-0.22 (0.35)	0.31 (0.42)	0.25 (0.31)
Employed	-0.28 (0.47)	-0.09 (0.61)	0.29 (0.49)	-0.14 (0.69)	-0.22 (0.46)	-0.07 (0.55)	0.27 (0.4)
Race (Base: Other)							
Asian	0.22 (0.43)	-0.2 (0.59)	-0.3 (0.48)	0.18 (0.66)	0.2 (0.45)	0.05 (0.54)	0.2 (0.38)
Black	-0.61 (0.61)	0.02 (0.69)	-0.18 (0.6)	0.01 (0.71)	0.59 (0.56)	0 (0.66)	-0.17 (0.5)
White	-0.16 (0.38)	-0.03 (0.51)	-0.24 (0.41)	0 (0.63)	0.25 (0.39)	0.42 (0.49)	-0.16 (0.33)
Income							
- $50k	0.32 (0.46)	-0.33 (0.6)	-0.14 (0.5)	-0.19 (0.67)	0.44 (0.47)	-0.43 (0.53)	-0.4 (0.43)
$50-100k	0.3 (0.41)	0.16 (0.53)	-0.01 (0.45)	-0.06 (0.64)	0.07 (0.42)	0.39 (0.47)	-0.03 (0.38)
$100-150k	0.14 (0.45)	0.36 (0.55)	-0.62 (0.5)	-0.09 (0.66)	-0.07 (0.45)	-0.04 (0.53)	0.06 (0.4)
$150k-	0.12 (0.41)	0.26 (0.51)	0.03 (0.44)	0.43 (0.63)	-0.08 (0.42)	-0.03 (0.47)	-0.02 (0.38)
Student	0.39 (0.43)	0.23 (0.57)	0.02 (0.49)	-0.02 (0.69)	0.12 (0.43)	0.59 (0.5)	-0.09 (0.39)

n = 7258 (Base = Micromobility)	Bus	Household vehicle	No trip	Other vehicle	Rail	Ridehailing	Walk
Having children	-0.26 (0.47)	0.3 (0.6)	-0.22 (0.54)	-0.12 (0.7)	-0.37 (0.49)	-0.41 (0.59)	0.21 (0.41)
Age (Base: Over 55)							
Age 35 -55	-0.19 (0.42)	-0.46 (0.53)	-0.22 (0.43)	-0.14 (0.65)	-0.26 (0.41)	-0.22 (0.5)	-0.35 (0.37)
Under age 35	-0.4 (0.43)	0.31 (0.52)	-0.23 (0.45)	0.34 (0.63)	0.25 (0.42)	0.3 (0.49)	0.06 (0.38)
Distance * Driving license	-0.25 (0.43)	0.44 (0.55)	-0.12 (0.48)	0.17 (0.61)	0.24 (0.43)	0.17 (0.49)	-0.76 (0.43)

Table 6. Cross validation prediction metrics for bike-share models

	Model I	Model II	Model III	Model IV	Model V
elpd	-908.3	-857.4	-822.6	-830.1	-838.6
Accuracy	21.8% (0.5%)	25.1% (0.5%)	31.2% (0.6%)	31.3% (0.6%)	32.5% (0.6%)
True Positive Rate					
Micromobility	8.3% (1.2%)	9.5% (1.2%)	9.9% (1.3%)	9.9% (1.3%)	10.8% (1.3%)
Bus	14.2% (1.2%)	18.5% (1.4%)	22.1% (1.4%)	22.2% (1.4%)	23.5% (1.5%)
Household vehicle	3.7% (1.1%)	6.4% (1.6%)	7.4% (1.7%)	7.8% (1.7%)	9.4% (1.9%)
No trip	9.9% (1.3%)	13.4% (1.5%)	16.7% (1.7%)	17.3% (1.7%)	18.9% (1.7%)
Other vehicle	1% (1.5%)	1.5% (1.9%)	1.7% (2%)	1.7% (1.9%)	1.7% (1.9%)
Rail	19.1% (1.2%)	25.7% (1.4%)	35.5% (1.5%)	35.8% (1.6%)	37% (1.5%)
Ridehailing	6% (1.2%)	7.8% (1.4%)	10% (1.6%)	9.8% (1.5%)	10.9% (1.6%)
Walk	37.8% (1.2%)	39.4% (1.2%)	48% (1.2%)	48% (1.2%)	48.9% (1.2%)
False Positive rate					
Micromobility	8.5% (1.1%)	10% (1.2%)	10.4% (1.3%)	10.3% (1.2%)	11.1% (1.2%)
Bus	15.3% (1%)	20.3% (1.2%)	23.1% (1.2%)	23.3% (1.2%)	24.6% (1.2%)
Household vehicle	4.1% (1.2%)	7.1% (1.6%)	8.1% (1.7%)	8.5% (1.7%)	10.4% (1.9%)
No trip	9.4% (1.1%)	12.4% (1.2%)	15.5% (1.4%)	16% (1.4%)	17.3% (1.4%)
Other vehicle	0.6% (0.9%)	0.9% (1.1%)	1% (1.2%)	1% (1.2%)	1% (1.1%)
Rail	20.2% (1%)	27.1% (1.1%)	35.5% (1.2%)	35.6% (1.2%)	36.8% (1.2%)
Ridehailing	5.7% (1.1%)	7.5% (1.2%)	9.3% (1.3%)	9.1% (1.3%)	10.3% (1.4%)
Walk	36.1% (0.7%)	37.6% (0.8%)	48.3% (0.8%)	48.4% (0.8%)	49.5% (0.8%)
F1 Score					
Micromobility	8.4% (1.1%)	9.7% (1.2%)	10.1% (1.3%)	10.1% (1.2%)	10.9% (1.2%)
Bus	14.8% (1.1%)	19.3% (1.2%)	22.6% (1.2%)	22.7% (1.2%)	24% (1.3%)
Household vehicle	3.9% (1.1%)	6.7% (1.6%)	7.7% (1.7%)	8.1% (1.7%)	9.8% (1.9%)
No trip	9.6% (1.1%)	12.9% (1.3%)	16.1% (1.5%)	16.6% (1.4%)	18% (1.5%)
Other vehicle	2.1% (0.8%)	2.3% (1.1%)	2.4% (1.2%)	2.4% (1.1%)	2.3% (1%)
Rail	19.6% (1%)	26.4% (1.2%)	35.5% (1.2%)	35.7% (1.2%)	36.9% (1.2%)
Ridehailing	5.8% (1.1%)	7.7% (1.3%)	9.6% (1.4%)	9.5% (1.4%)	10.6% (1.4%)
Walk	36.9% (0.9%)	38.5% (0.9%)	48.1% (0.9%)	48.2% (0.9%)	49.2% (0.9%)
Weighted F1 Score	21.7% (0.5%)	24.9% (0.5%)	31.3% (0.5%)	31.4% (0.5%)	32.5% (0.5%)

Mode Substitution Model for E-scooter-share Trips

Table 7. Summary of estimates of mode substitution model for e-scooter-share trip (full model) including the posterior mean and standard deviation

n = 3436 (Base = Micromobility)	Bus	Household vehicle	No trip	Other vehicle	Rail	Ridehailing	Walk
Intercept	-0.48 (1.24)	-2.1 (1.55)	-0.22 (1.29)	-3.56 (1.64)	-2.9 (1.56)	-0.69 (1.36)	3.14 (1.09)
Person-level Std. Dev.	0.7 (0.43)	1.01 (0.62)	0.89 (0.47)	0.58 (0.46)	0.58 (0.44)	0.41 (0.31)	0.79 (0.34)
Market-level Std. Dev.	0.59 (0.36)	0.87 (0.55)	0.58 (0.39)	0.95 (0.65)	0.54 (0.41)	0.35 (0.28)	0.25 (0.19)
Trip/Tour Attributes							
Distance (log mile)	0.66 (0.49)	-0.09 (0.61)	-0.82 (0.49)	0.67 (0.62)	0.57 (0.6)	0.82 (0.55)	-1.52 (0.45)
Time of day (Base: Midnight)							
AM Peak	-0.12 (0.57)	0.19 (0.63)	-0.35 (0.57)	0.19 (0.66)	0.33 (0.63)	-0.19 (0.62)	0.32 (0.47)
Night	-0.17 (0.51)	0.16 (0.58)	-0.19 (0.5)	0.27 (0.62)	-0.43 (0.63)	0.71 (0.55)	-0.11 (0.43)
Off Peak	0.39 (0.47)	0.05 (0.55)	-0.07 (0.48)	-0.1 (0.61)	-0.31 (0.59)	-0.34 (0.54)	-0.04 (0.41)
PM Peak	0.15 (0.49)	-0.12 (0.56)	-0.13 (0.51)	-0.13 (0.65)	0.02 (0.6)	-0.03 (0.54)	-0.19 (0.42)
Weekend	0.14 (0.41)	-0.28 (0.54)	0.05 (0.44)	0.01 (0.6)	-0.41 (0.58)	-0.14 (0.49)	0.03 (0.33)
Trip purpose							
Change mode	0.33 (0.62)	-0.16 (0.69)	-0.54 (0.65)	-0.02 (0.71)	0.06 (0.7)	-0.02 (0.68)	-0.2 (0.55)
Home	0.24 (0.48)	-0.15 (0.55)	-0.21 (0.5)	0.21 (0.62)	0.17 (0.61)	-0.13 (0.52)	0.19 (0.42)
Meal	-0.51 (0.55)	0.41 (0.58)	0.49 (0.5)	-0.13 (0.66)	-0.36 (0.66)	-0.1 (0.57)	-0.38 (0.44)
Shopping and errand	0.25 (0.48)	0.08 (0.58)	-0.25 (0.51)	-0.31 (0.65)	0.74 (0.58)	-0.09 (0.55)	0.22 (0.41)
Social / Recreation	0.15 (0.54)	-0.14 (0.62)	0.38 (0.52)	-0.22 (0.65)	-0.16 (0.63)	0.11 (0.56)	-0.26 (0.47)
Work / School	0.18 (0.56)	-0.01 (0.64)	-0.36 (0.61)	0.17 (0.66)	-0.27 (0.68)	0.39 (0.61)	0.2 (0.48)
Precipitation	-0.33 (0.56)	0.06 (0.6)	-0.07 (0.56)	0.4 (0.65)	-0.08 (0.65)	0.11 (0.56)	-0.54 (0.43)
# Trip	-0.1 (0.35)	-0.71 (0.49)	0.47 (0.36)	-0.05 (0.53)	0.58 (0.46)	-0.53 (0.46)	0.01 (0.28)
Transit Access	-0.12 (0.68)	-0.07 (0.73)	-0.21 (0.7)	-0.05 (0.74)	0.01 (0.73)	-0.01 (0.73)	0.64 (0.63)
Transit Egress	0.79 (0.6)	-0.15 (0.7)	-0.02 (0.65)	-0.06 (0.72)	0.32 (0.71)	-0.17 (0.69)	-0.25 (0.56)

n = 3436 (Base = Micromobility)	Bus	Household vehicle	No trip	Other vehicle	Rail	Ridehailing	Walk
Land Use (Origin)							
Civic	-0.21 (0.72)	-0.06 (0.73)	0.21 (0.72)	0.02 (0.74)	0.03 (0.74)	-0.02 (0.74)	-0.08 (0.68)
Commercial	-0.09 (0.59)	0.01 (0.63)	0.13 (0.6)	-0.25 (0.7)	-0.06 (0.68)	-0.04 (0.63)	0.38 (0.52)
Health	-0.04 (0.74)	-0.01 (0.75)	0.03 (0.73)	-0.01 (0.76)	-0.02 (0.73)	0.01 (0.76)	0 (0.75)
Industrial	0.37 (0.7)	0.21 (0.74)	-0.13 (0.7)	-0.01 (0.74)	0 (0.75)	-0.09 (0.73)	-0.19 (0.65)
Recreation/ park	-0.4 (0.65)	-0.31 (0.68)	-0.09 (0.65)	-0.34 (0.7)	-0.13 (0.71)	0.01 (0.67)	0 (0.56)
Residential	0.42 (0.55)	0.25 (0.62)	-0.28 (0.57)	-0.03 (0.67)	0.29 (0.65)	0.13 (0.6)	0.33 (0.48)
Retail	0.28 (0.65)	-0.07 (0.69)	-0.04 (0.67)	0.16 (0.71)	0 (0.7)	-0.1 (0.68)	-0.02 (0.58)
Land Use (Destination)							
Civic	-0.2 (0.73)	0.04 (0.74)	0.33 (0.74)	-0.04 (0.75)	0.09 (0.76)	-0.08 (0.74)	-0.27 (0.7)
Commercial	-0.37 (0.59)	-0.06 (0.68)	-0.03 (0.6)	-0.07 (0.7)	-0.2 (0.66)	-0.19 (0.67)	-0.01 (0.52)
Health	-0.07 (0.75)	-0.05 (0.74)	-0.05 (0.73)	-0.03 (0.75)	-0.06 (0.74)	-0.01 (0.74)	-0.05 (0.72)
Industrial	0.6 (0.67)	-0.12 (0.72)	-0.02 (0.7)	0.26 (0.75)	0.16 (0.74)	-0.18 (0.73)	-0.42 (0.65)
Recreation/ park	-0.37 (0.64)	0.08 (0.7)	0.07 (0.64)	-0.05 (0.71)	0.22 (0.69)	-0.02 (0.68)	0.58 (0.56)
Residential	0.08 (0.56)	0.25 (0.64)	-0.24 (0.58)	-0.28 (0.68)	-0.06 (0.65)	0.31 (0.62)	0.21 (0.5)
Retail	0.56 (0.62)	-0.2 (0.69)	-0.2 (0.66)	-0.12 (0.72)	-0.07 (0.69)	-0.02 (0.68)	-0.04 (0.58)
Individual Characteristics							
Driving license	-0.55 (0.52)	0.69 (0.63)	-0.55 (0.51)	0.03 (0.66)	-0.32 (0.61)	-0.59 (0.57)	-0.02 (0.43)
Woman	-0.17 (0.45)	0.64 (0.53)	0.26 (0.44)	0.09 (0.59)	-0.15 (0.59)	-0.22 (0.51)	-0.01 (0.34)
Employed	1.07 (0.49)	-0.3 (0.67)	0.73 (0.5)	-0.18 (0.69)	-0.2 (0.64)	-0.37 (0.63)	-0.26 (0.45)
Race (Base: Other)							
Asian	0.34 (0.59)	-0.11 (0.7)	0.23 (0.62)	0.17 (0.69)	-0.16 (0.72)	0.35 (0.66)	0.03 (0.54)
Black	-0.37 (0.58)	0.52 (0.67)	0.01 (0.57)	-0.19 (0.7)	0.24 (0.65)	0.05 (0.65)	0.04 (0.48)
White	-0.12 (0.46)	0.15 (0.58)	-0.39 (0.47)	-0.14 (0.61)	-0.05 (0.59)	0.01 (0.53)	-0.2 (0.39)
Income							
- $50k	0.08 (0.5)	-0.52 (0.58)	1.05 (0.52)	0.43 (0.62)	0.05 (0.6)	-0.37 (0.56)	-0.01 (0.44)
$50-100k	-0.31 (0.5)	-0.25 (0.56)	-1.08 (0.57)	0.03 (0.61)	0.1 (0.59)	-0.26 (0.54)	0.03 (0.42)
$100-150k	-0.3 (0.58)	0.88 (0.6)	-0.1 (0.61)	-0.15 (0.68)	0.07 (0.67)	0.25 (0.57)	0.05 (0.49)
$150k-	-0.24 (0.57)	0.2 (0.61)	-0.28 (0.61)	-0.22 (0.71)	-0.09 (0.67)	0.38 (0.59)	0.26 (0.49)
Student	0.32 (0.49)	-0.41 (0.64)	0.14 (0.52)	0.01 (0.64)	-0.18 (0.63)	-0.06 (0.58)	-0.48 (0.41)

n = 3436 (Base = Micromobility)	**Bus**	**Household vehicle**	**No trip**	**Other vehicle**	**Rail**	**Ridehailing**	**Walk**
Having children	-0.21 (0.57)	-0.14 (0.67)	0.9 (0.56)	0.08 (0.68)	-0.28 (0.68)	-0.37 (0.65)	0.45 (0.48)
Age (Base: Over 55)							
Age 35 -55	0.13 (0.52)	0.12 (0.61)	0.33 (0.55)	0.19 (0.63)	-0.28 (0.6)	0.26 (0.57)	-0.18 (0.47)
Under age 35	-0.37 (0.52)	0.1 (0.6)	0.37 (0.55)	-0.07 (0.63)	-0.25 (0.6)	-0.21 (0.56)	0.28 (0.47)
Distance * Driving license	0 (0.52)	0.35 (0.61)	-0.54 (0.56)	0.6 (0.6)	-0.2 (0.61)	0.05 (0.55)	-0.93 (0.49)

Table 8. Cross validation prediction metrics for e-scooter share models

	Model I	**Model II**	**Model III**	**Model IV**	**Model V**
elpd	-593.1	-550.3	-540.1	-537.6	-540.0
Accuracy	29.1% (0.7%)	34.7% (0.9%)	38.4% (0.9%)	38.6% (0.8%)	39.6% (0.9%)
True Positive Rate					
Micromobility	9.3% (1.7%)	11.3% (2%)	11.5% (2%)	11.6% (2%)	11.9% (2%)
Bus	11.4% (1.5%)	15.8% (1.9%)	20.7% (2.1%)	21.4% (2.1%)	23.5% (2.1%)
Household vehicle	4.6% (2%)	8% (2.7%)	9% (2.8%)	9.2% (2.9%)	12.9% (3.2%)
No trip	12.5% (1.5%)	33.9% (2.7%)	36.3% (2.5%)	36.8% (2.4%)	40.2% (2.4%)
Other vehicle	2% (1.6%)	5.4% (2.9%)	8.1% (3.5%)	7.7% (3.4%)	10.7% (4.1%)
Rail	2.3% (1.5%)	3.9% (2.1%)	8.8% (3.1%)	9.3% (3.1%)	9.6% (3.1%)
Ridehailing	4.8% (1.5%)	5.7% (1.6%)	7.8% (1.9%)	7.9% (2%)	8.6% (2%)
Walk	53.1% (1.5%)	55.4% (1.6%)	60.2% (1.5%)	60.1% (1.5%)	59.9% (1.5%)
False Positive rate					
Micromobility	8.8% (1.5%)	10.7% (1.7%)	11.2% (1.7%)	11.3% (1.7%)	11.9% (1.8%)
Bus	14.5% (1.7%)	19.7% (2.1%)	25.2% (2.2%)	25.8% (2.1%)	26% (2%)
Household vehicle	3.3% (1.4%)	6% (1.9%)	6.8% (2.1%)	6.9% (2.1%)	10.8% (2.5%)
No trip	16.4% (1.7%)	38.5% (2.4%)	41.7% (2.3%)	41.9% (2.3%)	43.1% (2.1%)
Other vehicle	2.5% (1.9%)	6.4% (3.3%)	9.2% (3.7%)	8.6% (3.6%)	11.3% (4%)
Rail	2.8% (1.8%)	4.7% (2.5%)	10.1% (3.4%)	10.6% (3.4%)	10.7% (3.3%)
Ridehailing	6.4% (1.9%)	7.5% (2%)	10% (2.2%)	10.2% (2.3%)	11.2% (2.4%)
Walk	45.1% (0.8%)	49.3% (1%)	53.6% (1%)	53.9% (0.9%)	55.4% (0.9%)
F1 Score					
Micromobility	9% (1.6%)	11% (1.8%)	11.3% (1.8%)	11.4%(1.8%)	11.9% (1.9%)
Bus	12.7% (1.5%)	17.5% (1.9%)	22.7% (2.1%)	23.3% (2%)	24.7% (2%)
Household vehicle	3.8% (1.6%)	6.8% (2.2%)	7.7% (2.3%)	7.9% (2.4%)	11.7% (2.7%)
No trip	14.1% (1.5%)	36% (2.4%)	38.8% (2.2%)	39.2% (2.2%)	41.6% (2%)
Other vehicle	2.7% (1.5%)	5.9% (3%)	8.6% (3.5%)	8.1% (3.4%)	10.9% (3.9%)
Rail	2.8% (1.5%)	4.4% (2.2%)	9.3% (3.1%)	9.8% (3.2%)	10.1% (3.1%)
Ridehailing	5.5% (1.7%)	6.4% (1.7%)	8.7% (2%)	8.9% (2.1%)	9.7% (2.1%)
Walk	48.8% (1%)	52.1% (1.1%)	56.7% (1%)	56.8% (1%)	57.6% (1%)
Weighted F1 Score	27.6% (0.6%)	23.9% (0.8%)	37.6% (0.8%)	37.8% (0.8%)	39.0% (0.8%)