RESEARCH REPORT

Institute of Transportation Studies | UNIVERSITY OF CALIFORNIA

Micromobility Trip Characteristics, Transit Connections, and COVID-19 Effects

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16. Abstract

While micromobility services (e.g., bikeshare, e-bike share, e-scooter share) hold great potential for providing clean travel, estimating the effects of those services on vehicle miles traveled and reducing greenhouse gases is challenging. To address some of the challenges, this study examined survey, micromobility, and transit data collected from 2017 to 2021 in approximately 20 U.S. cities. Micromobility fleet utilization ranged widely from 0.7 to 12 trips per vehicle per day, and the average trip distance was 0.8 to 3.6 miles. The median (range) rates at which micromobility trips substituted for other modes were 41% (16–71%) for car trips, 36% (5–48%) for walking, and 8% (2–35%) for transit, 5% (2–42%) for no trip. In most cities, the mean actual trip distance was approximately 1.5 to 2 times longer than the mean distance of a line connecting origin to destination. There was a weak and unclear connection between micromobility use and transit use that requires further study to more clearly delineate, but micromobility use had a stronger positive relationship to nearby rail use than to nearby bus use in cities with rail and bus service. The COVID-19 pandemic led to more moderate declines in docked than in dockless bike-share systems. Metrics that would enable better assessment of the impacts of micromobility are vehicle miles traveled and emissions of micromobility fleets and their service vehicles, and miles and percentage of micromobility trips that connect to transit or substitute for car trips.

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Glossary

Acronym	Definition
CARB	California Air Resources Board
CMS	Clean Miles Standard
CPUC	California Public Utilities Commission
GBFS	General Bikeshare Feed Specification
MDS	Mobility Data Specification
MM	micromobility
TNC	transportation network company
VMT	vehicle miles traveled

Euclidean distance: a direct line drawn from the origin to destination for a trip, independent of the actual roads used.

Executive Summary

Executive Summary

While micromobility services (e.g., bikeshare, e-bike share, e-scooter share) hold great potential for providing clean travel, estimating the effects of those services on vehicle miles traveled and reducing greenhouse gases is challenging. Many cities collect various micromobility usage metrics to regulate services, but there is a lack of detailed micromobility metrics for calculating sustainability benefits. This study: (1) leverages survey data and public feeds for micromobility usage to assemble estimates that are useful for cities to start monitoring the sustainability of micromobility services, (2) examines the usage trends before and after the initial shock of the pandemic, and (3) analyzes the effects of micromobility services on transit use through city- and stop-scale analysis of micromobility trips and transit ridership.

Our exploration in city report data reveals that the trip frequency in most study cities is relatively modest—below 2,500 trips/day. Micromobility fleet utilization ranged widely, from 0.7 to 12 trips per vehicle per day, and the average trip distance ranged from 0.8 to 3.6 miles. To assess which transportation modes were being substituted for by micromobility rides, we analyzed survey data from various cities (Figure ES-1). The median (range) rates at which micromobility trips substituted for other modes were: 41% (16–71%) for car trips, 36% (5–48%) for walking, and 8% (2–35%) for transit, 5% (2–42%) for no trip. In almost all the study cities, at least 35% of micromobility trips replaced car trips. That a large share of micromobility trips is substituting for transit trips in some, but not all, cities should be explored in more detail.

Accurately measuring trip distance is a crucial element in assessing the impact of micromobility—on transportation; on access to jobs, goods, services; and on the environment. However, the availability of trip distance data to researchers, planners, and policy makers has been limited. In some cases, the distance of a straight line connecting the origin and destination of a trip—the Euclidean distance—is more readily available and used as a substitute for actual trip distances. Our comparison of trip distance from different data sources shows that, in most cities, the mean of actual trip distance from city-report data is approximately 1.5 to 2 times longer than the mean Euclidean distance between trip start- and end-points from GBFS data. However, a calculation combining the Euclidean distance with trip duration can provide a more accurate estimate of actual trip distance.

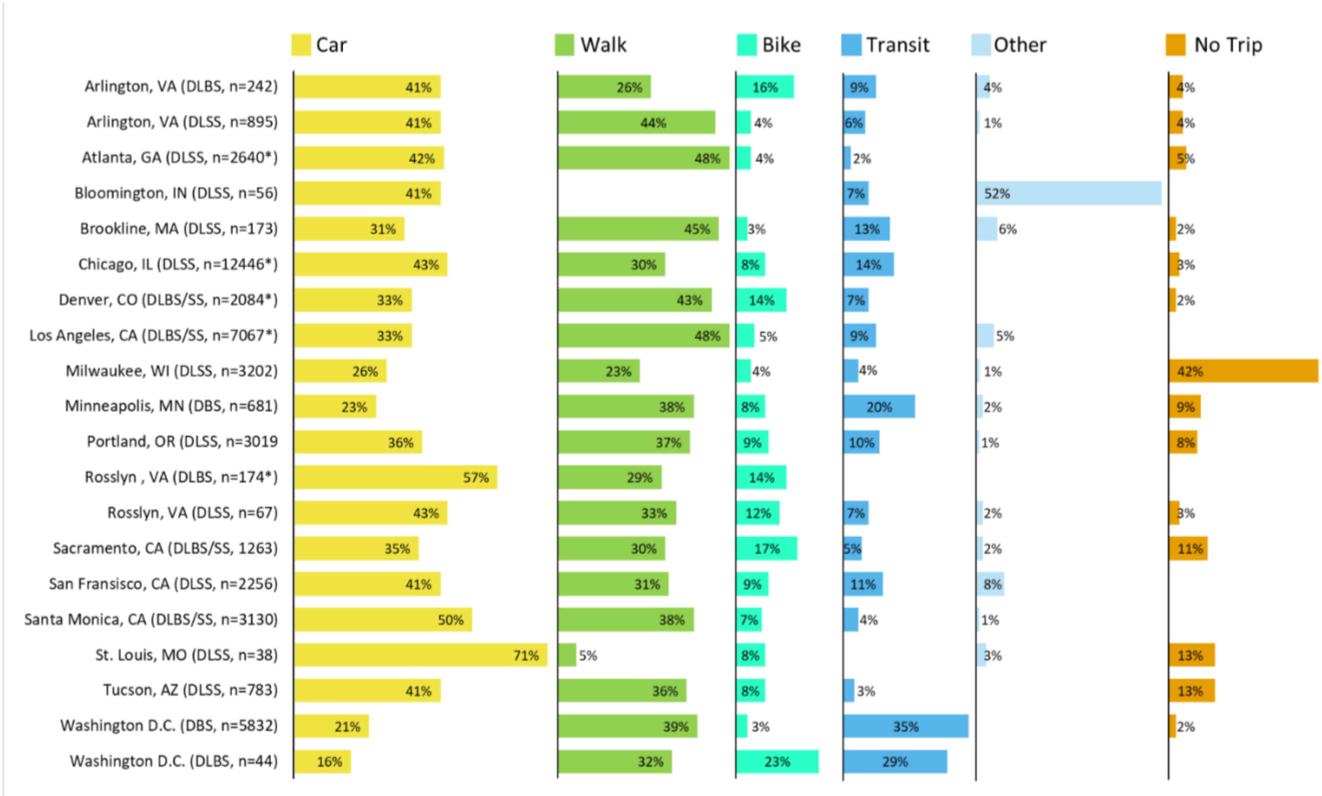

Figure ES-1. Micromobility mode substitution and travel change from city-report data. Note: "Car" includes private vehicle, taxi, ride-hailing, ride-sharing, etc.; "Walk" includes walk, skateboard, etc.; "Bike" includes personal bike, scooter, etc. (n indicates sample size; * indicates full survey sample size, otherwise mode substitution question specific sample size is provided; DBS, docked bike-share, DLSS, dock-less bike-share, DLBS, dock-less e-scooter-share)

The COVID-19 pandemic had dramatic effects on micromobility. Our analysis shows that most cities' docked bike-share systems experienced more moderate declines in ridership than did dockless systems and showed recoveries to near pre-pandemic levels, especially on weekends. Almost all dock-less services, however, saw a decline in trips leading up to the pandemic, and had services suspended after the initial shock. Interestingly, there was a uniform increase in trip duration of docked bike-share across all observed cities after the initial shock of the pandemic. This trend was also observed in dock-less systems of each city before service suspensions in March 2020.

Our study shows a weak and unclear connection between micromobility usage and transit ridership, as shown in Figure ES-2. Here, Portland is a clear outlier, with increased micromobility use correlating with increased transit use, especially on weekdays. This may be a result of the extensive light-rail system in Portland, as suggested by the following finding: In all the studied cities with rail and bus services (Atlanta, Miami, Portland, and Sacramento), there were positive associations between micromobility use and rail ridership, and the relationship between micromobility use and transit use was stronger for rail than for bus service. Further research, beyond the scope of this study, is needed to more clearly describe the relationship between micromobility use and transit use and what policies and planning decisions can enhance their synergy and make transportation more equitable and environmentally sustainable. Nonetheless, the finding here may be of value to policy makers who compare the benefits of light rail systems to those of bus lines, suggesting that a synergistic relationship between micromobility and transit is perhaps more likely with high-quality light rail service in place. However, we caution against drawing definite conclusions from these results about synergy between modes, given the lack of data available on actual multimodal trips.

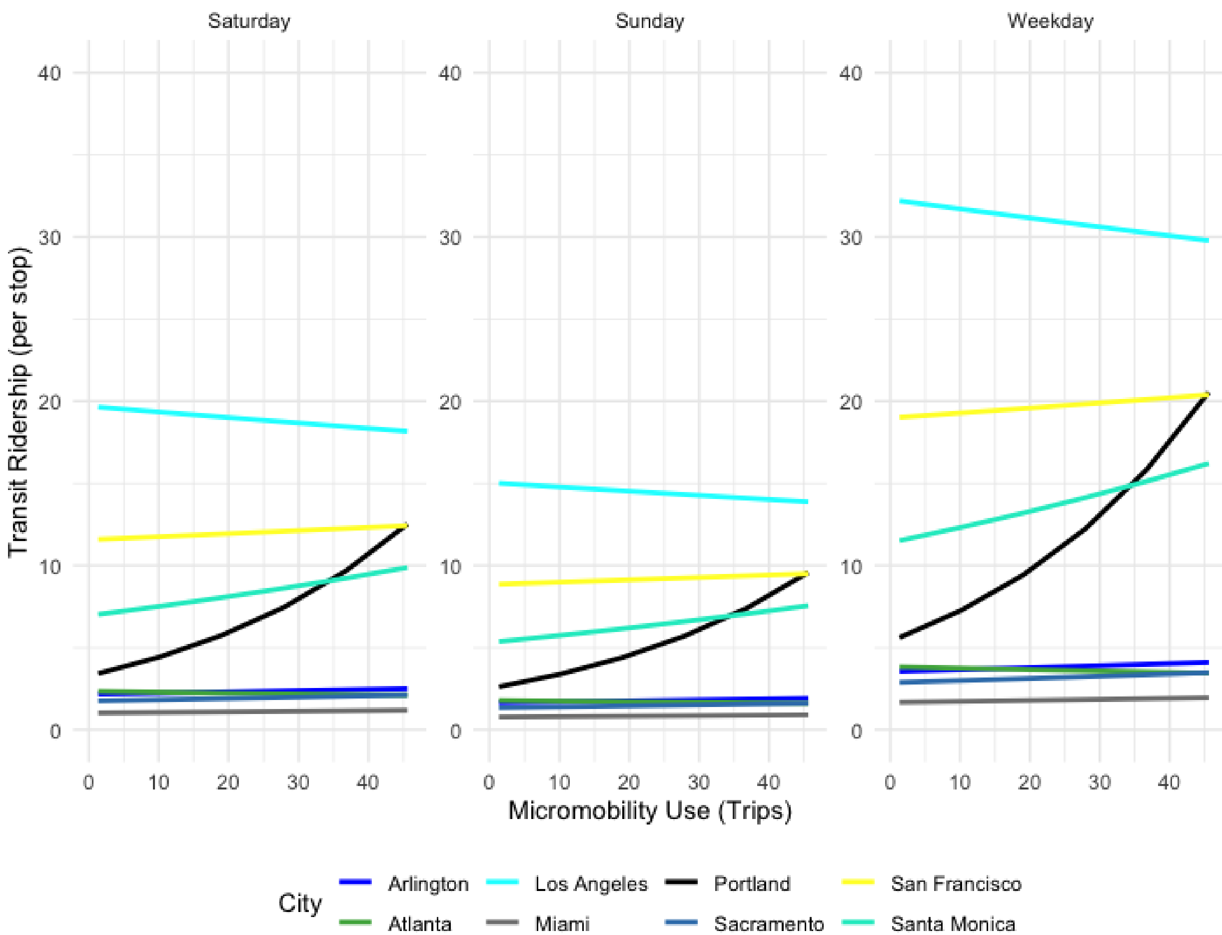

Figure ES-2. Predicted counts of transit ridership per bus stop by week period and city

Several findings can be useful for cities and regulators to better track the sustainability impact of micromobility services. Some of our findings lead naturally to metrics that can be used to estimate sustainability benefits from micromobility services (e.g., system miles), others are still exploratory (transit boarding and micromobility use relationships) and will require further study before integrating them into policy tools. In addition, we propose a suite of metrics that should be collected now, some that should be collected in the future, and a few options for how they could be used to monitor the sustainability of micromobility services, such as clean mile credits. Some of these metrics, as shown in Table ES-1, are vehicle miles traveled and emissions of micromobility fleets and their service vehicles, miles and percentage of micromobility trips that connect to transit and/or that substitute for car trips.

Table ES-1. Recommended metrics for monitoring sustainability of micromobility (MM) services

Types of Metric	Metric
Micromobility (MM) Vehicle Metrics	• MM fleet vehicle miles traveled (VMT) • MM vehicle emission factor
Ridehail Substitution Metrics	• % of MM trips that substitute ridehail trips • Length of MM trips that substitute ridehail trips
Car Substitution Metrics	• % of MM trips that substitute car trips • Length of MM trips that substitute car trips
Transit Connection Metrics	• % of MM trips that connect to transit • Length of MM trips that connect to transit • % of transit trips that substitute car trips • Length of transit trips that substitute car trips
Operation Van Metrics	• Van VMT (operations) • Operation van emission factor

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Introduction

While micromobility services (e.g., bikeshare, e-bike share, e-scooter share) hold great potential for providing clean travel, estimating the effects of those services on vehicle miles traveled and reducing greenhouse gases is challenging. One challenge is in assessing travel mode substitution from car trips to micromobility trips and micromobility connected transit trips. Unlike measuring emission reductions from vehicles and fuels, measuring emission reductions from changes in human behavior—such as substituting one transportation mode for another—is inherently more challenging because of heterogeneity in mode replacement and the challenges of quantifying such behavior. Furthermore, the rapid evolution of micromobility services from 2018 to early 2022 have forced cities to regulate them to curb immediate social harm (e.g., safety, nuisances, etc.) with little consideration of how to support them as car alternatives in the long run (e.g., by re-focusing streets away from efficient movement of cars and toward safe movement for vulnerable road users). Another complication in assessing the potential benefits and costs of micromobility is the difficulty in estimating the miles traveled via micromobility and those miles that connect with transit. This difficulty comes mainly from what data on micromobility use is collected and who has access to that data.

Government agencies are just beginning to discuss ways of incentivizing micromobility services. California has taken one step in this direction through Senate Bill (SB) 1014 (2018) Clean Miles Standard (CMS) and Incentive Program. With this law, the California Air Resources Board (CARB) and the California Public Utilities Commission (CPUC) are considering micromobility service use as a part of “qualified zero-emission vehicles” in its regulations of transportation network companies (TNCs: Uber and Lyft). Therefore, estimates of the impact micromobility services can have on reducing emissions is paramount for CMS.

We leverage existing data published from 2017 to 2020 and collect new data in 2020 and 2021 to support future Clean Miles Standard regulation. CARB and the CPUC are currently developing and implementing new requirements for TNCs to reduce emissions. Since TNCs have historically provided micromobility services, CARB is interested in better understanding the characteristics of micromobility systems including travel frequency, distance, transit and TNC connections, and mode substitution.

This study also has important sustainability implications outside of the Clean Miles Standard. While many cities collect various micromobility usage metrics to regulate services, there is a lack of detailed micromobility metrics for calculating sustainability benefits. Cities tend to collect numbers of trips, their rough origins and destinations, and average trip distance. These metrics often lack important details about usage such as the distribution of trip distances (which is usually heavily skewed toward short trips and strongly influences mode substitution). Some cities include data requirements as a part of permits to operate. For example, some cities require public facing data feeds such as the General Bikeshare Feed Specification (GBFS) and/or the public agency specific feed in the Mobility Data Specification (MDS). These feeds make it easier for cities to calculate the needed metrics for monitoring overall usage for operations, sustainability, and other transportation goals. Importantly, cities rarely collect information about non-revenue-generating emissions (vans and trucks) from operating micromobility fleets. These are important for understanding the overall use-phase emissions of micromobility services.

Beyond usage metrics, cities and regions need estimates of expected mode substitution and induced travel from micromobility services. Research shows that micromobility is substituting for car trips and other traditional modes of travel such as transit (Fukushige et al., 2021). Also, several studies show that individuals are using micromobility to connect to transit (Fitch et al., 2020), which in-turn increases transit ridership (Martin & Xu, 2022; Oeschger et al., 2020). The transit agencies are also taking notice of this effect by including micromobility while planning for the first and last mile connection to public transit (Mohiuddin, 2021). These substitution and connection effects of the micromobility services are important in estimating the overall emission effect of the micromobility in the current transport landscape. However, this requires collecting data through surveying users and is inherently counterfactual in nature. Therefore, it is subject to validity concerns regarding estimating emissions. Nonetheless, without these metrics, estimating the impact of micromobility services on the sustainability of transportation, even in the use-phase, is challenging.

In this study, we leverage survey data and public feeds for micromobility usage to assemble estimates that are useful for cities to start monitoring the impacts of micromobility services on the sustainability of transportation. We do not have access to non-revenue-generating vehicle miles traveled, so our analysis focuses only on the user side of the emissions equation. However, we propose simple metrics for future evaluations which will require new data from micromobility operators.

To analyze the user side emissions from micromobility services we use existing disaggregate information about micromobility vehicle availability (General Bikeshare Feed Specification: GBFS) to infer trip characteristics (e.g., frequency, distance) at the entire system (or near entire system) level (i.e., the population of trips). The advantage of this data over survey data is in estimating trip characteristics with precision. The disadvantage is the inability to link system level trips to mode substitutions. Because our study took place during the unprecedented time of the COVID-19 pandemic, we also collect additional GBFS data for the same operators and cities during the project to improve estimates of trip characteristics and to understand the impact of shelter-in-home and other public policy responses to the COVID-19 pandemic on micromobility use. This will help us understand the effects of COVID-19 on micromobility services and in turn provide guidance for regulations and policies that can adapt to COVID-19 impacts. Lastly, we analyze the effect of micromobility services on transit use through city- and stop-scale analysis of micromobility trips and transit ridership. This analysis will be used to provide guidance for estimating micromobility-transit connections to support future revisions to the CARB’s Clean Mile Standard and other relevant policies and regulations.

Methods

Data Collection

This study uses system data from two sources: 1) System-level data on micromobility trips web-scraped from the General Bikeshare Feed Specification (GBFS), and 2) Local ridership data at the transit stop level as available in local form by contacting related authorities. It also includes summarized data from published reports of city-level surveys.

System (GBFS) Data

We acquired system-wide micromobility data by web-scraping the real-time status of micromobility services in 15 cities, including Austin, TX, Atlanta, GA, Buffalo, NY, Denver, CO, Los Angeles, CA, Santa Monica, CA, Memphis, TN, Miami, FL, Portland, OR, San Ramon, CA, Tampa, FL, Washington, D.C., Arlington, VA, San Francisco, CA, and Sacramento, CA, provided by the companies between November, 2019 and October, 2020.

The data specification varies by city and type of service. One type of data specification derives from docked bike-share systems. This type of service requires users to rent and return a bike at designated bike stations, so that trip origins and destinations are always at the stations. The acquired data shows the number of available bikes for each station at a timestamp, but no unique bike identifier for each bike at each station. Because of the lack of unique bike identifiers at each station, we subtracted the number of available bikes at current timestamp from the one at previous timestamp to observe the status change of stations. We considered the absolute value of the negative change and the positive change as the number of incoming and outgoing bike trips, respectively. We recognize this method as having potential bias to undercount trips in the case that two or more bikes are rented and returned nearly simultaneously. Although this issue makes for less accurate trip statistics, the data still gives insight of the trend of docked bike-share.

Another type of data specification derives from dock-less micromobility services. This type of service enables users to return a bike or scooter anywhere within the service boundary. Unlike the previous data, the acquired data with this type shows the list of available micromobility vehicles (e-bike and e-scooter). When a vehicle becomes available for users, the information for the vehicle appears in the real-time data. We use the disappearance and then reappearance of individual bikes, based on a unique identifier to create a database of micromobility trips, which we then use to count the number of trips to and from the area around transit stops and stations.

One challenge with this latter method of using micromobility trip data to count trips is that bikes also disappear and reappear from the data when false trips occur, so that we need to remove the false trips from the trip dataset. One type of false trip comes from operational activities (e.g., battery charging, rebalancing, repair). We excluded trips during which the battery level increased because these are almost certainly operational events rather than actual trips. We also removed trips at average speeds greater than 20 mph (a value calculated by dividing Euclidean distance by travel time), because the vehicles speed maximal speed is 20 mph and actual trip distances are always equal to or longer than Euclidean distance. (The Euclidean distance is the distance along a straight line from origin to destination.) In addition, we removed trips of 4 hours or longer, which constituted a small percentage of total potential trips (approximately 0–3% by city), because these trips are likely to be operational events rather than actual trips.

Another type of false trip may occur when users cancel trips. To correct for this, we excluded trips with the exact same longitude and latitude for both the origin and destination. (Even if someone checked out and returned the vehicle at the same location, the longitude and latitude would be slightly different the “origin” and “destination”.) We did find some trips of short Euclidean distances and short duration, which are also not likely to be actual trips. We assume that these cases occurred when users reserved but canceled vehicles and removed them from the dataset. Because some obstacles such as tall buildings lower the accuracy of geolocation, bike location could change slightly if users canceled bikes at such locations. We removed trips of 10 meters or shorter Euclidean distances and those with less than 5 minutes in duration.

Local Transit Ridership Data

By reaching out to local transit officials, we requested and received transit ridership data from 8 US municipalities that operated micromobility services. The transit data cover an 8-month period from September 2019 to April 2020. The ridership data are location-specific at the stop-level, meaning that each data point is a geographic transit stop location, along with said transit stop’s daily average ridership over the 8-month period. Some cities aggregated ridership by month, others by 3-month periods (annual quarters).

Local Micromobility Mode Substitution

We reviewed surveys of micromobility users conducted by cities and operators and summarized the respective mode substitutions, average trip distances, and system trip frequencies (Table 1). These data serve as a comparison with the GBFS summarized data on trip distances and frequency, and they are the only available evidence of mode substitution from micromobility services.

Table 1. Basic Statistics of the Transit Data Used from Selected Nine Cities

Name	Bus	Rail	Number of Bus Stop Observations	Number of Rail Stop Observations	Level of Data	Micromobility Service
Arlington	√		7,411		Monthly average ridership	e-bike and e-scooter
Atlanta	√	√	144,125	2,628	Period wise average ridership	e-scooter
Los Angeles	√		101,014		Monthly average ridership	e-bike and e-scooter
Miami	√	√	21,265	53	Monthly average ridership	e-scooter
Portland	√	√	52,302	1,779	Period wise average ridership	e-bike
Sacramento	√	√	12,785	990	Period wise average ridership	e-bike
San Francisco	√		7,077		Period wise average ridership	e-bike
Santa Monica	√		930		Period wise average ridership	e-bike and e-scooter

Analysis Types

We used the collected data in three analyses:

1. Descriptive analysis of city-level micromobility survey data in cities across North America;
2. Descriptive analysis of impact of COVID-19 on micromobility use based on GBFS data;
3. Analysis of micromobility use influencing transit ridership based on transit data and GBFS data.

Descriptive Analysis of City Report Data

We summarize the micromobility reports from different city surveys in Table 2. This table shows, for different cities, the number of trips, the average trip duration, and the period when data from the micromobility services were collected. Generally, cities tend to run micromobility pilots before giving full permits to the micromobility providers and most of the data summarized in Table 2 and used in this study are from pilot periods. There is substantial variability among cities in terms of micromobility fleet utilization and trip distances. The fleet utilization ranges from 0.7 to 12 trips per day per micromobility vehicle. The average trip distance ranges from 0.8 to 3.6 miles.

Table 2. Basic Statistics of Service Efficiency and Trip Distance from City Report Data

City	Vehicle Type	# Veh	#Trip/ day/ veh	Trip Distance (Mean miles)	Time Period	Trip Sample Size	Source
Alexandria	e-scooter	780	*1.2*	1.0	Jan. 2019 to Sep. 2019	230,000	City of Alexandria(City of Alexandria, 2019a)
Arlington	bike share	700	*1.0*	2.0	2018	261,129	Department of Environmental Service, Arlington(Matlesky & Department of Environment, 2018)
Arlington	e-bike/e-scooter	863	1.9	0.9	Oct. 2018 to Jun. 2019	453,690	Department of Environmental Service, Arlington (Matlesky & Department of Environment, 2018)
Atlanta	e-scooter	3,682 to 6523	2.6	1.0	Feb. 2019 to Dec. 2019	438,500	City of Atlanta (City of Atlanta, 2020)
Baltimore	e-scooter	3,000-13,000	3.0	1.6	Aug.15, 2018 to Jan.31, 2019	723,252	Department of Transportation, Baltimore City (Department of Transportation Baltimore City, 2019)
Boston Region	e-bike	N/A	N/A	1.3	Apr. 2018 to Sep. 2019	301,000	Metropolitan Area Planning Council (Akhavan et al., 2019)
Brookline	e-scooter	200	*4.3*	1.1	Apr. 1 to Oct., 2019	156,000	Lime (Lime, 2019)
Chicago	e-scooter	2,500	3.0	1.5	Jun.15, 2019 to Oct. 15, 2019	407,296 (821,615)	City of Chicago (The City of Chicago, 2020)
Denver	e-bike	500	1 to 2	1.5	Aug. 2018 to Jan. 2019	58,330	Denver Public Works
Denver	e-scooter	1,265	4 to 12	0.9	Aug. 2018 to Jan. 2019	819,927	Denver Public Works (Denver Public Works, 2019)
East Portland	e-scooter	N/A	N/A	1.6	Jun.23, 2018 to Nov.20, 2018	44,155	PBOT (Portland Bureau of Transportation, 2019)
Harrisonburg	e-scooter	N/A	5.0	0.8	Sep10, 2018 to Oct. 11, 2018	26,779	(City of Ithaca, 2019)
Hoboken	e-scooter	300	10.0	0.8	May20, 2019 to Nov.20,2019	673,990	(Baer, 2019)
Los Angeles	e-bike/e-scooter	17,498	*1.0*	1.2	Dec.31, 2018 to Apr.15,2019	1,865,629	(The City of Los Angeles, 2020)
Los Angeles (Metro)	bike/e-bike share	1,000	*0.7*	3.6	Jul. 7, 2016 – Jun. 30, 2020	1,060,737	(The City of Los Angeles, 2020)

City	Vehicle Type	# Veh	#Trip/ day/ veh	Trip Distance (Mean miles)	Time Period	Trip Sample Size	Source
Milwaukee	e-scooter	684	3.6	N/A	Jul.23, 2019 to Nov. 30, 2019	350,130	(City of Milwaukee, 2020)
Minneapolis	e-bike	N/A	N/A	2.2	Jun. 10, 2010 to Nov. 2010	225,544 (100,817)	(Metro Bike, 2010)
Portland	e-scooter	2,043	*2.9*	1.1	Jun.23, 2018 to Nov.20, 2018	700,369	(Portland Bureau of Transportation, 2019)
Sacramento Region	e-bike/e-scooter	N/A	N/A	2.1	2019	976	(Fitch et al., 2020)
San Francisco (Bay Wheels)	bike/e-bike share	2,600	*1.7*	N/A	Jun. 28, 2017to Jun. 30, 2020	N/A	(San Francisco Municipal Transportation Agency, n.d.)
San Francisco (Scoot, Skip)	e-scooter	625	2 to 3	1.0	Oct. 2018 to Feb. 2019	242,398 (24,925)	(San Francisco Municipal Transportation Agency, 2019)
Santa Monica	bike share	500	*1.4*	1.9	Nov.12, 2015 – Dec.,31, 2018	819,160	(City of Santa Monica, 2019)
Santa Monica	e-bike/e-scooter	2,500	4.0	1.3	Oct. 2018 to Sep. 2019	2,673,819	(City of Santa Monica, 2019)
Seattle	dockless bike share	3,000 to 7,000	N/A	1.2	2019	2,200,000	(Seattle Department of Transportation, 2020)
Spokane City	bike/e-scooters	N/A	N/A	1.1	May to Nov. 2019	581,000	(City of Spokane, 2019)
St. Louis	e-scooter	N/A	N/A	0.5	Apr. to Jul. 2018	160000	(Hibbard, 2018)
Tucson	e-scooter	688	1.3	0.9	Sep.12, 2019 to Feb.12, 2020	173981	(City of Tucson, 2020)
Washington DC	bike/e-scooters	4700	1.35 to 3.14	N/A	Sep. 2017 to Jun. 2018	N/A	(Government of the District of Columbia, 2018)

* The parenthesis in the sample size represents the sample size for mean trip distance. Abbreviated when the sample size for the trip distance and trips/day/veh is the same.

** Italic font in #trips/day/veh indicates that the authors estimated it based on reported information (the number of sample days, fleet size, and the number of sample trips) in the city reports

We compared the summary statistics on trip distance from city-report data and from GBFS data. One disadvantage of using GBFS data is the difficulty in estimating actual average trip distance. The fact that actual trip distance is similar to or higher than the Euclidean distance implies risks in underestimating the effect of VMT reduction from the implementation of micromobility services. We first compared average actual trip distance from the city-report data and average Euclidean distance between trip start- and end-points from GBFS data in five regions (Washington, D.C./Arlington, Los Angeles/ Santa Monica, Sacramento/Davis, Denver, Atlanta) to understand the bias of aggregated data. We used different periods in city-report data and GBFS data due to the availability of the data.

We also examined the relationship of actual trip distance to Euclidean distance and trip duration at a disaggregate level as the distribution of actual trip distance is usually heavily skewed toward short trips. We used bike-share data from bike-share in Portland, Oregon, as this published data contains the detail of trip information, including the coordinates of trip start- and end-points and actual trip distance. We used a gaussian model with only two variables, including Euclidian distance between trip start- and end-points and trip duration. We fit only simple models for easy applicability to other micromobility data.

Descriptive Analysis of Impact of COVID-19 on Micromobility Use from GBFS Data

We summarized system-level micromobility data from the GBFS to understand the trend of number of trips per bike, e-bike, or e-scooter per day, average trip duration per trip and average trip distance per trip before and during COVID-19. We estimated each metric on weekday and weekend by month. We excluded data for days with missing periods.

To estimate the number of trips per bike, e-bike, or e-scooter per day, we counted the number of trip and fleet size for each day. Using the cleaned GBFS data we counted the number of free bikes/scooters for each timestamp and set the maximum number for each day as fleet size. For docked bike-share systems where we did not collect bike free status data, we used collected fleet size information of the beginning of the month in Open Bike Share Data as fleet size for all days of the corresponding month of the systems.

For a comparative analysis of micromobility use before versus during COVID-19, we considered data in March 2020 or after as “during” COVID-19, although cases of COVID-19 infection were revealed to have occurred in the United States before March 2020. One major reason for this approach is that many cities introduced shelter-in-place orders or relevant policies in March 2020, strongly influencing travel patterns.

Relationship Between Micromobility Use and Transit Use

In this analysis we examined the relationship between use of micromobility use of public transit. We used micromobility and public transit ridership data in eight cities including four California cities (i.e., Los Angeles, Sacramento, San Francisco, and Santa Monica), Arlington, VA, Atlanta, GA, Miami, FL, and Portland, OR. The number of transits stops (i.e., bus and rail) and ridership data collection is summarized in Table 1. In this study, we only focus on analyzing how micromobility services relate to transit boardings (e.g., first-mile). People may use micromobility to egress from public transit (e.g., last-mile), but at least one study found the relationship between micromobility trips near transit stops to be similar for access and egress (Mohiuddin et al., 2021). One advantage of dock-less micromobility service is that users can drop off their vehicles near their destination, such that their trip purpose (transit connection in this case) is more likely to be associated with a point of interest near the trip end. We counted the number of micromobility trips ending within the buffer area of each public transit stop/station with the length of 50 m, 100 m, and 200 m, and used those counts to relate to transit boardings.

To gain insight on the demographics and travel behavior of people living near transit stops, we joined block group census data to each nearby transit stop location, including gender, race, income, age, and travel behaviors. Finally, walkability scores as published by the United States Environmental Protection Agency were also joined to each transit stop.

We used Poisson regression to examine the relationship between micromobility use and public transit use. We considered five different types of predictor variables: micromobility trips, temporal variables, socioeconomic variables, mode share, and walkability index. Table 3 shows the list of predictor variables used in the model. While we included these variables, we only comment on the predictor variable micromobility trips in this report. In essence we include the other predictor variables only to adjust for their relationships with transit use to better assess the relationship between micromobility trips and transit use. We used the R package glmer to fit a Poisson mixed effects model (n=289,891) (Bates et al., 2013) with varying intercepts for transit stop/station, city, and period, to account for stop-, city-, and period-level variation beyond that explained in other predictors. We used the logarithm as the link function with the following tuning parameters and settings: 0 for nAGQ, bobyqa for optimizer, and 10000 for maxfun.

Table 3. Transit Model Predictor Variables

Variable	Description	Data Source
Micromobility Trips	Number of micromobility trips ending withing a buffer area of transit facilities with the radius of 50 m, 100 m, and 200 m	GBFS
Temporal Variables		
Day Type	Whether transit ridership occurred on a weekday, Saturday, or Sunday	Transit Ridership Reports
Period	Whether transit ridership occurred between Sept-Dec 2019 (period 1), or Jan-Mar 2020 (period 2)	Transit Ridership Reports
Socioeconomic Variables		
Population Density	Population density of transit stop census block group	2019 ACS Survey
Percentage of Female	Percentage of female residents in transit stop census block group	2019 ACS Survey
Percentage of Black	Percentage of Black residents in transit stop census block group	2019 ACS Survey
Percentage of Low Income	Percentage of low-income households in transit stop census block group	2019 ACS Survey
Percentage of Student	Percentage of students in transit stop census block group	2019 ACS Survey
Mode Share		
Car	Percentage of auto commuters in transit stop census block group	2019 ACS Survey
Transit	Percentage of transit commuters in transit stop census block group	2019 ACS Survey
Active Transportation	Percentage of cycling or walking commuters in transit stop census block group	2019 ACS Survey
Walkability Index		
Walkability Index	A score measuring the walkability of a census block group (out of 20), established by the United States EPA, based on indicators such as commercial-residential mix, diversity of employment types, and street intersection density.	US EPA

Results and Discussion

Descriptive Analysis of City Report Data

To better understand micromobility usage trends in the US, we conducted a review of all available user survey data as published by municipalities and operators. Our primary motivation behind the review was to understand the way that micromobility affected the demand for other modes of transport using survey-based mode substitution. Our review of survey data also revealed average trip frequencies, distances, and durations.

Basic Statistics of Service Efficiency and Trip Distance from City Report Data

The micromobility trip frequency in most study cities is relatively modest, staying below 2,500 trips/day. On the higher end, San Francisco, Santa Monica, Seattle, San Diego, Chicago, and Portland all boast over 5,000 trips/day. Los Angeles is a clear outlier, reporting over 17,500 trips/day. Micromobility trip distances, by nature, are short. In most cities surveyed, the length of an average trip was 1 mile or less. Minneapolis and Sacramento had average trips of over 2 miles, with Los Angeles again presenting itself as a considerable outlier with an average trip distance of 3.5 miles.

Mode Substitution from City Report Data

Mode substitution refers to the mode that users *would* have used for a trip if micromobility were not an option. Figure 1 shows the extent to which micromobility substituted for different modes in the cities studied. In almost all the study cities, at least 35% of micromobility trips replaced car trips. Rosslyn, Virginia (Demeester et al., 2019) and St. Louis, Missouri are positive outliers, with over 60% of their riders replacing car trips with micromobility trips. The next most popular mode that micromobility substitutes for is walking.

It is worth noting that a significant portion of micromobility trips substitute for walking trips in most of the cities. Also, micromobility trips are substituting for a considerable percentage of transit trips, mostly in big cities such as Washington D.C., Minneapolis, and Chicago (Fishman et al., 2013; The City of Chicago, 2020). The median (range) rates at which micromobility trips substituted for other modes were: 41% (16–71%) for car trips, 36% (5–48%) for walking, and 8% (2–35%) for transit, 5% (2–42%) for no trip. This suggests that transit substitution is primarily a concern in larger cities. Lastly, some cities showed substantial increases in trip making from micromobility services (percent of “no trip” in Figure 1 indicating the trip would not have taken place had it not been for the micromobility service).

Generally, Cities asked the respondents about their last micromobility trips and asked them which mode they would have used for that trip if micromobility service were not available. The surveys from the Cities of Chicago, Hoboken, and Alexandria allowed respondents to select multiple options for the mode substitution questions (City of Alexandria, 2019b; The City of Chicago, 2020). The City of Milwaukee used the “no trip” response as a screening question and only asked about which mode they would have used if micromobility were not available to those who did not respond "no trip" to the initial mode substitution question (6-t, 2019; City of Milwaukee, 2020). However, we recalculated those shares for this case to make them comparable with the other cities.

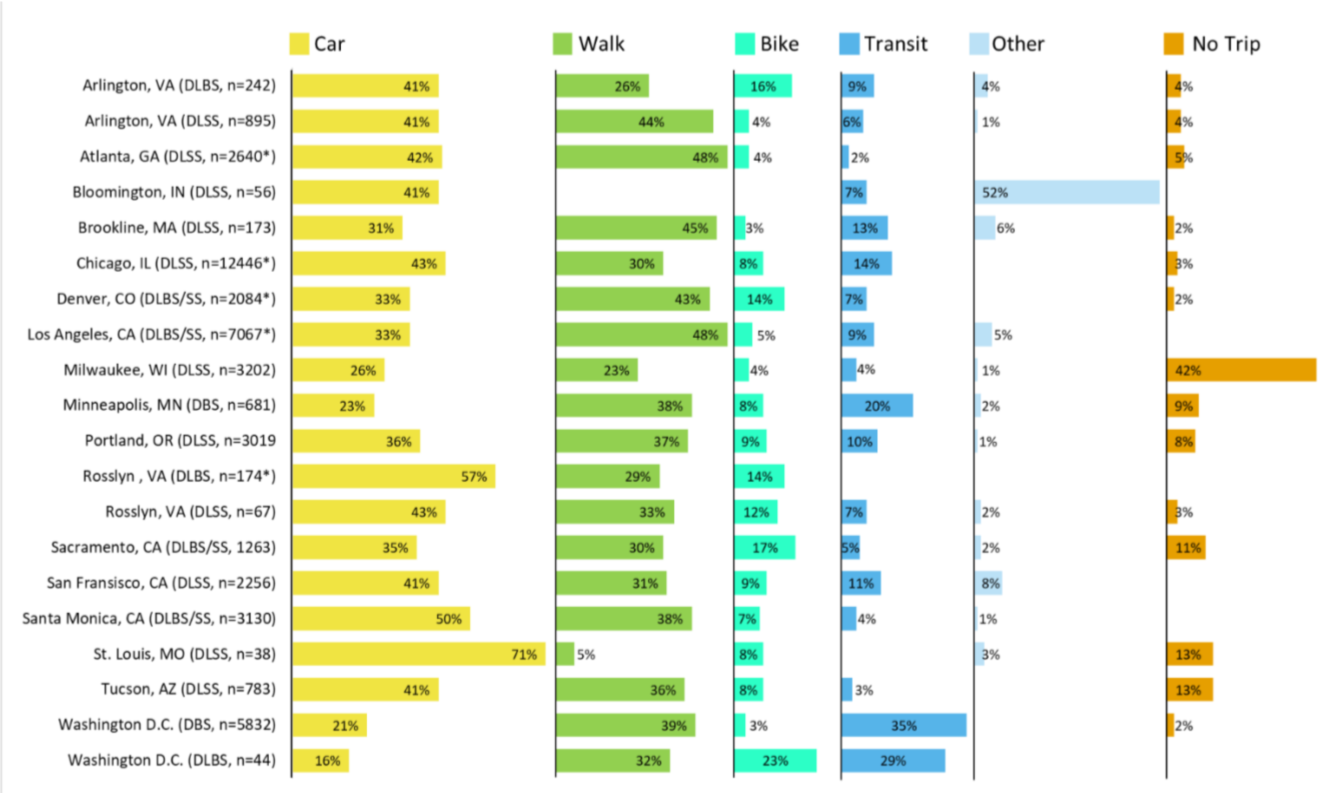

Figure 1. Micromobility mode substitution and travel change from city-report data. Note: "Car" includes private vehicle, taxi, ride-hailing, ride-sharing, etc.; "Walk" includes walk, skateboard, etc.; "Bike" includes <u>personal</u> bike, scooter, etc. (n indicates sample size. * indicates full survey sample size, otherwise mode substitution question specific sample size is provided. DBS: docked bike-share, DLSS: dock-less bike-share, DLBS: dock-less e-scooter-share)

Comparison of Trip Distance from City Report Data and GBFS Data

Our comparison shows that the mean actual trip distance from city-report data is approximately 1.5 to 2 times longer than the mean of Euclidean distance between trip start- and end-points taken from GBFS data (Figure 2 and Figure 3). The mean of Euclidean distance between trip start- and end-points for dock-less e-scooter-share in the region of Washington, D.C./Arlington, Los Angeles/Santa Monica, and Atlanta was between 0.5 to 0.7 miles, but the mean of actual reported trip distance was around 1 mile. The mean Euclidean distance and mean actual trip distance for docked and dock-less bike-share services in these three regions are 1 mile and 1.5 to 2 miles, respectively, longer than of dock-less e-scooter-share. The exception is bike/e-bike-share in LA Metro having a high mean of actual trip distance of 3.6 mile.

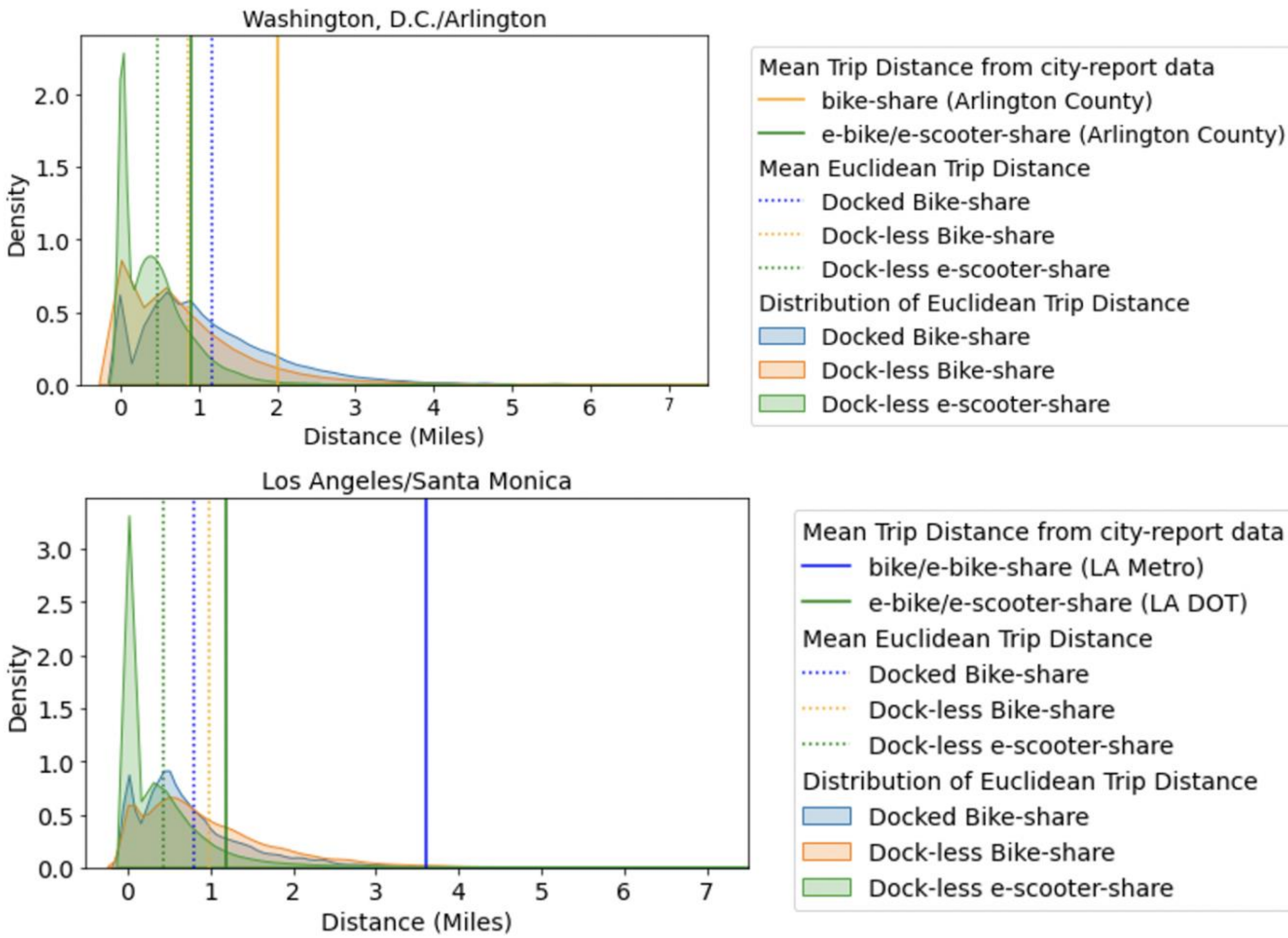

Figure 2. Distribution of Euclidean distance from GBFS trip data and mean of the Euclidean distance and actual trip distance from city-report data by types of micromobility: Washington, D.C./Arlington, LA/Santa Monica

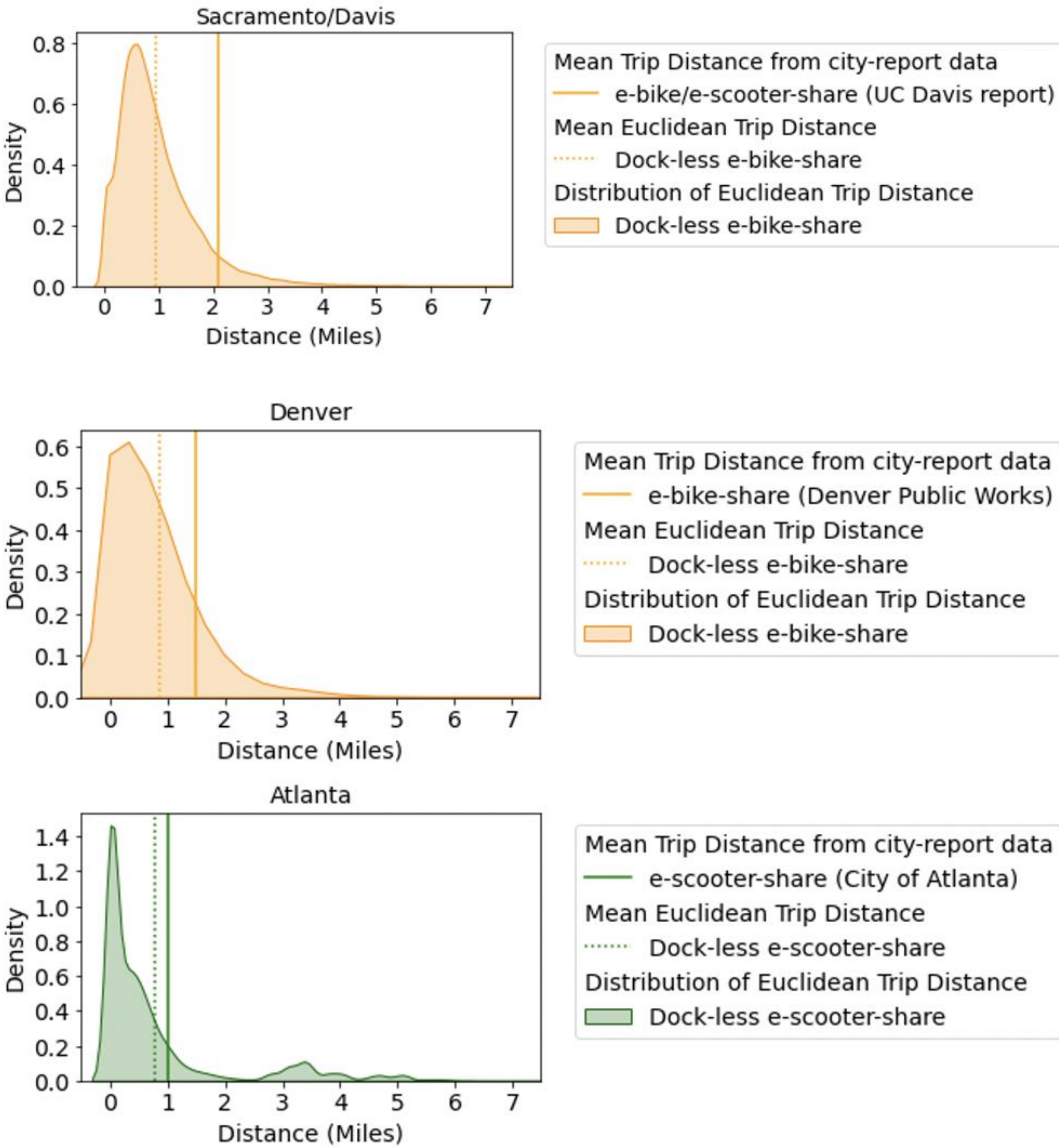

Figure 3. Distribution of Euclidean distance from GBFS trip data and mean of the Euclidean distance and actual trip distance from city-report data by types of micromobility: Sacramento/Davis, Denver, Atlanta

Relationship Between Actual Trip Distance and Euclidean Distance

The comparison of Euclidean distance between trip start- and end-points and actual trip distance in Portland shows that the mean Euclidean distance was 0.9 miles and the mean actual trip distance was 2.0 miles. Also, Figure 4 shows that the distribution of actual trip distance is more skewed to the right than of the Euclidean distance. The higher variance of actual trip distance at a shorter Euclidean distance suggests a strong demand for round trips (Figure 5 left). Figure 5 and our simple estimates (See results in Appendix A: Trip Distance Model Parameter Summaries) suggest that trip duration can act as a better indicator to estimate actual trip length than Euclidean distance. That there are some unreasonable data points having higher Euclidean distance than actual trip distance implies some measurement error.

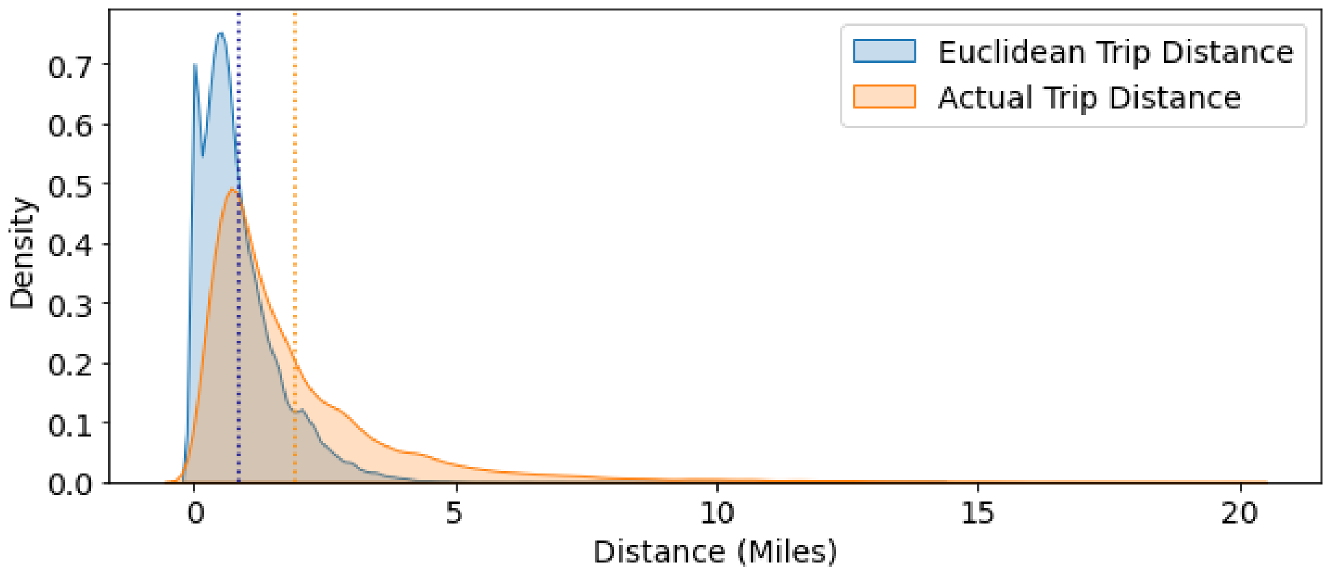

Figure 4. Comparison of Distribution of Euclidean distance and Actual Trip Distance: Portland

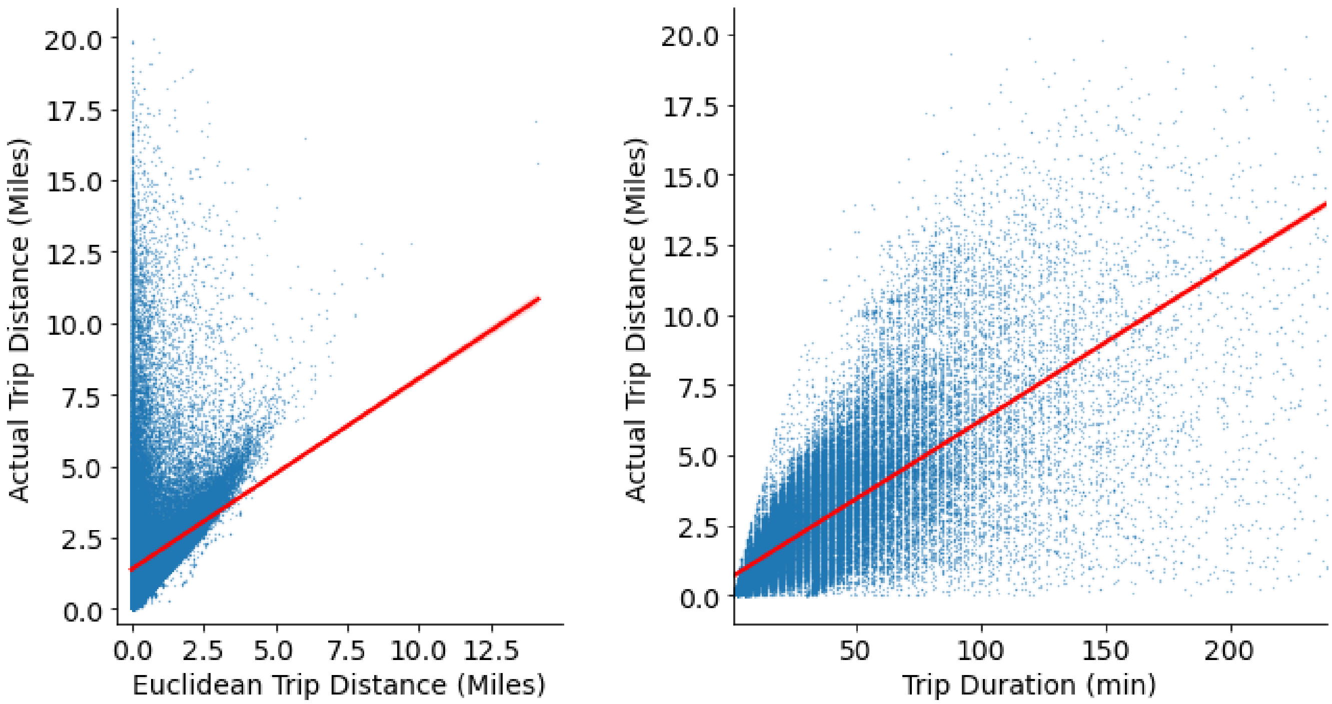

Figure 5. Relationship between Euclidean Trip Distance and Actual Trip distance (Left) and between Trip Duration and Actual Trip Distance (Right). Red lines are an approximation of the linear relationship between each pair of attributes.

Although Euclidian distance is not a good measure of vehicle miles traveled, when paired with trip duration, actual trip length can be estimated with great accuracy from a simple gaussian model[1] (Figure 6). This suggests that cities that have not collected data on trip distances can estimate them easily.

[1] We split trip dataset into two third of the dataset as train data and the rest as test data. We fit the train data to models with only Euclidean distance (Model 1), only trip duration (Model 2), and both (Model 3), then validated the models with the test data. Root-mean-square error (RMSE) for each model were 2.18 miles, 1.39 miles, and 1.21 miles, respectively.

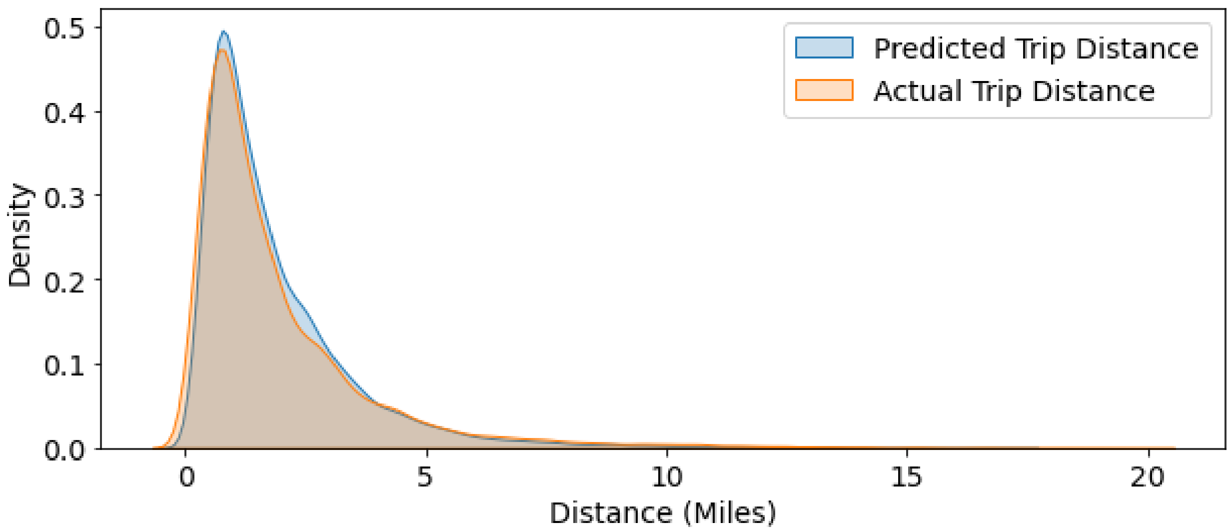

Figure 6. Comparison of Distribution of Predicted Trip Distance (based on Euclidean distance combined with trip duration and a gaussian model) and Actual Trip Distance: Portland

Descriptive Analysis: Impact of COVID-19 on Micromobility Use

The COVID-19 pandemic had dramatic effects on micromobility. Before the pandemic, short trips for dining and leisure were perfect candidates for micromobility usage. COVID-19 all but eliminated the demand for these trips. These issues were compounded by a widespread aversion to touching or interacting with shared surfaces to reduce the spread of disease. Despite operators' best efforts to sanitize vehicles and promote their availability, global micromobility ridership plummeted.

We examine the usage trends before and after the initial shock of the pandemic. Usage trends are observed for docked bike-share, dock-less bike-share, and dock-less scooter-share. Docked bike-share observations provide the richest dataset because most docked bike-share services remained operational throughout the pandemic. Dock-less service, however, experienced interruptions as operators halted activity and pulled vehicles from cities during the pandemic. Three metrics are described: average trips per bike per day, average trip distance, and average trip duration.

Number of Trips per Vehicle from GBFS Data

Docked bike-share in San Francisco shows just how substantial an effect the pandemic had on micromobility usage. In January 2020, each docked vehicle averaged over 3 rides per day. By April 2020, that average had dropped to 0.5 rides per day and did not get much higher than that during all of 2020. Other cities' docked bike-share systems experienced more moderate declines in ridership, and showed recoveries to near pre-pandemic levels, especially on weekends (Figure 7). The data collected in Washington DC and Memphis stand out in this regard. Washington DC docked bike-share saw an initial dip in rides per day but was back to normal levels by June 2020.

In some cases, ridership not only recovered but increased after the early part of the pandemic, at least for some trip types. For example, a 75% *increase* in rides per day on weekends was observed in Washington DC from April to June of 2020 (Figure 7). Docked bike-share in Memphis also saw a 40% increase in rides per day after the onset of the pandemic in March 2020. Almost all dock-less services, however, saw a decline in trips leading up to the pandemic, and had services suspended after the initial shock (Figure 8 and Figure 9).

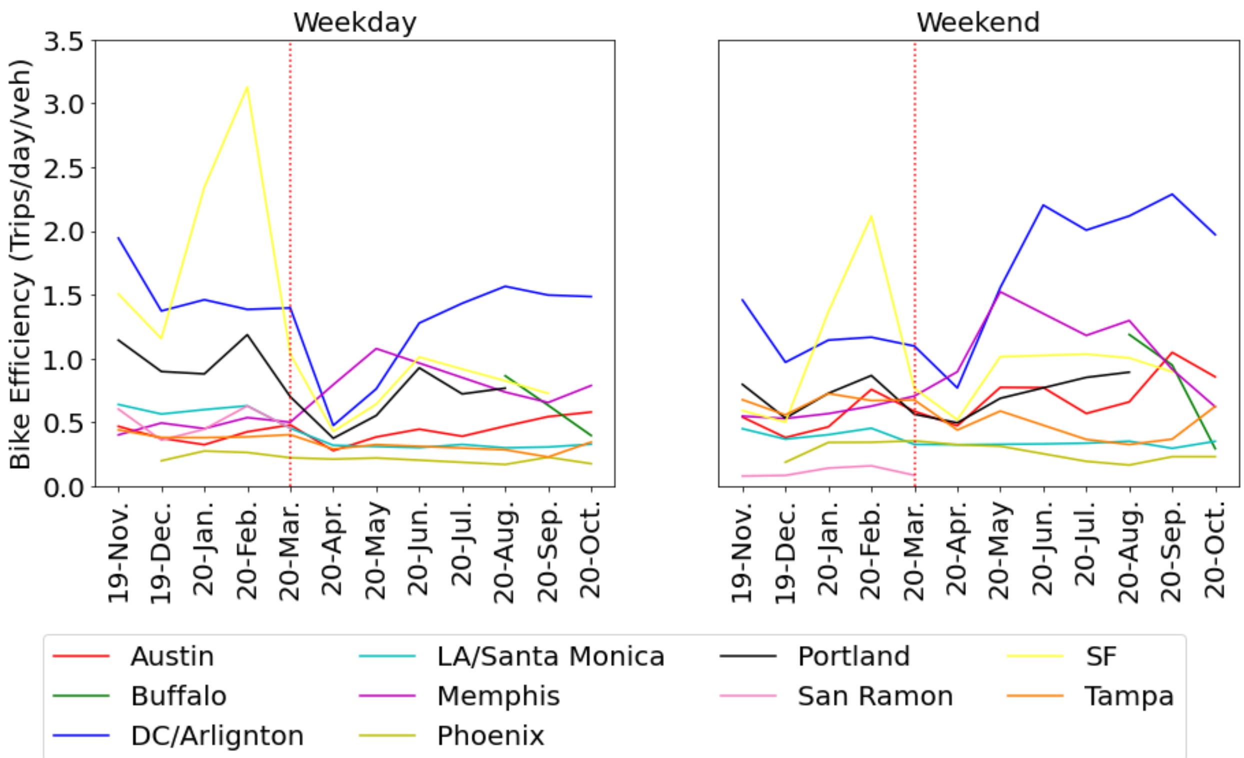

Figure 7. Number of Trips per Vehicle: Docked bike-share

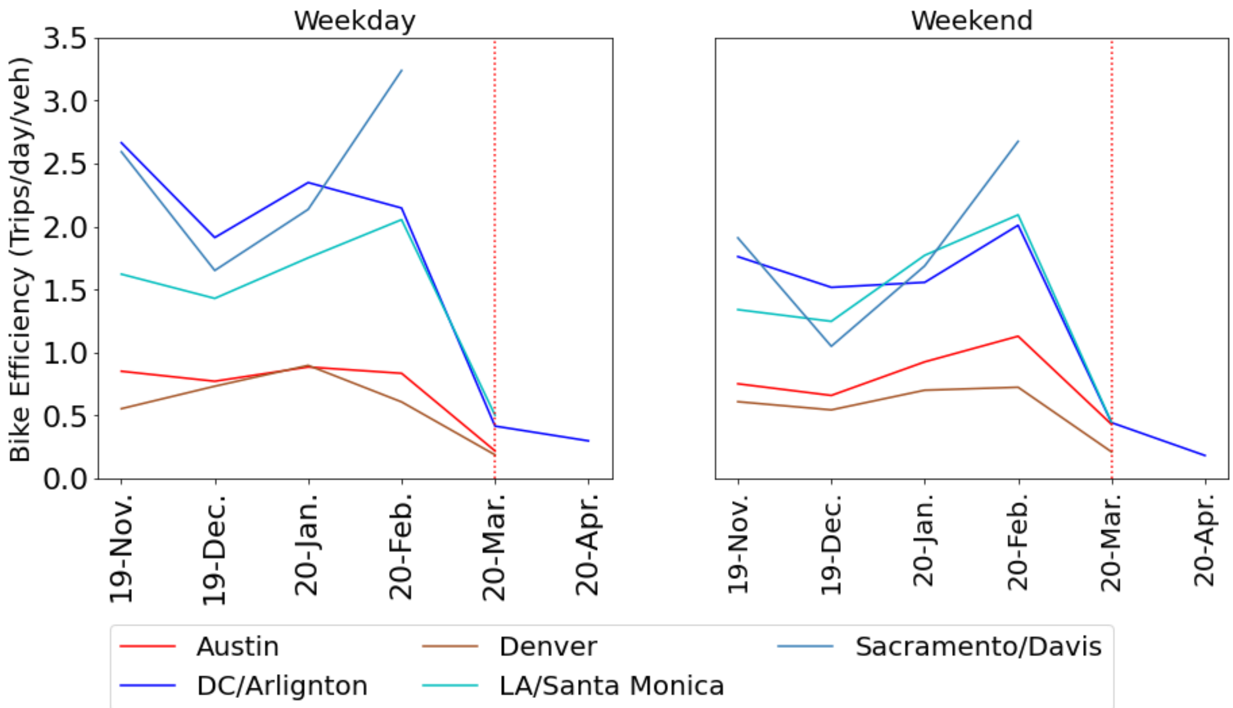

Figure 8. Number of Trips per Vehicle: Dock-less bike-share

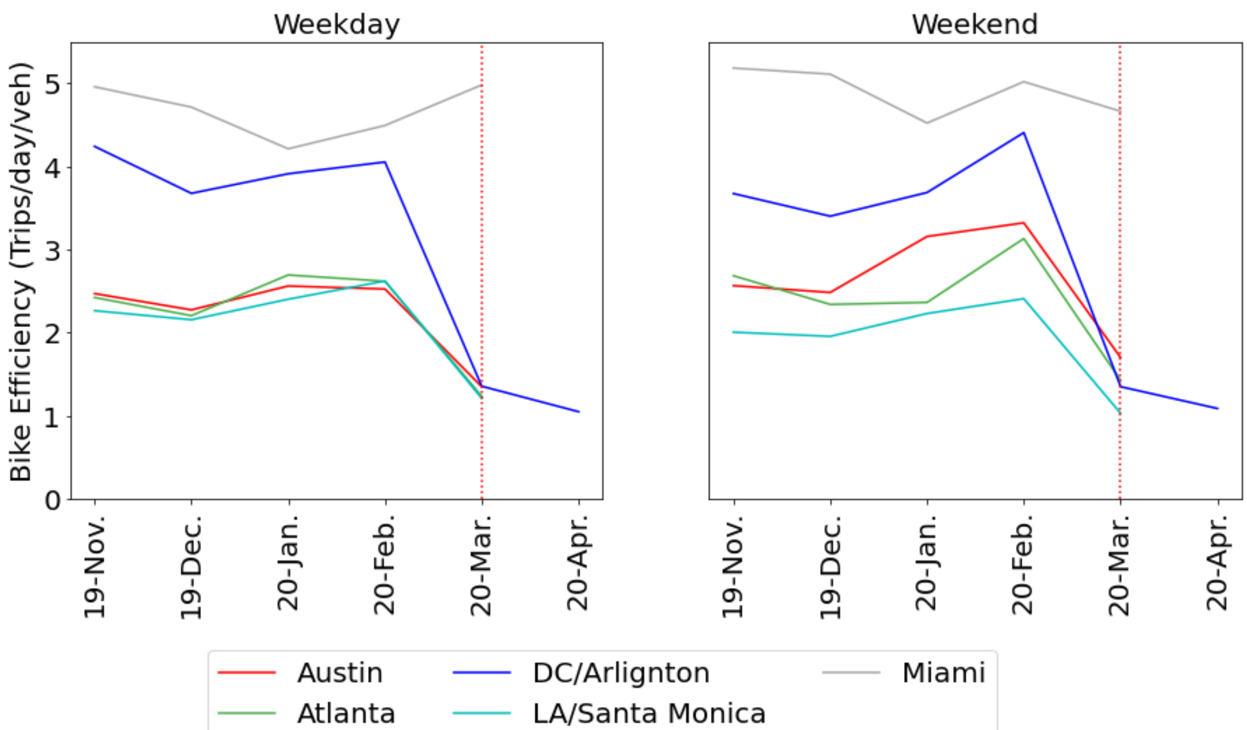

Figure 9. Number of Trips per Vehicle: Dock-less e-scooter share

Trip Distance from GBFS Data

Trip distances[2] in this section were measured as the Euclidean (straight-line) distance between trip origins and destinations. In general, trip distances did not change in response to the pandemic, with two exceptions. Docked bike-share trips in Portland saw a spike in average distance, a 100% increase (Figure 10). Later in the year, trip distances settled down to 50% higher than pre-pandemic levels. Trip distances of dock-less systems in Washington DC were substantially affected. In that city, dock-less bikes saw a 50% decrease in average distance, while dock-less scooters saw a 30% increase in distance (Figure 11 and Figure 12).

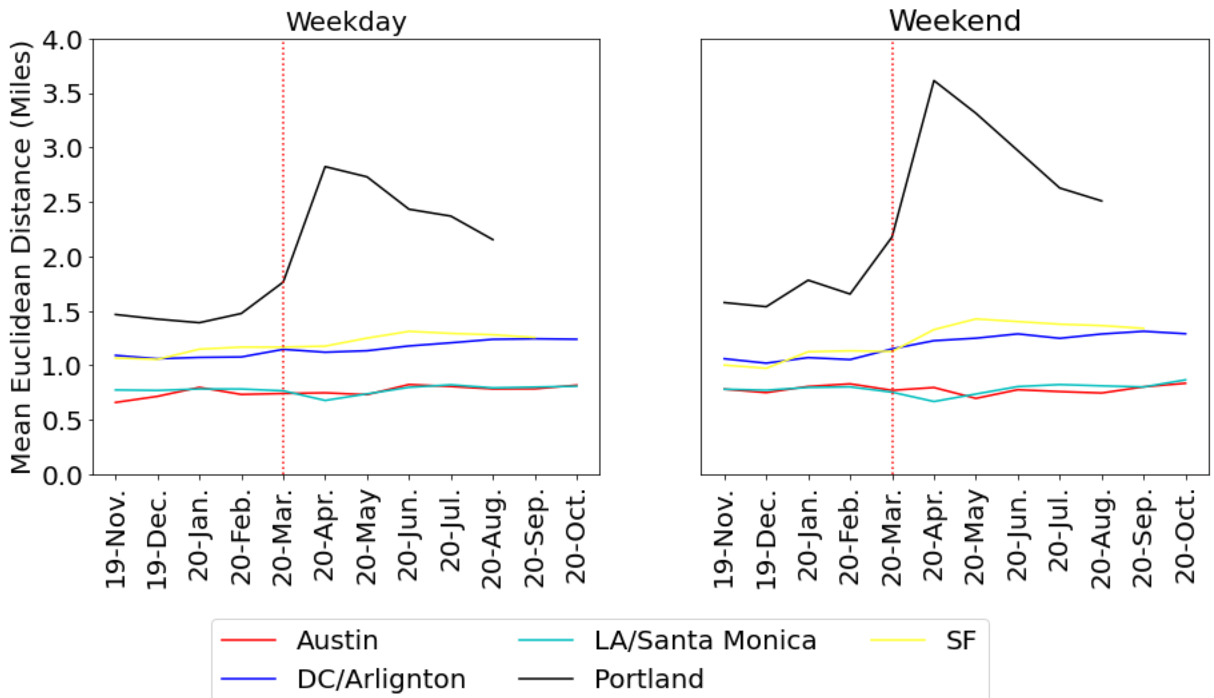

Figure 10. Average Trip Distance: Docked bike-share

[2] Trip distance of docked bike-share in Portland is actual trip distance.

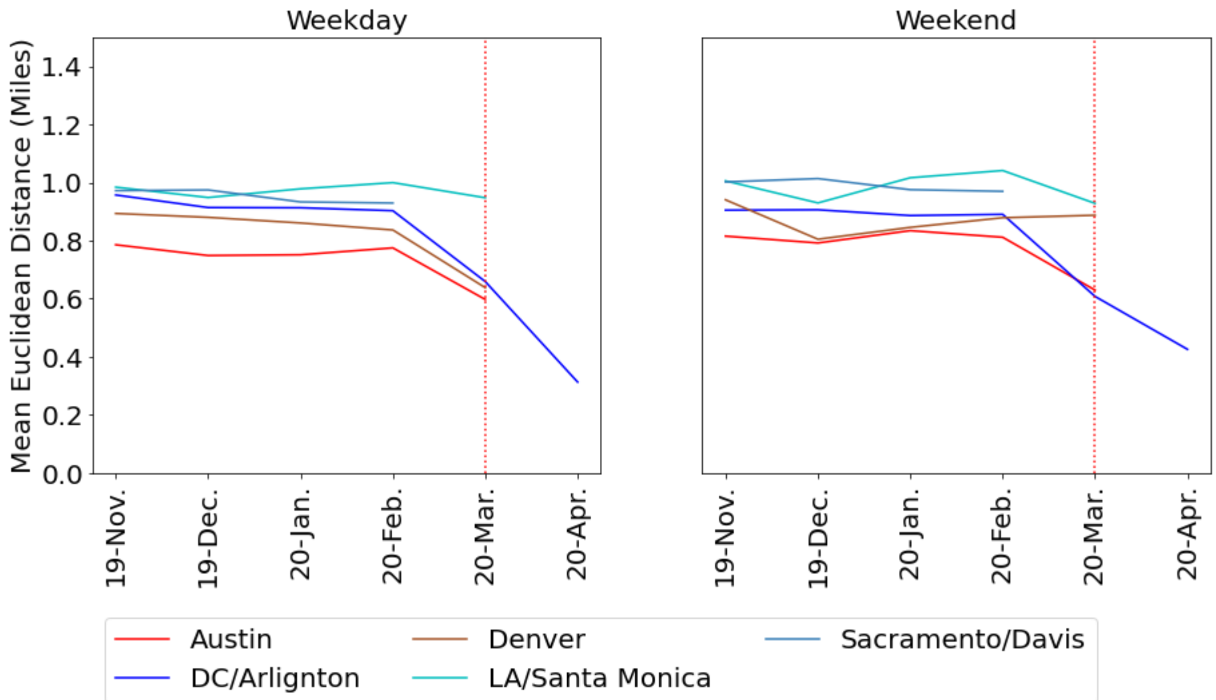

Figure 11. Average Trip Distance: Dock-less bike-share

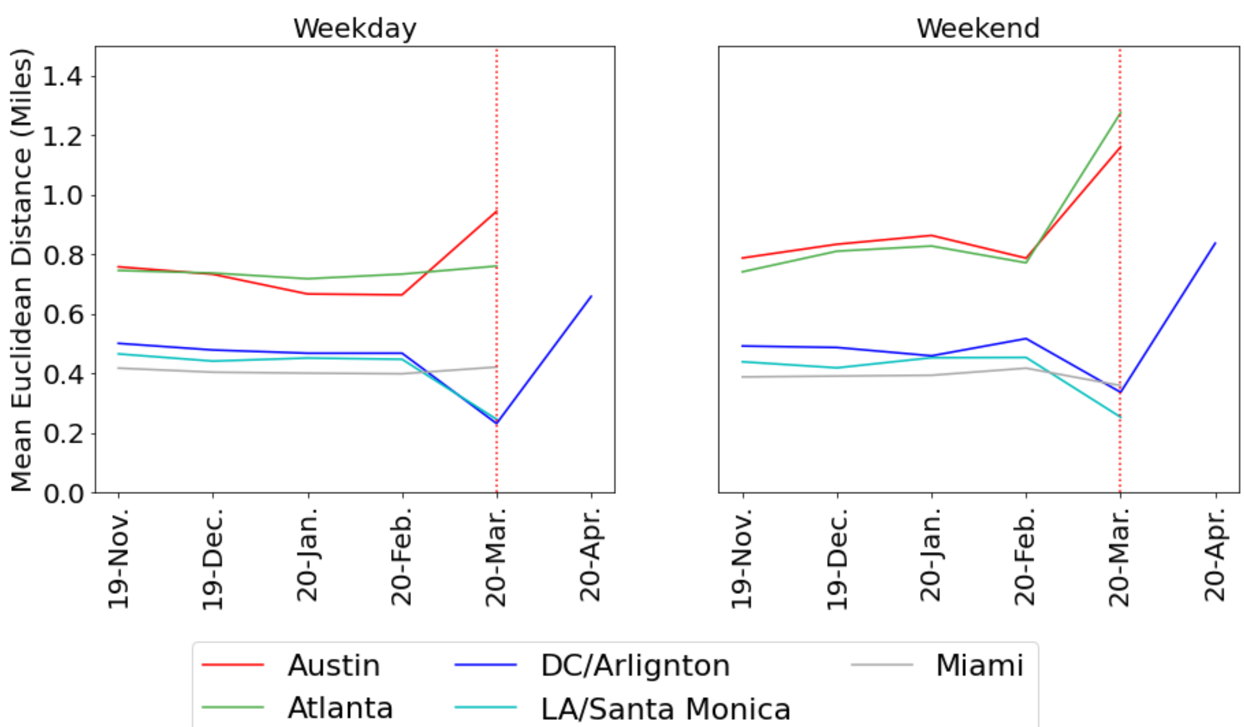

Figure 12. Average Trip Distance: Dock-less e-scooter share

Trip Duration from GBFS Data

Perhaps the most surprising trend is the uniform increase in trip duration of docked bike-share across all observed cities, which peaked in April and May 2020, then declined slightly (Figure 13, Figure 14, and Figure 15). This increase cannot be entirely due to the change of the seasons from winter to summer, as the majority of these study cities are located in mild climates. Trip duration of dock-less systems in each city increased even before service suspensions in March.

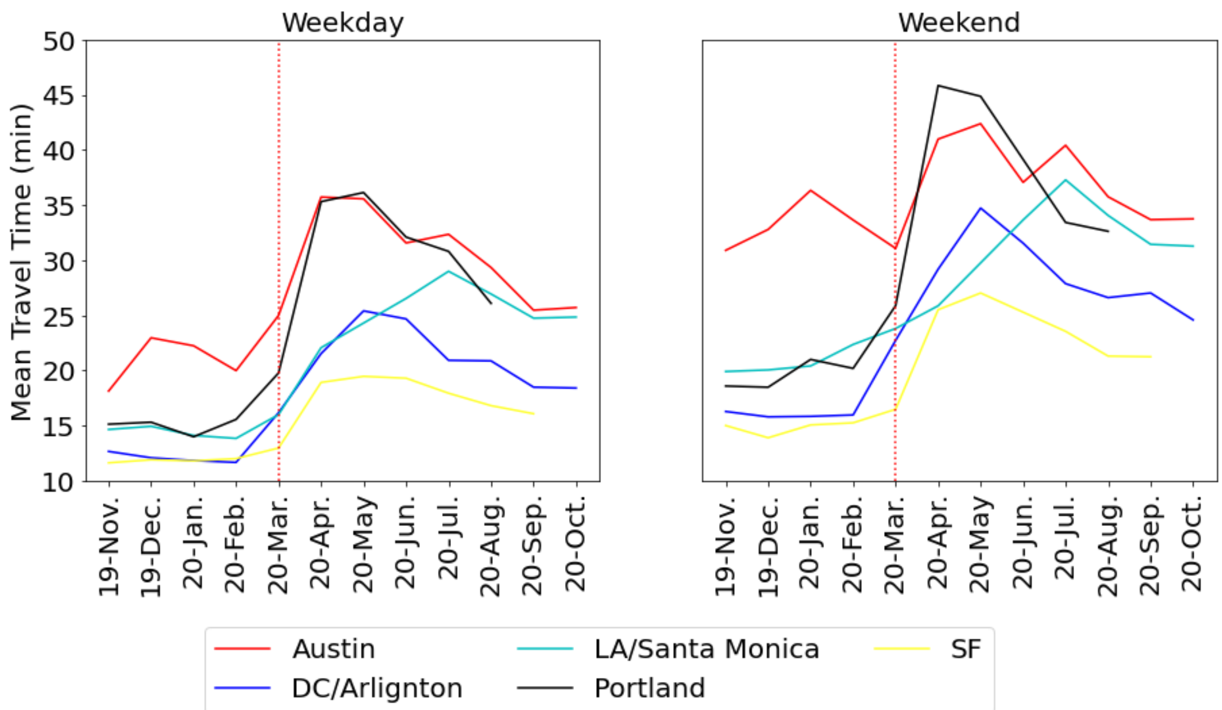

Figure 13. Average Trip Duration: Docked bike-share

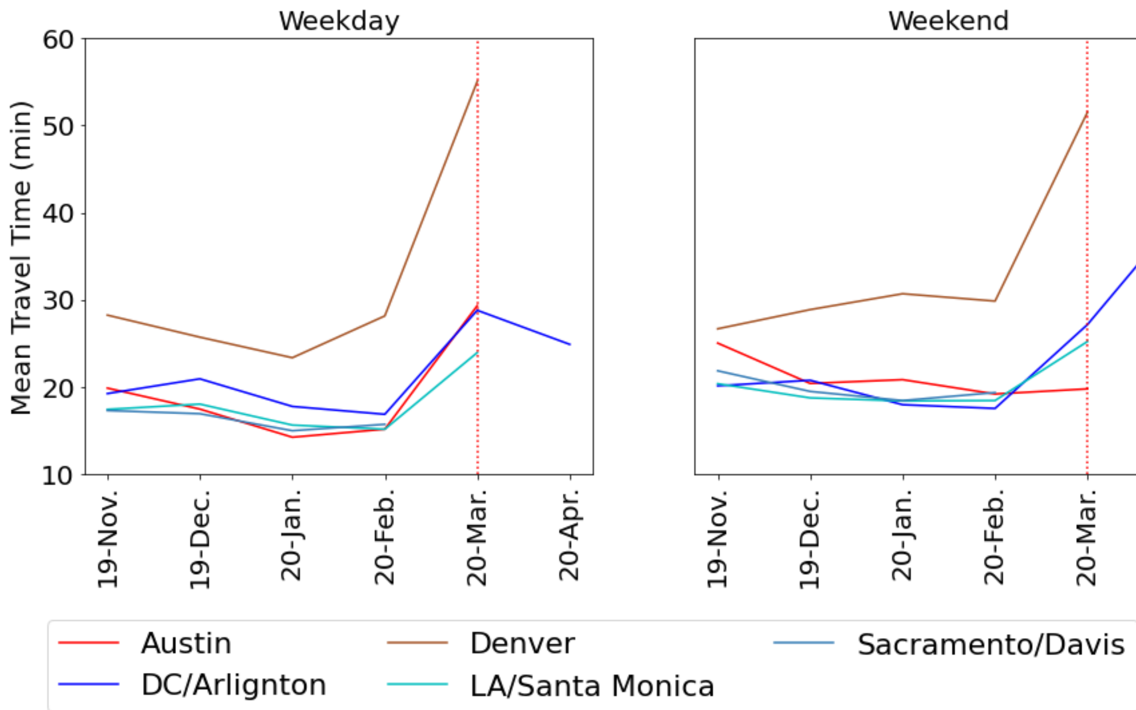

Figure 14. Average Trip Duration: Dock-less bike-share

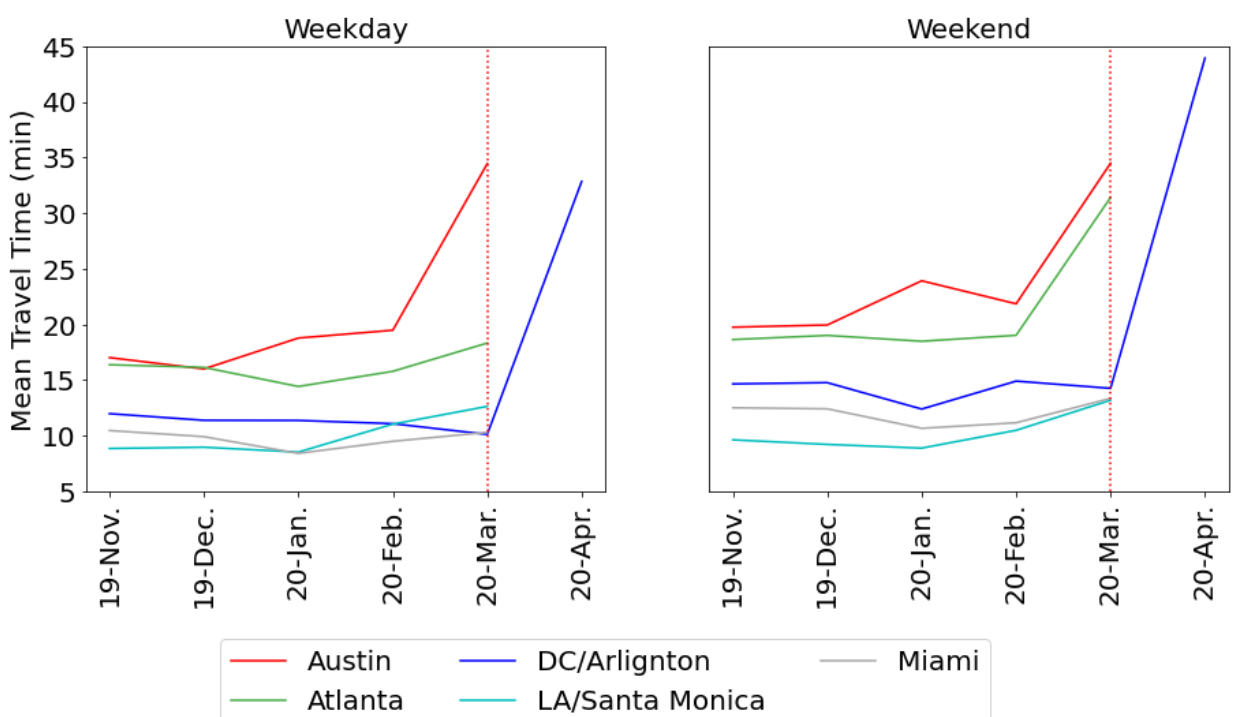

Figure 15. Average Trip Duration: Dock-less e-scooter share

Micromobility and Public Transit

Our Poisson regression analysis (See Appendix B for parameter summaries) found that public transit use is associated with micromobility use, controlling for temporal factors, socioeconomic factors, and a built-environment factor (i.e., walkability index). Transit facilities surrounded by micromobility trips had higher ridership, but the relationship varied by city and types of transit facilities. Figure 16 shows a distinct positive association between micromobility trips surrounding transit stops and transit ridership in the city of Portland. Higher micromobility trips surrounding a bus stop in other cities—including San Francisco, Santa Monica, Arlington, Miami, and Sacramento—are also associated with higher transit ridership, but the relationship is weaker than with rail, as seen by comparing the flatness of the curves for a given city between Figure 16 (bus stops) and Figure 17 (rail stops). However, a negative association between micromobility trips surrounding transit stop and transit ridership are observed in Los Angeles and Atlanta (Figure 16). Some of these negative correlations have been reported in at least one prior study (Graehler et al., 2019)

In the case of rail transit, our results show that all cities (Atlanta, Miami, Portland, and Sacramento) have positive associations between micromobility use and rail ridership (Figure 17), and that the relationship between micromobility use and transit is larger for rail compared to bus service (Figure 16 and Figure 17). The micromobility relationship with rail transit is strongest in Portland, which can be seen from the steep slope of the effect plot (Figure 17).

The degree to which these findings constitute real micromobility to transit connections remains unknown, as we did not have data on actual multi-modal trips. However, given the relatively flat curves in Figure 16 for most cities, we think this is evidence that micromobility services are not acting as an access mode for bus service very often. At least only some cities show potential for this connection. The same is less true for rail, as the four cities with rail transit showed at least slightly positive relationships between micromobility use and ridership.

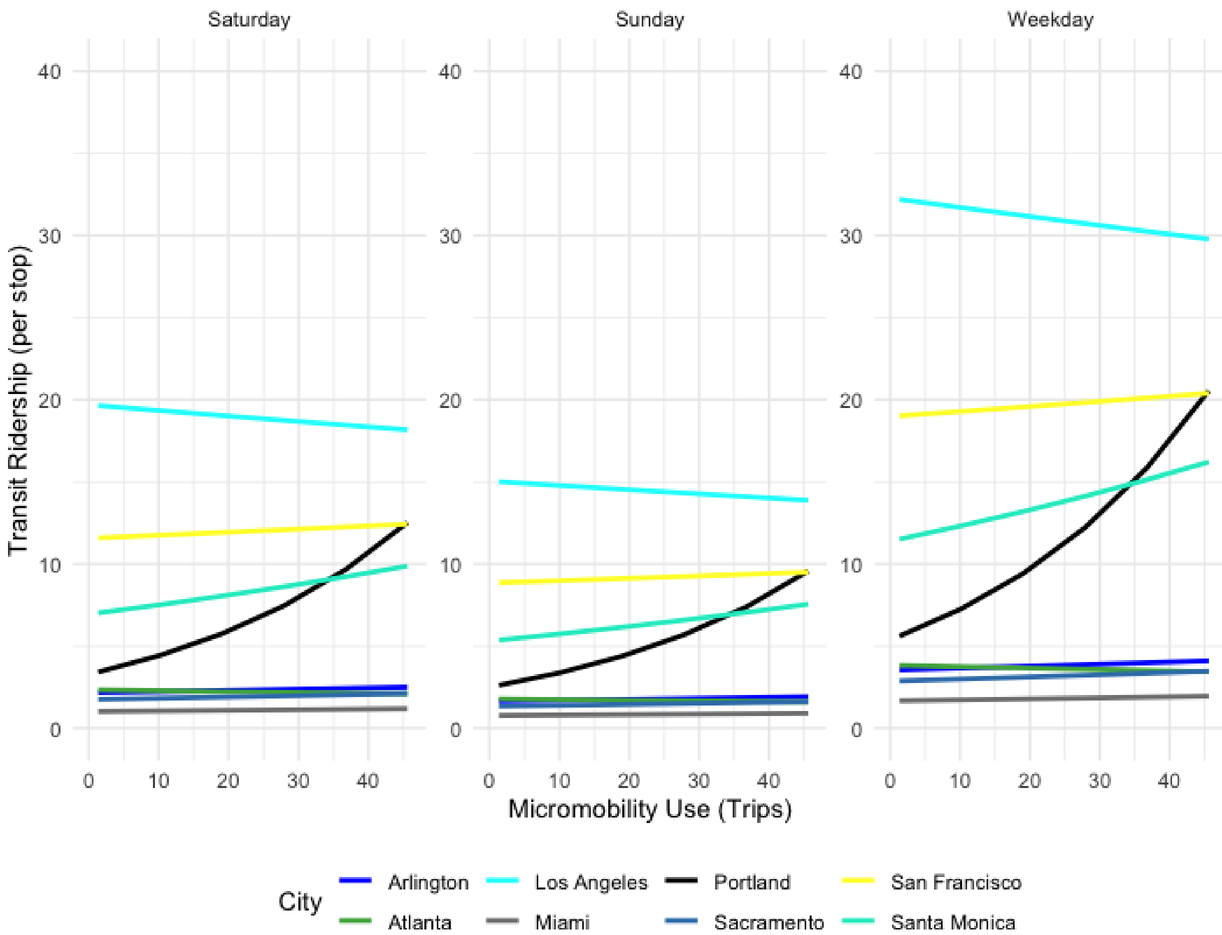

Figure 16. Predicted counts of transit ridership per bus stop by week period and city

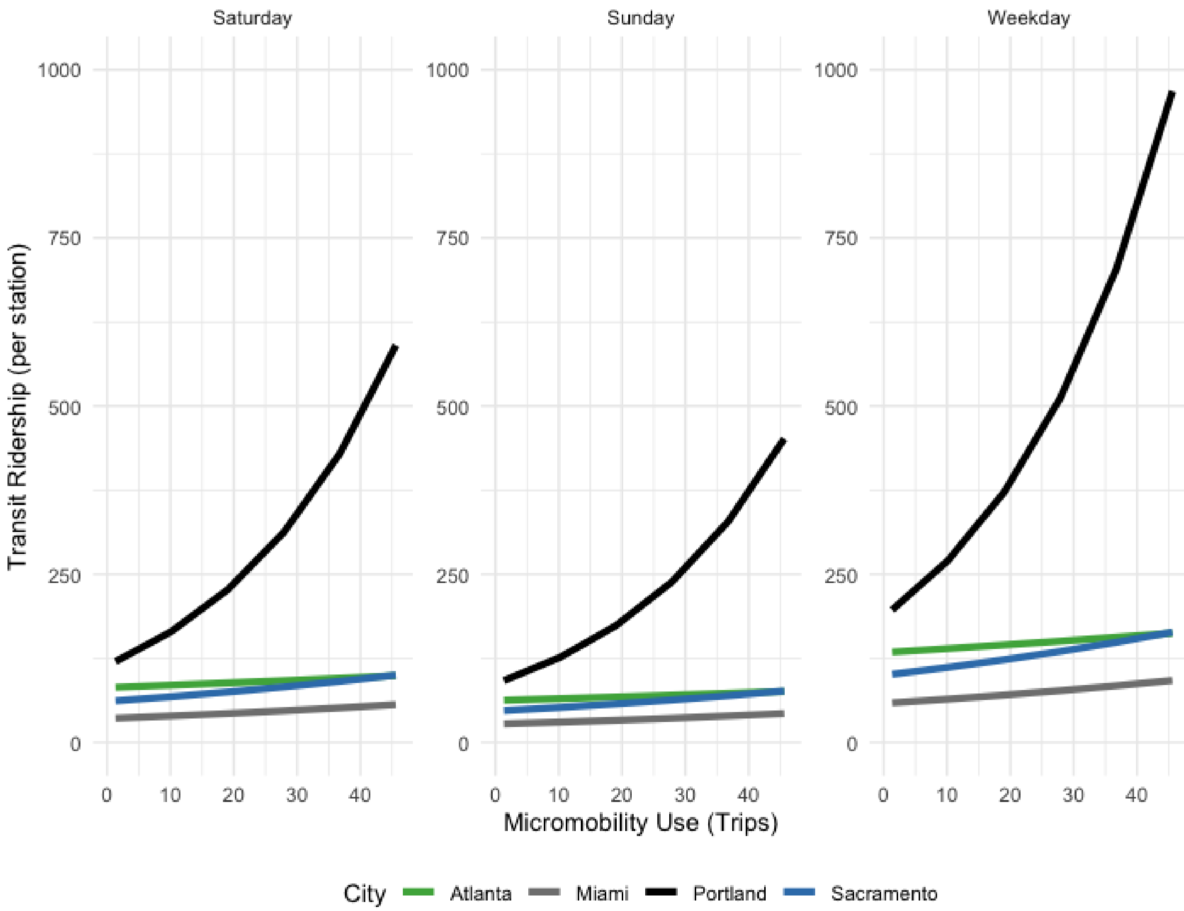

Figure 17. Predicted counts of transit ridership per railway station by week period and city

Conclusions and Policy Implications

A key to assessing the positive and negative impact of micromobility on the sustainability of transportation involves determining: the number of micromobility trips taken per day in an area with micromobility services; the number of miles traveled via micromobility; and the degree to which micromobility trips substitute for car travel and substitute for or increase (by first/last mile coverage) transit use. Our analysis of data from approximately 20 U.S. cities reveals that the trip frequency is relatively modest—below 2,500 trips/day. In almost all the study cities, at least 35% of micromobility trips replaced car trips and 8% replaced transit trips. That a higher percentage of micromobility trips substituted for transit trips in large cities than in small cities suggests that transit substitution is only a concern in some cities. One challenge in assessing impact is the limited availability of data on actual distances for trips taken by micromobility. This can be estimated—when origin and destination data are available—by the distance of a line connecting these two points, i.e., the Euclidean distance. Our comparison shows that, in most cities, the mean of actual trip distance from city-report data is approximately 1.5 to 2 times longer than the mean Euclidean distance from GBFS data. However, this underestimation by Euclidean distance can be partially corrected by combining it with data on trip duration.

As an industry, micromobility was deeply impacted by COVID-19, with rider miles traveled declining by 50-60% worldwide (Heineke, 2020). While changes in ridership varied across all our study areas, our findings clearly indicate that docked bike-share systems out-performed dockless systems during the pandemic. While the flexible and versatile nature of dockless systems allowed private operators to quickly remove or suspend services in US cities, docked systems proved to be a more stable and reliable provider of mobility during the pandemic. This distinction between docked and dockless performance during the pandemic may be particularly important in shaping future transportation planning and policy. Docked systems, where docks require utility connections and/or public right-of-way, are generally more financially supported by municipalities as a mobility service for residents. Even during periods of low ridership, docked systems generally remained in operation during the pandemic. Private dockless providers, however, curtailed or suspended operations when ridership and profits dropped. Policymakers can advocate for city-owned docked systems as a reliable mobility option by encouraging increased investment in docked micromobility programs.

Our study of the pre-pandemic relationship between micromobility usage and transit ridership revealed varied results by transit type. Our model showed a weak and unclear connection between micromobility usage and bus ridership but found higher light rail ridership at stations with more micromobility trips ending nearby. For both bus and rail ridership, the city of Portland represented a unique outlier, demonstrating a very strong positive relationship between micromobility use and transit use. These findings on micromobility use in relation to bus vs. train use and the findings in Portland can be valuable to policy makers and planners comparing the benefits of light rail systems to those of bus lines and considering their synergy with micromobility. Some transit operators have already started considering the potential of micromobility services to strengthen the transit system by including them in first and last mile planning (Mohiuddin, 2021).

Although these analyses have important limitations, several findings may be useful for cities and regulators in tracking the sustainability impacts of micromobility services. We use these findings to provide policy guidance in Table 4. Some of our findings lead naturally to metrics that can be used to estimate sustainability benefits from micromobility services (e.g., system miles), others are still exploratory (transit boarding and micromobility use relationships) and will require further study before integration into policy tools. In addition, we propose a suite of metrics that should be collected now, some that should be collected in the future, and a few options for how they could be used to monitor the impact of micromobility services on the sustainability of transportation.

Table 4. Recommended metrics for monitoring the impacts of micromobility (MM) services on the sustainability of transportation

Metric	Relevance	Method of Measurement	Data Source	Availability
		Micromobility (MM) Vehicle Metrics		
MM Fleet VMT	Quantifying the total VMT of an MM fleet allows calculation of its baseline emissions and clean miles	Determine the total VMT of MM vehicles.	MM operators	Depends on data-sharing agreements
MM Vehicle Emission Factor	Vehicle emission factors allow for the calculation of total fleet emissions	Determine the emissions associated with the electricity that is required to power MM vehicle travel.	MM vehicle efficiency specifications from operators, emissions associated to local electricity	Depends on data-sharing agreements
		Car Substitution Metrics		
% of MM trips that substitute car trips	Knowing how many MM trips replace car trips is important in calculating the car VMT that MM replaces	Surveys and GPS travel diaries can provide car mode substitution rates. It is important to track ridehail trips separately from owned cars.	Public research	City-specific data is now widespread, local data must be collected
Length of MM trips that substitute car trips	Knowing the length of MM-substituted car trips is important in calculating the car VMT that MM replaces	Surveys and GPS travel diaries can provide estimates of MM-substituted car trip lengths	Public research	City-specific data is rare, local data must be collected

Metric	Relevance	Method of Measurement	Data Source	Availability
		Transit Connection Metrics		
% of MM trips that connect to transit	MM providers can be credited with clean miles when connecting users to transit	Surveys, GPS travel diaries, and analysis of MM demand near transit stops can provide transit connection rates. Integration of transit and micromobility payment is needed for most accurate assessments.	Public research	City-specific data is now widespread, local data must be collected
Length of MM trips that connect to transit	Transit-connecting MM trips can be counted as if they were clean transit miles	Surveys and GPS travel diaries can provide estimates of transit-connecting MM trips. Integration of transit and micromobility payment is needed for most accurate assessments.	Public research	City-specific data is rare, local data must be collected
% of transit trips that substitute car trips	MM providers can be credited with clean miles for the transit trips that they connect to, which have substituted for car trips	Surveys and GPS travel diaries can provide estimates of transit-substituted car trips	Public research	This metric will vary by city; it is relatively well studied through national and area-specific household travel surveys
Length of transit trips that substitute car trips	MM providers can be credited with clean miles for the transit transit-substituted car trip miles that they connect to	Surveys and GPS travel diaries can provide estimates of transit-substituted car trips	Public research	This metric will vary by city; it is relatively well studied through national and area-specific household travel surveys

Metric	Relevance	Method of Measurement	Data Source	Availability
		Operation Van Metrics		
Van VMT (operations)	Van miles can be counted against the clean miles of the fleet	Determine the total VMT of operation vans	MM operators	Depends on data-sharing agreements
Operation van emission factor	Van emission factors allow for the calculation of van-related emissions	Determine the average fuel efficiency of vans	MM operators	Depends on data-sharing agreements

For state-level regulation of Clean Mile Credits, CARB might consider mandating reporting for many of the variables in Table 4. Many municipalities that foster micromobility seek improved integration between transit and micromobility (Fuller et al., 2021). One step toward improved integration can be apps that allow users to seamlessly and simultaneously purchase micromobility rentals and transit passes. With this improvement in place, it will be possible to count not just the mileage of a micromobility trip, but also the miles traveled by any connecting transit trip that micromobility facilitated. Rewarding credits for these connected transit miles can better reflect the clean miles impact of micromobility. Once the tracking of transit connections is feasible (e.g., through shared payment for micromobility to transit), CARB should also require collecting total connecting miles of transit and consider credits for full trip length. This approach would provide much greater accuracy than the transit connection metrics in Table 4 and aligns with on-going projects such as the California Integrated Travel Project (Cal-ITP).

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Appendix A: Trip Distance Model Parameter Summaries

Table 5. Trip Distance Model Parameter Summaries

Observed trips = 289,891	Model 1			Model 2			Model 3		
Fixed effects	Estimate	Std.Error	t-score	Estimate	Std.Error	t-score	Estimate	Std.Error	t-score
Euclidean Dist (mile)	1.572	0.005	314.3				0.680	0.003	212.1
Trip Duration (min)				0.006	0.000	672.3	0.057	0.000	565.9
R-squared	0.404			0.756			0.814		
Adjusted R-squared	0.404			0.756			0.814		

Appendix B: Transit Model Parameter Summaries

Table 6. Transit Model Parameter Summaries

Observed trips = 289,891	Buffer Distance								
	50 m			100 m			200 m		
Fixed effects	**Estimate**	**Std.Error**	**t-score**	**Estimate**	**Std.Error**	**t-score**	**Estimate**	**Std.Error**	**t-score**
(Intercept)	1.09	0.39	2.78	1.23	0.39	3.12	1.19	0.39	3.03
Micromoibility Use									
Bus Stop	0.03	0.02	1.38	0.05	0.03	1.74	0.05	0.03	1.66
Railway station	0.08	0.00	26.90	0.07	0.00	28.40	0.06	0.00	39.74
Railway Station	3.59	0.07	52.64	3.57	0.07	52.43	3.56	0.07	52.27
Temporal									
Sunday	-0.27	0.00	-407.13	-0.27	0.00	-405.87	-0.27	0.00	-406.08
Weekday	0.50	0.00	907.12	0.50	0.00	902.79	0.49	0.00	871.04
Socioeconomics									
Population density	0.00	0.00	13.05	0.00	0.00	12.74	0.00	0.00	12.86
Female (%)	0.51	0.04	12.41	0.50	0.04	12.05	0.51	0.04	12.23
Black (%)	-0.17	0.03	-6.50	-0.17	0.03	-6.27	-0.17	0.03	-6.38
Low Income (%)	0.06	0.02	3.12	0.05	0.02	2.71	0.06	0.02	3.10
Student (%)	-1.01	0.06	-18.26	-0.98	0.06	-17.63	-0.98	0.06	-17.76
Mode Share									
Car	-1.03	0.10	-10.33	-1.19	0.10	-11.93	-1.13	0.10	-11.29
Transit	0.50	0.10	5.28	0.32	0.10	3.40	0.38	0.10	4.00
Active Transportation	0.45	0.14	3.25	0.30	0.14	2.16	0.28	0.14	2.02
Walkability Index									
Walkability Index	0.06	0.00	43.32	0.06	0.00	43.70	0.06	0.00	43.45
Random effects	**Variance**	**Std.Dev.**		**Variance**	**Std.Dev.**		**Variance**	**Std.Dev.**	
Transit Stop	3.01	1.74		3.01	1.74		3.01	1.73	
City	0.99	1.00		0.99	0.99		0.99	0.99	
City:Micromobility Use	0.00	0.07		0.01	0.09		0.01	0.08	
Period	0.06	0.24		0.06	0.24		0.06	0.24	
AIC	3964769			3967185			3965842		
BIC	3964981			3967396			3966053		

Log likelihood	-1982365	-1983572	-1982901

Table 7. Conditional modes of the random effects by city

	50 m		100 m		200 m	
	Intercept	Micromobility Use	Intercept	Micromobility Use	Intercept	Micromobility Use
Arlington	-0.578	-0.036	-0.569	-0.039	-0.578	-0.022
Atlanta	-0.500	-0.106	-0.494	-0.115	-0.504	-0.071
Los Angeles	1.630	-0.057	1.639	-0.073	1.625	-0.066
Miami	-1.331	-0.018	-1.320	-0.043	-1.330	-0.020
Portland	-0.145	0.079	-0.130	0.093	-0.122	0.209
Sacramento	-0.787	-0.107	-0.777	0.151	-0.786	-0.013
San Francisco	1.099	-0.029	1.103	-0.045	1.098	-0.036
Santa Monica	0.611	0.023	0.547	0.071	0.597	0.018

Appendix C: Micromobility Service by City

Table 8. List of Micromobility Service by City

	Micromobility Service			Data Source	GBFS Data Available
	Docked bike	**Dock-less bike**	**E-scooter**		
Arlington	Capital Bikeshare	N/A	Lime, JUMP, Bird, Razor, Skip (All suspended in 03/2020)		JUMP
Atlanta	Relay Bike Share	JUMP	JUMP, Bird, Wheels, Boaz Bikes, Bolt (All suspended in 03/2020) Bird, Spin, Helbiz, Veoride (Resumed in 07/2020)		JUMP scooters, Relay Bike Share
Austin	Austin B-cycle Domain B-cycle (docked count is for both systems)	JUMP	Bird, Lime, Spin, Wheels (All suspended in 03/2020; Bird resumed in 04/2020 with phased rollout; Lime and Spin resumed in 05/2020; Wheels resumed in 06/2020		JUMP bikes, JUMP scooters
Bishop Ranch	BriteBikes (Suspended only in 03/2020)	N/A	N/A		BriteBikes
Davis	N/A	JUMP (Suspended in 03/2020)	N/A		JUMP bikes
Denver	Denver B-cycle (Closed in 01/2020)	JUMP (Suspended 04/2020; resumed 05/2020)	Lime, Lyft, Razor, Bird, Spin (Bird and Lime suspended 03/2020; resumed 04/2020 with phased rollout)		JUMP bikes, B-cycle
Detroit	Mo Go	N/A	Bird, Spin, Lime (All suspended 03/2020; Bird and Spin resumed 05/2020)		Lime, Spin, Bird
LA	Metro Bike Share Los Angeles	JUMP	JUMP, Lime, Wheels, Bolt, Sherpa, Clevr, Bird, CLOUD, Lyft, Spin (Wheels and Lime suspended in 03/2020; Wheels resumed in 06/2020)		JUMP bikes, Metro Bike Share, JUMP scooters, Lime, Spin, Bird, Lyft, Wheels
Memphis	Explore	N/A	Bird		Explore Bike Share

	Micromobility Service			Data Source	GBFS Data Available
Miami	Citi Bike Miami (Suspended only in 03/2020)	JUMP	Lime, Lyft, Spin, Bird, JUMP (All suspended in 03/2020)		JUMP scooters
Portland	Biketown	No service	Spin, Razor, Lime, Bird (Lime and Bird suspended their service in 03/2020, but resumed in 05/2020		Biketown, Bird
Sacramento	N/A	JUMP (Suspended in 03/2020)	JUMP (Suspended in 03/2020)		JUMP scooters
Santa Monica	Breeze	JUMP (Suspended in 03/2020)	Bird, Lyft		Breeze, bird
San Francisco	Bay Wheels	JUMP, Spin	JUMP, Lime, Scoot, Spin (JUMP, Lime and Scoot suspended in 03/2020; Scoot resumed in 05/2020)		JUMP bikes, JUMP scooters
Tampa	Coast Bike Share	JUMP	Spin, Bird, Lime, JUMP (Bird and Lime suspended in 03/2020; Spin and JUMP suspended in 05/2020; All resumed in 07/2020)		JUMP scooters, Coast Bike Share
Washington DC	Capital Bikeshare	JUMP, Helbiz	JUMP, Lyft, Skip, Spin		JUMP bikes, JUMP scooters, Lime, Lyft, Spin, Bird

Source: USDOT Bureau of Transportation Statistics, General Bikeshare Feed Specification (https://github.com/NABSA/gbfs)