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Authors
Dean, Matthew
Zuniga-Garcia, Natalia

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Shared E-Scooter Trajectory Analysis During the COVID-19 Pandemic in Austin, Texas

Matthew D. Dean[1] and Natalia Zuniga-Garcia[1]

Abstract

By March of 2020, most cities worldwide had enacted stay-at-home public health orders to slow the spread of COVID-19. Restrictions on nonessential travel had extensive impacts across the transportation sector in the short term. This study explores the effects of COVID-19 on shared e-scooters by analyzing route trajectory data in the pre- and during-pandemic periods in Austin, TX, from a single provider. Although total shared e-scooter trips decreased during the pandemic, partially owing to vendors pulling out of the market, this study found average trip length increased, and temporal patterns of this mode did not meaningfully change. A count model of average daily trips by road segment found more trips on segments with sidewalks and bus stops during the pandemic than beforehand. More trips were observed on roads with lower vehicle miles traveled and fewer lanes, which might suggest more cautious travel behavior since there were fewer trips in residential neighborhoods. Stay-at-home orders and vendor e-scooter rebalancing operations inherently influence and can limit trip demand, but the unique trajectory data set and analysis provide cities with information on the road design preferences of vulnerable road users.

Keywords

innovative public transportation services and technologies, scooters, origin and destination data, spatial data, public transportation, data and data science, urban transportation data and information systems

The global COVID-19 pandemic has had a large-scale impact on the transportation sector. Concerns about virus transmissibility, work-from-home (WFH) policies, and supply-side adjustments affecting modal availability contributed to a decline in travel, particularly following the passage of stay-at-home orders (also called shelter-in-place) that closed nonessential businesses (*1*). In Austin, TX, the first two presumptive positive cases of COVID-19 in the public health region were reported on March 13, 2020, coinciding with the cancellation of in-person classes across universities, colleges, and school districts. Table 1 provides an overview of several key public health emergency orders or actions taken in response to the pandemic. The result was a significant change to everyday activities under stay-at-home orders followed by a gradual return as businesses reopened (*2–5*). Figure 1 shows the relative change of trips ending at a destination type to baseline conditions in the Austin region in early 2020 (*6*). More trips ended at residential locations, suggesting a rise in home-based trips (i.e., “unlinking” of activities), whereas other destinations had varied declines. The most significant decline in trips was to transit stations and workplaces. Relative to prepandemic times, the initial lockdown period led to more time spent at home, though that gradually declined, whereas visits to parks recovered more quickly than indoor destinations.

Although public transit was most affected in this mobility analysis and the regional provider, Capital Metropolitan Transportation Authority (CapMetro), instituted service reduction measures across many routes (*10*), reductions in personal vehicle travel (*11*), and ride-sharing vehicles (*12*) was also observed. Transportation mode choice is determined in part by mode availability, and the decrease in the supply of public transit and ride-sharing may have forced zero-vehicle households (i.e., captive transit riders) to switch to other modes like

[1]Department of Civil, Architectural and Environmental Engineering, The University of Texas at Austin, Austin, TX

Corresponding Author:
Matthew D. Dean, mattdean@utexas.edu

Table 1. Timeline of Lockdown and Reopening COVID-19 Pandemic Events in Austin, TX

Date	Event
March 6, 2020	Local state of disaster declared
March 12, 2020	Local disaster declaration extended indefinitely
March 13, 2020	Austin Public Health announces two presumptive positive cases; UT Austin, St. Edward's University, Austin Community College, and Austin Independent School District cancel classes
March 14, 2020	Ban on gatherings with 250 or more persons
March 19, 2020	Ban on gatherings with 10 or more persons in a confined space; closure of dining at restaurants and bars; Austin Public Health announces evidence of community spread
March 20, 2020	Austin adopts Texas social distancing and gathering requirements
March 24, 2020	Austin adopts a stay-at-home order (includes ban of nonfamily gatherings)
April 27, 2020	Phase One Opening of select businesses (at 25% capacity)
May 1, 2020	Expiration of stay-at-home order
May 18, 2020	Phase Two Reopening of select businesses (at 50% capacity)
June 3, 2020	Phase Three Reopening of businesses (no capacity requirements)
July 2, 2020	Face covering requirement

Note: UT = University of Texas.
Source: Limón (*7*); Villalpando (*8*); Texas Department of State Health Services (*9*).

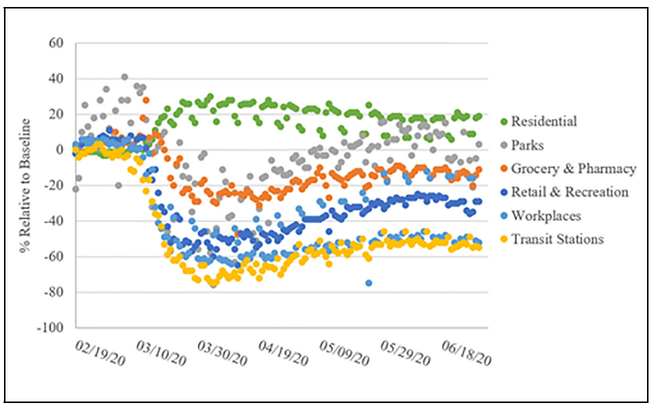

Figure 1. Daily mobility trends for the Austin region.
Source: Google LLC.

shared micromobility, active transportation, or to abandon trips entirely. However, secondary effects of reduced vehicle travel may also influence active transportation users, such as those using shared e-scooters. One might expect that a reduction in traffic volumes during the pandemic could reduce the perceived risk of using shared e-scooters on previously busy streets, especially for risk-averse users. On the other hand, increases in vehicle speeds may push users to low-traffic, smaller roads (*13*).

Several studies investigate the association between COVID-19 and traveler activities, behavior, and perceptions of risk (*3–5, 14–16*), whereas others focus on the pandemic's effect on shared micromobility and public transit (*1, 17–24*). However, few examine shared e-scooters (*15*, *22*), which are a relatively new phenomenon. Although those studying shared micromobility modes have access to anonymized trip data but neither route choice nor trip purpose by destination type, there have been efforts to impute trip activities from prior GPS-logged trip surveys (*22*). Since e-scooters tend to orient themselves to casual riders for short trips (*25, 26*), their usage under emergency public health orders and in-person restrictions for nonessential businesses is not well understood. Additionally, only three prior studies were given access to e-scooter trajectory data, with one focusing on identifying trip distance spent on sidewalks, bike lanes, and roadways (*27*). As a result, there is a gap in the knowledge of how shared e-scooter trips changed during the COVID-19 pandemic compared with the months preceding the pandemic.

To this end, we made use of shared e-scooter trajectory data, representing a sample of 1.4% of the total trips made in Austin, TX, before the pandemic and up to 60% of the trips during the reopening phase of the pandemic. Trip information was paired with other sources, such as roadway infrastructure inventory and demographic information, to analyze the characteristics of observed roadway design preferences. A negative binomial (NB) count model was developed to analyze the average number of e-scooter trips along 0.1-mi roadway segments. By examining this unique trajectory data, this study explored the following research questions: (1) How have shared e-scooter trip characteristics changed during the pandemic? (2) Where did users of shared e-scooters travel during the pandemic? (3) What are the conclusions for cities in building a sustainable, equitable transportation system, given the observed roadway design preferences of shared e-scooter users?

Literature Review

Shared e-scooters are a nascent mode within the relatively new field of shared micromobility. Most studies to date have focused on the difference between this mode and other forms of shared micromobility, including looking at who uses these devices, what the trip purpose is, and understanding their spatiotemporal demand. Whereas early studies on shared micromobility have found users are mostly well-educated young adults without children, and with access to multiple modes of transportation, there is anecdotal evidence to suggest a more diverse user set than previously identified (*28*). However, provider service areas can exclude equitable access to diverse groups of people by manipulating service areas to dilute high-demand areas and meet legal density caps (*29*). The difficulty of obtaining rider demographics through opt-in forms and data sharing with mobility providers has often led to information on shared e-scooters users coming from intercept surveys (or other survey methods).

Most spatial analyses of shared micromobility focus on station-based or dockless bike-share systems (*22*). For example, one study compared shared e-scooters with station-based bike-share trips in Washington, D.C., and found that casual bike-share riders behave more similarly to dockless e-scooter users than bike-share members (*30*). Shared e-scooter trips in Austin, TX, were studied using a spatial error model to understand interactions with bus service at both trip ends (*31*). They found no evidence within their framework of first- and last-mile interactions but found that population density and the University of Texas at Austin (UT Austin) campus had a positive influence on total trips. They paired this analysis with a survey of mostly students, finding 44% of respondents had used an e-scooter in the past to attend class, 17% to attend a meeting, 15% for social trips, and 11% to go to work. Nearly half of the respondents used this mode instead of walking, whereas a fifth used it to replace a bus trip. A descriptive analysis of the same data set in Austin also observed a correlation between trips and student-housing neighborhoods (*29*).

Since the start of the pandemic, research has focused on more popular and established travel modes (e.g., personal cars and public transit) and understanding how travel behavior may change in the long-term as cities reopen. The remaining portion of this section first summarizes studies that evaluated COVID-19 impacts on shared mobility, with an emphasis on shared e-scooters, and then summarizes studies that have analyzed micromobility patterns using trajectory data (to study route choice and segment-level preferences).

Prior COVID-19 Shared Micromobility Work

The focus in the literature has centered on docked bike-share systems using publicly available trip data to study ridership trends (i.e., time-series data) within or across cities. In New York City, a 9-month time-series analysis of the station-based bike-share system, Citi Bike, showed that trip duration increased significantly compared with the prior year (*24*). The effect of the stay-at-home order had a significant negative effect on subscriber trips, which remained lower than 2019 levels throughout the pandemic, but no effect was found for casual trips, which increased during the pandemic. Compared with the city-wide subway system, bike-share use had a less severe decline in ridership and may have even captured former subway riders, though this study only captured data in February and March 2020 (*19*). In Chicago, the station-based bike-share system, DIVVY, exhibited a similar shift from commuter to casual users, a faster rebound in bike-share trips than transit, and an increase in average trip duration (*21*). This analysis found that usage during the pandemic correlated well with the existing riders of micromobility (e.g., Caucasian, high income, residing in high-density areas). A comparison between New York City, Chicago, and Boston observed increases in average trip duration across all cities, especially following the initial peak in local COVID-19 cases (*17*).

An early study outside the United States conducted a 1-month before–during analysis of Zurich micromobility trips from four services (i.e., docked bike, docked e-bike, dockless e-bike, dockless e-scooter) (*22*). As expected, they observed a reduction in workday trips from station-based services (which captures more commuting trips). At the same time, the trip duration of all bike modes increased, which the authors speculate is a result of a switch from other public modes to bike-share. They observed an 8%, 13%, and 20% decrease in e-scooter origins at imputed work, shopping, and leisure places of interest, respectively (attributed to the lockdowns).

A few recent studies include the results from surveys of shared micromobility riders. A survey of San Antonio bike-share members found that COVID-19 had not disrupted half of the respondents' use of the system. Interestingly, those not working because of the pandemic reported using the bike-share more frequently than before the pandemic (*20*). One study had shared e-scooter companies operating in Chicago distribute a survey to users to understand trip frequency and mode substitution during COVID-19 (*18*). Most respondents (59%) took between one and three trips in the previous month, whereas a small share (8.5%) took more than 10 trips. The study developed an order probit model to explain trip frequency. They found reduced-fee transit access, Chicago's bike-share (DIVVY) membership, zero- or one-vehicle households, household incomes less than $50,000, and young adults (aged 18 to 35) all increased shared e-scooter trips. A little more than one-third (36%) of respondents used this mode to get to/from transit service (bus or rail), whereas 22% said they often used e-scooters to avoid transit entirely. Interestingly, 50% of respondents said they had never used an e-scooter before.

In short, ridership across several U.S. station-based bike-share systems declined by an average of 44% from March to May 2020 compared with the same period in 2019 (*32*). As noted in research by Hu et al. (*21*) and Wang and Noland (*24*), bike-share ridership rebounded to prepandemic levels in the summer of 2020 and was more resilient than other shared modes, such as public transit. There is evidence that e-scooters support casual riders and more leisure trips, and that during the pandemic station-based bike-share programs had more casual riders. This could be in part a result of (1) programs to give healthcare workers/essential workers free bike-share passes (*33*), (2) a reduction in the availability of dockless e-scooters after some providers suspended operations (*34*), and (3) a mode shift from other shared modes, like public transit (*34, 35*).

Prior Trajectory Analysis and Route Choice Modeling Work

The authors are aware of only three studies that obtained trajectory data from shared micromobility trips. Each study explored a different micromobility type—dockless and docked bike-share and e-scooters—and employed different methodologies for examining route choice preferences. The first study classified each trip into path archetypes and developed a discrete route choice model (*36*), whereas the second and third studies solely used a map-matching process to classify infrastructure usage and user type differences (*27, 37*). The studies were given access to trajectory data but not rider demographic information. However, an evaluation of demand across a region could give insights into potential user types and route preferences based on roadway segment characteristics.

Over 9,100 trips were analyzed from Phoenix, AZ's bike-share system in 2014 to 2015 to determine cyclist route preferences by user type (e.g., member or casual) through a path size logit modeling approach (*36*). A map-matching algorithm combined proximity-based alignment and route continuity checks to identify the actual path taken and five alternatives, if plausible. Members took more direct routes and preferred roads with less traffic and tended to avoid one-way streets. Although station-based, riders are permitted to park the bicycle outside of a station for an added fee. A study in Washington, D.C. also compared member and casual trips (*37*). Nearly 3,600 trips from 94 station-based bikes were captured in the spring of 2017 to compare trip lengths, between-station dwell times, and the proportion of mileage on infrastructure types. Casual riders took trips that were nearly twice as long in distance and three times longer in duration than members. A heat map for trajectory points showed casual riders visited tourist points of interest, resulting in over 60% of their mileage being on parkland. In contrast, 50% of mileage by members was on roads without bicycle infrastructure and 33% with infrastructure.

The third study obtained nearly 80,000 e-scooter trips in Austin and used a proximity-based mapping algorithm to identify where users traveled on the road (*27*). On average, 18% of an average trip was spent on sidewalks, 11% on bike lanes, and 33% on travel lanes in mixed traffic—the other 38% was unclassified (i.e., parking lots and parks). Surprisingly, 60% of trips taken on travel lanes were on principal arterials, suggesting riders take possibly more direct, unimpeded, broad roads when traveling on the road. Median speed varied by infrastructure type but was around 10 mph (16 km/h).

As mentioned in Wergin and Buehler, GPS trajectory data has advantages over stated and revealed preference surveys when studying route preferences, namely by removing respondent recollection error and respondent behavioral changes from tracking (*37*). However, the process of mapping trajectory data to geographic information system network data is laborious and requires data filtering and an appropriate mapping algorithm (*36*). Map-matching was not performed in Wergin and Buehler owing to casual users' circuitous routes and high utilization of park trails, paths, and sidewalks (*37*). Data filtering varies by study. Very short and long trips by duration and distance are often excluded, as are trips with abnormal speeds (*27, 36*). Trips with faulty points can be identified by line segment lengths that exceed the trip's mean by a few standard deviations (*37*).

Background

Data Description and Processing

A licensed shared e-scooter vendor operating about 1,000 devices in Austin, TX (Spin) provided trip and trajectory data for a prior study (*27*). The data set comprised records from February 14, 2019, to June 3, 2020, for a total of 96,000 trips. Each trip comes with a unique trip identification (ID) number, start and end time, start and end location (latitude and longitude), trip duration, and trip distance. Trajectory data for each unique trip ID provided location points (latitude and longitude) in decimal degrees to five decimal places, corresponding to a precision of 1.1132 m at the equator. The trajectory information was recorded every 5 s for a total of more than 11 million data points during the period of analysis.

Figure 2. (*a*) Map of Austin, Texas' roadway network used in this analysis (0.1-mi segments) and (*b*) fictitious trajectory along Austin's Shoal Creek Trail and simplified roadway network.

Data Filtering Methodology

The raw trip records underwent a filtering process to remove trips with faulty trajectory recordings and trips under a certain distance. The developed filtering algorithm first calculated the distance traveled between two consecutive points of the same trip. If the estimated speed exceeded 20 mph and the distance traveled between consecutive points was greater than 30 m, the trip was removed from the study owing to concerns about data accuracy (*38*). The purpose was to remove accidental trips such as when the e-scooter is moved to a charging depot or where trip speeds are unreasonable.

For the first part of this analysis (i.e., pick-up and drop-off locations), the study included "unproductive" trips (i.e., the user decides to cancel the ride after noticing an issue with the device a few seconds into the trip). This preserved actual demand for this mode from the data set, though one cannot determine whether the user ultimately took another e-scooter, took an alternative mode, or abandoned the trip altogether. The second part of this analysis looked at trip duration and route preferences. For this section, we used Austin's roadway network to aggregate e-scooter trajectory data into 0.1-mi roadway segments. The roadway network came from the Texas Department of Transportation (TxDOT) roadway inventory and was converted into uniform roadway segments of 0.1 mi, resulting in nearly 10,000 segments (Figure 2*a*). The resulting network aligned well with the service regions of the shared e-scooter providers in town and did not include highway links where e-scooters are prohibited.

To match trajectories with roadway segments, we developed a geometric map-matching algorithm to find the nearest roadway segment for each trajectory point and estimate the distance between the trajectory point and the closest roadway segment (*36*). Only trajectories within a buffer region of 5 m from the roadway network were considered. It is important to note that users can ride e-scooters outside the roadway network (e.g., parks, sidewalks, and parking lots). However, in this study, the route choice was analyzed from a roadway usage perspective. For example, Figure 2*b* depicts a fake trajectory along Austin's Shoal Creek Trail. The filtering algorithm only captured roadway segments at the southern end that followed the gridded roadway network. This procedure attempted to accurately match trajectory points to roadway segments and allow for the exclusion of the occasional trajectory point outside of the 5-m buffer.

***Map-matching to count process*:**

- Each trajectory point is uniquely indexed with a trip ID number and a sequence number. Similarly, the 1-mi roadway segments are indexed with a unique identifier.
- The shortest distance between the trajectory points and the roadway segments is estimated using PostGIS.
- The roadway ID of the closest segment to each trajectory point is assigned.
- Trajectory points with a distance greater than 5 m are filtered.

- The number of unique trajectory trips per roadway segment per day are counted.
- The count of unique trajectory trips per day per segment are averaged, according to each period (pre- and during-pandemic).

Additional Data Sources

To explain changes in pick-up and drop-off locations and roadway usage, this study obtained roadway, socioeconomic, and transit information from five sources: TxDOT, City of Austin, American Community Survey (ACS), Capital Area Metropolitan Planning Organization (CAMPO), and CapMetro. TxDOT supplied roadway inventory information from the year 2018, which included administrative, geometric, and traffic variables. Socioeconomic information from 2019 was transformed from census block groups and applied to traffic analysis zones (TAZs). The 2018 ACS 1-year Estimates was used to select population density, job density, household size and incomes, and general demographics (e.g., age, gender, and race). The City of Austin provided sidewalk and bike lane information and e-scooter count data aggregated by census tract. Lastly, CAMPO provided TAZ records from 2018, and CapMetro provided bus stop location data from 2020. All information was joined to the individual roadway segments in Austin, TX. Table 2 lists the summary statistics of all variables that were tested for inclusion in statistical modeling.

Methods

The first research aim was to explore the spatiotemporal differences in shared e-scooter trips before and during the pandemic. The second aim was to analyze changes in shared e-scooter trip counts by roadway segment to understand how the pandemic may have affected the route choice of this mode. Bike-share users take more direct routes (*36*), and casual users' trips are twice as long as those of bike-share members (*37*). Shared e-scooter users are casual riders (*25, 26*) undertaking recreational trips; this represents a challenge for modelers wishing to use discrete route choice models given the circuitous and indirect paths typically associated with this trip type. Although people make route choices, this understudied mode might reveal roadway design preferences from real-world route choices. Trips were divided by the two time periods using March 13 as the start of the pandemic locally in Austin, TX. Although this date was a week after a local disaster was declared, it was the date when the Austin Public Health declared two presumptive positive cases (i.e., when the pandemic "arrived"). As a result of the pandemic, the shared e-scooter company paused operations in Austin, TX, on March 27, 2020, and resumed operations on April 22, 2020 (*39*). Figure 3, *a* to *d*, respectively show a temporal plot of total trips for all shared e-scooter trips in Austin; for all trips provided by Spin in the data set; Spin's market share by trips; and periods during the pandemic, as determined by key dates in Table 1.

The spatiotemporal analysis used basic summary statistics to qualitatively report the changes in trip departure times, duration, and trip ends. For this section of the study, we used an equal prepandemic period as the total during-pandemic period to remove biases in the growth of e-scooter use. Maps with overlaid trip routes across a pre- and during-pandemic period were used to supplement findings. Statistical analysis was conducted in R and maps were generated using TransCAD.

Table 2. Summary Statistics of Variables for Road Segments ($n = 8{,}915$)

Variable	Mean	SD	Min.	Median	Max.
Average daily trip counts (prepandemic)	0.23	1.08	0.00	0.01	22.47
Average daily trip counts (during pandemic)	0.48	2.37	0.00	0.00	47.68
Daily vehicle miles traveled (VMT)	2,694.21	6,165.76	3.18	217.89	51,075.37
Number of lanes	2.30	0.75	1.00	2.00	6.00
Shoulder width (ft)	0.11	0.94	0.00	0.00	18.00
Speed limit (mph)	55.66	7.38	10.00	59.50	60.00
Truck percentage	3.30	0.63	0.00	3.20	12.50
Sidewalk within a 50-ft buffer (indicator)	0.60	0.49	0.00	1.00	1.00
Bike lane within a 50-ft buffer (indicator)	0.30	0.46	0.00	1.00	1.00
Number of transit stops within a 0.1-mi buffer	5.98	4.58	0.00	5.00	30.00
Population density (per mi^2)	5,899.00	4,265.24	0.00	5,325.00	64,812.00
Total employment density (per mi^2)	5,758.70	16,142.61	0.00	2,239.50	419,402.70
Retail employment density (per mi^2)	1,116.50	3,479.85	0.00	446.10	120,286.60
Residential density (per mi^2)	2,727.00	2,186.34	0.00	2,366.00	46,386.00
Household size	2.22	0.66	0.00	2.16	4.06
Median income ($10,000)	4.55	2.51	0.00	3.98	16.58

Note: SD = standard deviation; Min. = minimum; Max. = maximum.

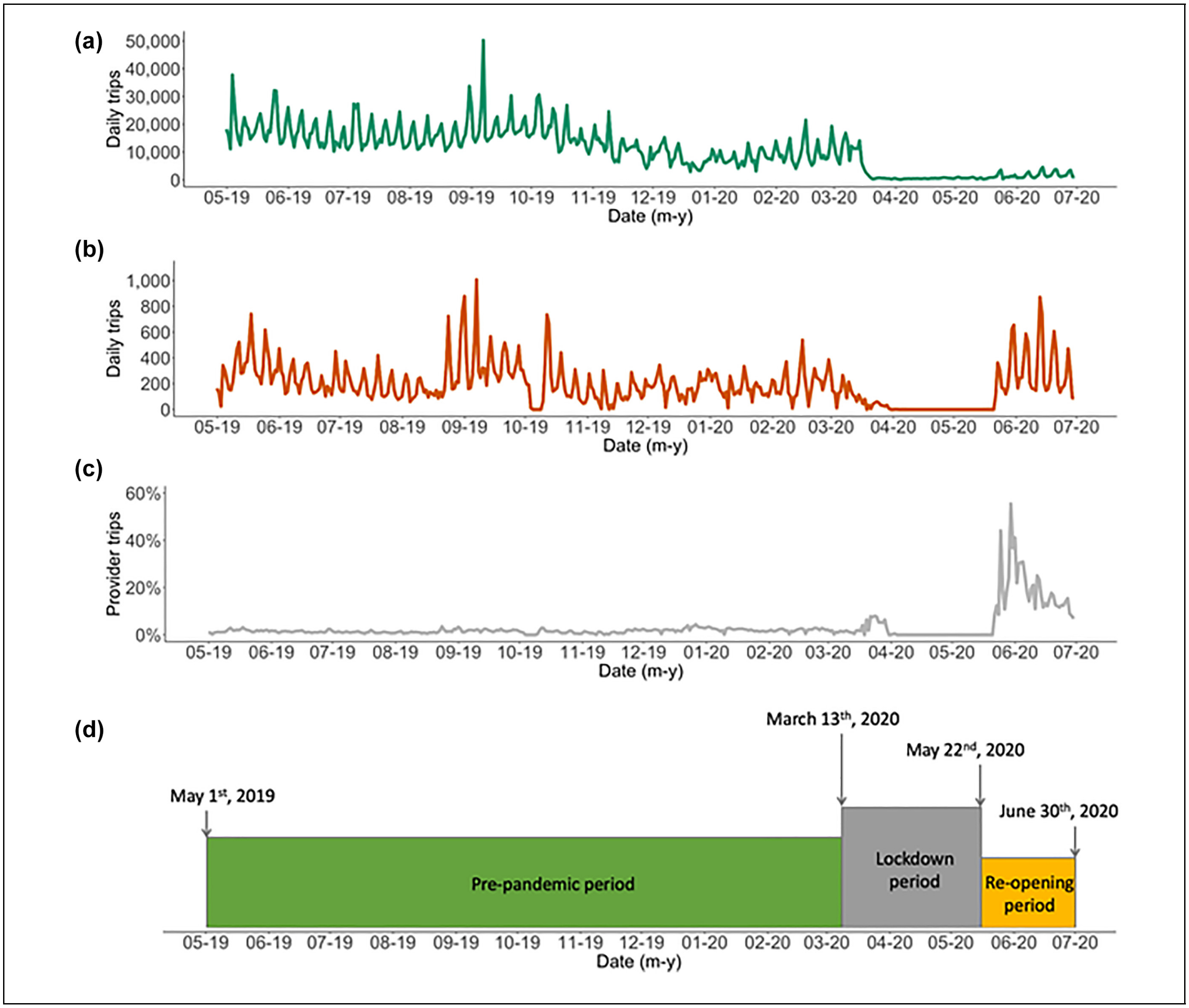

Figure 3. (*a*) Daily e-scooter trips in Austin (all companies), (*b*) daily e-scooter trips by the provider company, (*c*) daily percentage of market share of the provider company, and (*d*) timeline of defined periods.

Finally, an NB count model was used to analyze the average number of e-scooter trips along 0.1-mi roadway segments during two periods: before the pandemic and during the reopening period. This modeling structure allows for an analysis of the covariates during different periods by isolating their effect in a before-and-after setting.

The expected number of daily trip counts, $E(Y_i)$, along the i^{th} segment is expressed as follows:

$$E(Y_i) = exp\left(\beta_0 + \sum_k x_{ik}\beta_k + \varepsilon_i\right),$$

where
β_k is the k^{th} covariate;
ε_i is a random error term, which follows a Gamma distribution, $\varepsilon_i \sim Gamma(\gamma, \gamma)$;
Y_i represents the average daily e-scooter trip count with mean $E(Y_i) = \mu_i$ and variance $Var(Y_i) = \mu_i + \rho\mu_i^2$, and ρ is the dispersion parameter ($\rho = 0$ for a Poisson model).

Additionally, a sensitivity analysis was applied to the NB estimates to understand the covariates' effects in the before-and-after periods' models. Specifically, for each covariate, one standard deviation or binary change was applied. The modified variables were passed to the model to calculate the prediction. Then, the difference between the mean of original prediction and permuted prediction was calculated to represent the contribution of that covariate (i.e., practical significance). The sensitivity analysis

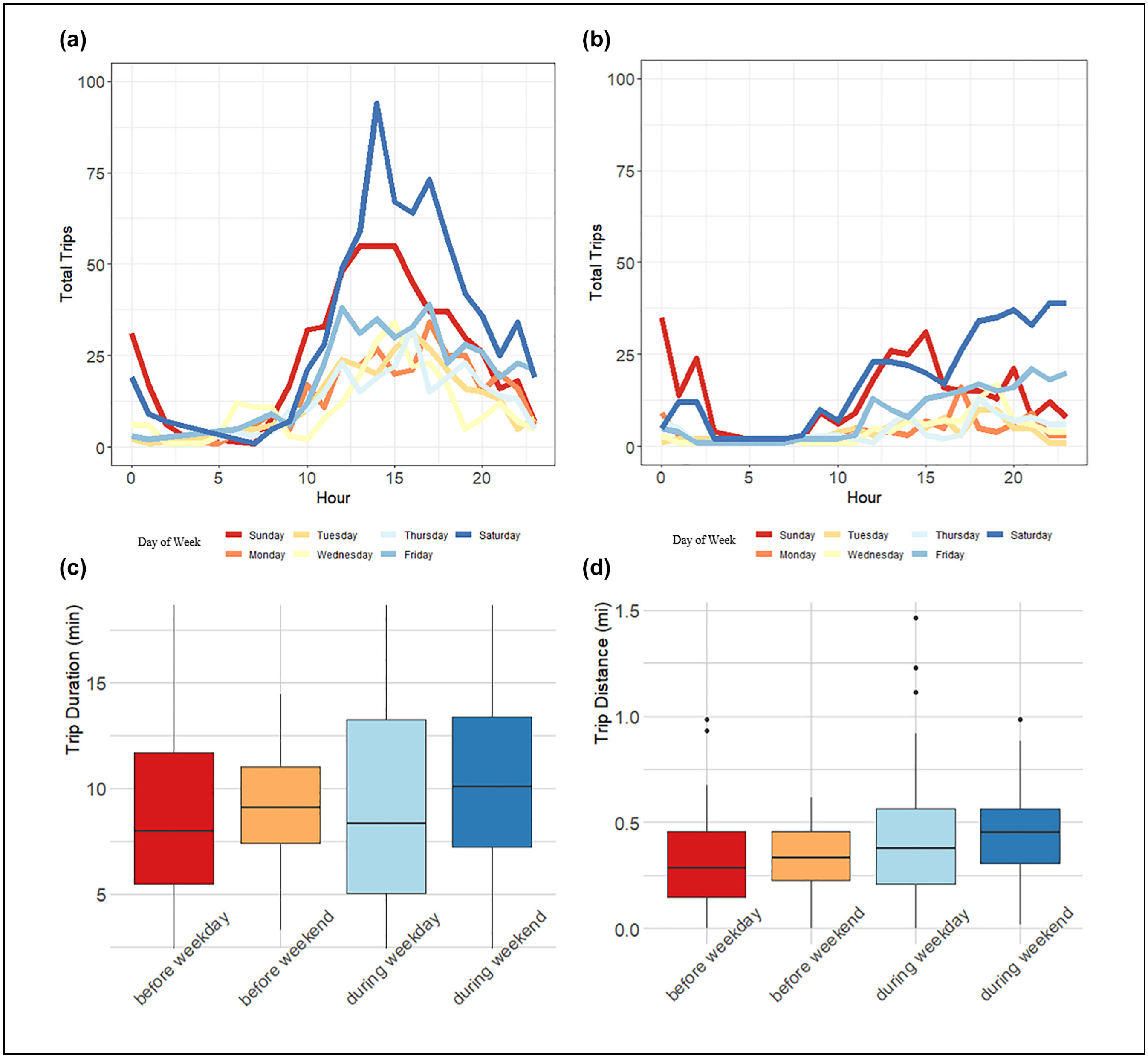

Figure 4. (*a*) Count of hourly trips by day of week (prepandemic), (*b*) count of hourly trips by day of week (during pandemic), (*c*) trip duration, and (*d*) trip distance.

allowed for a deeper understanding of the magnitude of the covariates used in the models, and facilitated interpretation of the results.

Results

Temporal Changes

Literature on COVID-19 effects on shared micromobility found that trips became longer in length and duration whereas departure times shifted away from traditional peak periods. Figure 4, *a* and *b*, indicate that weekends have higher daytime trip counts and that users are more active on shared e-scooters on Friday evenings than during any other period. Before the pandemic, trips tended to peak in the afternoon hours, especially on the weekend. During the pandemic (across both the lockdown and reopening phases), there was a decrease in daytime trips and a shift in the peak from afternoon to late-night and early morning hours, at least on the weekend. The former could indicate the effectiveness of stay-at-home orders and WFH policies, which both decreased overall mobility and increased the relative number of leisure activities (*40*). The shift to more late-night trips during the pandemic may be attributed to activity-time shiftsor a mode shift from ride-hailing to shared e-scooters to avoid contact with members outside of one's household (*5*); however, the alignment of these trips with nighttime social activities suggests that COVID-19 precautions may not have been the motivating factor.

To understand changes in trip length, trip duration and trip distance variables were partitioned into four categories: before versus during the pandemic crossed with weekday versus weekend (Figure 4, *c* and *d*). In general, users spent more time on shared e-scooters during weekends than on weekdays, probably owing to more flexible schedules. The pandemic seems to have attracted longer trips in both time and distance. There was a slight decrease in the number of shorter trips (by distance), which could be explained by a growth in outdoor exercise and general physical activity during the lockdown that may have replaced shorter shared e-scooter trips. At the same time, longer trips could be an indicator of a willingness to avoid shared modes (e.g., transit and ride-hailing), as suggested by respondents in research by Rahimi et al. (*18*).

Spatial Changes

In addition to changes in trip length and departure times, there were changes in origin and destinations for trips and trip routes taken before and during the pandemic. Figure 5*a* plots all trips that start or end in central Austin before and during the pandemic. Though Spin paused operations between lockdown and reopening, there was still a significant number of trip ends during the pandemic as in an equal number of days beforehand. The map shows a decline in trip ends in the pandemic outside the downtown gridded street network, namely in the north and southwest quadrants of the map. The northern cluster is centered around multifamily apartment buildings that predominantly serve university students. The pandemic shut down the UT Austin campus and moved classes online, reducing the need for e-scooters to/from class (a frequent trip purpose found in a previous study by Zuniga-Garcia and Machemehl [*31*]). Students may have also relocated to their primary residence at the start of the pandemic. The southwestern cluster includes residential neighborhoods and parkland. This suggests that people were staying at home and not using e-scooters for short trips. It also suggests a decline in e-scooters starting or ending at parks, which aligned with findings from Li et al. (*22*). Observations from trip ends alone are biased by the availability of e-scooters near one's origin and the likelihood of finding one at the intended destination (if making a roundtrip). The provider's relocation of devices may therefore have influenced trip-making patterns, especially if the provider changed their strategy under uncertain and unpredictable changes in demand during the pandemic.

To understand whether users were still traveling through these neighborhoods with lower origins and destinations, we created a map with pandemic trip routes (1,287) overlaid on prepandemic trip routes (2,360), shown in Figure 5*b*. The inset map shows trips made in the student-housing neighborhood (called West Campus)

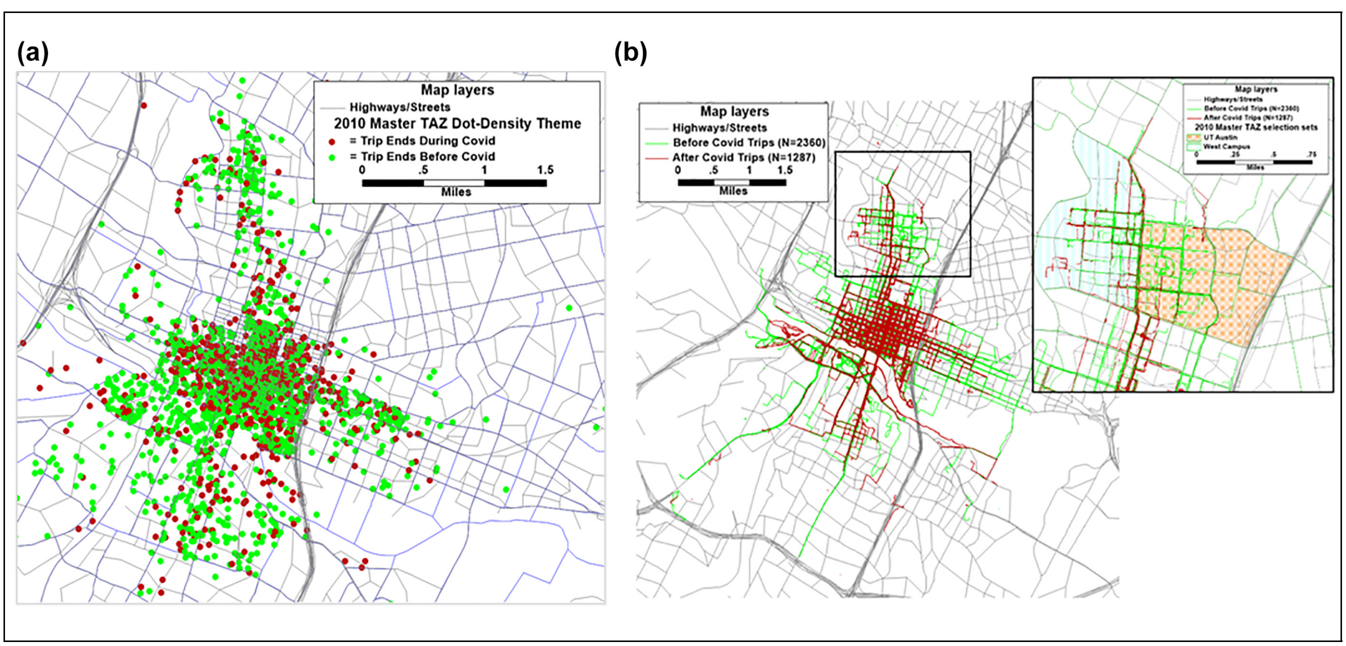

Figure 5. (*a*) Change in trip ends by time period and (*b*) change in overlaid trip trajectories by time period.

Figure 6. (*a*) Average daily trips (prepandemic), (*b*) average daily trips (during pandemic), (*c*) desire lines (prepandemic), and (*d*) desire lines (during pandemic).

and the UT Austin campus. There was a noticeable decline in on-campus and intra-West Campus e-scooter trips during the pandemic. The second observation from the larger map is that trips tended to be centered around the downtown gridded network. This means that although trips were longer during the pandemic, they were more concentrated in the downtown region. Moreover, whereas there were fewer trip ends at parks, the trip trajectory data showed trips taking trails and paths in parks while en route to their destination.

To better understand changes between trip ends, we created maps showing average trip count by road segment (Figure 6, *a* and *b*) and desire lines between TAZ centroids (Figure 6, *c* and *d*). Before the pandemic, trips tended to be distinctly separated between UT Austin and the downtown core. During the pandemic there seemed

Table 3. TAZ Socioeconomic Attributes Explaining Increased Trip Ends (Average)

Name	TAZs with any trips	Increase in origins	Increase in destinations
Population	669	751	852
Households	322	339	383
Household size (average)	1.63	1.50	1.64
Household income (median)	$40,800	$40,300	$43,600
Total employment	793	697	614
Basic employment	52.8	69.3	30.8
Retail employment	158	143	130
Service employment	466	390	437
University employment (non-UT)	104	88.7	7.96

Note: TAZ = traffic analysis zone; UT = University of Texas.

to be a greater link between West Campus/UT Austin and downtown, perhaps a result of mode shifting. Second, there were fewer trips made between residential areas and the downtown and fewer trips within downtown. Interestingly, there was an increase in east–west trips between two TAZs south of downtown that was not apparent beforehand. One explanation is that the pandemic led to more local travel, and that e-scooter use reflected this switch in destination choice behavior. A third observation was a decrease in the number of trips to/from nightlife hotspots. Before COVID-19, the Rainey Street TAZ (orange dot, Figure 6*c*) had at least five lines of medium thickness (i.e., five trips). Since bars and indoor dining of restaurants were shuttered or severely restricted in capacity during reopening, it is no surprise that a decrease in trips was observed.

Trip ends were joined with TAZ socioeconomic variables to explain changes in trip end counts between the two periods. Although 2010 TAZ shapefiles were used, this analysis used 2020 estimates of all variables. Table 3 compares TAZs experiencing an increase in either trip origins or destinations during the pandemic with TAZs having any e-scooter trip before the pandemic. Zones with an increase in trips were more populated than zones with any recorded trips. Zones with more destination trip ends than before the pandemic had more residents, larger household sizes, and higher median incomes than TAZs with increased trip origins. This suggests that this mode was used to travel home during the pandemic rather than between activities outside the home. Zones with increased trip origins had smaller average household sizes and median household incomes than zones with any recorded trips. Zones with increased destination trip ends were concentrated closer to downtown, whereas zones with increased origin ends included a portion of West Campus where students reside, which could explain the lower average household size and income variables.

One would also expect to see an increase in trips from zones with fewer jobs since more people were working from home. Although this hypothesis was true for total employment, it varied by type of employment. TAZs with higher destination numbers tended to have fewer jobs, especially less basic and retail employment. Zones with high non-UT Austin university employment did not see an increase in e-scooter trip activity. All of these results make intuitive sense given the impact of the pandemic on certain economic sectors.

Analysis of Roadway Choice

Two NB count models were developed to understand roadway choice between the pre- and during-pandemic periods. Table 4 presents the parameter estimates and Figure 7 shows the parameters' sensitivity analysis. The sensitivity plots show how average daily trip counts would change on a percentage basis if the data were to be moved by one standard deviation (or a binary change), all other conditions held constant. Table 4 indicates that the dispersion parameters (ρ) for both models were greater than zero, indicating that the data were overdispersed and an NB model was preferred over the Poisson regression model.

In relation to covariate analysis, the segments' daily VMT coefficient indicated that fewer e-scooter trips were expected on roadways with higher vehicle volumes. The sensitivity analysis showed that an increment of 6,000 daily VMT (roughly one standard deviation) led to a reduction of 10% in the average daily e-scooter trip count during the prepandemic period. During the pandemic, this reduction was higher (20%) indicating that users were traveling across roadway segments with lower vehicle volumes during this period. Similarly, the greater the posted speed limit and share of trucks, the less likely that roadway was to see a shared e-scooter trip. For example, an increment of 7 mph (approximately one standard deviation) in the posted speed led to a reduction of 15% of e-scooter trips during both periods. Interestingly, the greater the number of lanes and shoulder width, the

Table 4. Estimation Results of Negative Binomial for Daily e-Scooter Trip Counts per Roadway Segments

	Trips prepandemic			Trips during-pandemic		
	Coeff.	SE	*P*-value	Coeff.	SE	*P*-value
VMT	−1.87E-05	5.95E-06	0.00	−3.86E-05	6.12E-06	0.00
Number of lanes	0.13	0.04	0.00	0.08	0.04	0.04
Shoulder width (ft)	0.07	0.03	0.02	0.07	0.03	0.04
Speed Limit (mph)	−0.02	0.00	0.00	−0.02	0.00	0.00
Truck percentage	−0.14	0.05	0.00	−0.06	0.04	0.15
Sidewalk (indicator)	0.75	0.09	0.00	1.08	0.08	0.00
Bikelane (indicator)	0.70	0.07	0.00	0.47	0.06	0.00
Number of transit stops	0.10	0.01	0.00	0.12	0.01	0.00
Population density (per mi^2)	−5.77E-06	2.03E-05	0.78	4.50E-06	1.93E-05	0.82
Total employment density (per mi^2)	8.41E-06	9.49E-07	0.00	1.23E-05	1.06E-06	0.00
Retail employment density (per mi^2)	6.39E-05	3.76E-06	0.00	8.61E-05	4.36E-06	0.00
Residential density (per mi^2)	9.90E-05	3.44E-05	0.00	6.67E-05	3.40E-05	0.05
Household size	−0.88	0.06	0.00	−0.92	0.05	0.00
Median income ($10,000)	0.08	0.01	0.00	0.09	0.01	0.00
Intercept	−1.08	0.36	0.00	−0.82	0.34	0.02
No. of observations	8,915	na	na	na	na	na
Dispersion parameter (ρ):	1.04	na	na	0.69	na	na
McFadden's R^2	0.50	na	na	0.54	na	na
Likelihood ratio test (χ^2)	2,997	na	na	3,888	na	na
Prob $> \chi^2$	0.00	na	na	0.00	na	na
$2 \times$ loglikelihood	−6,793	na	na	−9,898	na	na

Note: VMT = vehicle miles traveled; Coeff. = coefficient; SE = standard error; *P*-value= probability value; na = not applicable.

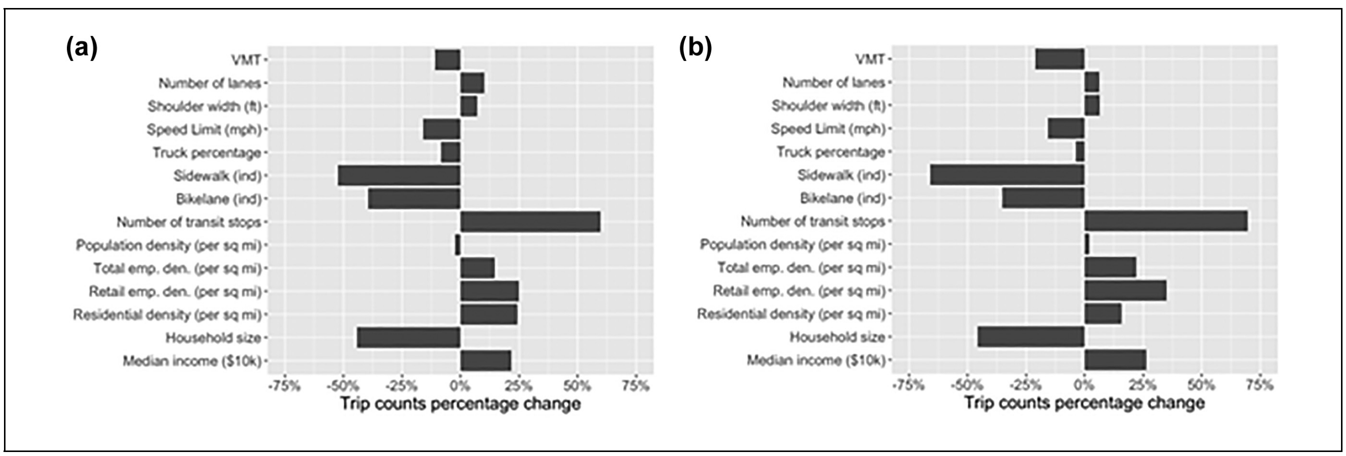

Figure 7. (*a*) Sensitivity analysis (prepandemic) and (*b*) sensitivity analysis (during pandemic).

higher the count of shared e-scooter trips. One additional lane increased the number of trips by more than 10% (prepandemic) and 5% (during pandemic). The results suggest that users were more cautious during the reopening period, with a preference for roadways with less vehicle volume and fewer lanes. Even as traffic volumes fell during the pandemic and e-scooters could take up more roadway space, they were less likely to take roads with more lanes (i.e., with higher expected VMT).

There were higher average daily trip counts on road segments with nonmotorized infrastructure (sidewalks and bike lanes). Predictably, the decline in traffic during the pandemic increased average vehicle speeds, which could explain why the coefficient for sidewalks increased from 0.75 to 1.08 and bike lanes decreased from 0.70 to 0.47. If so, e-scooter users preferred roadway segments with separated sidewalks to on-road bike lanes, even if they were protected. The number of transit stops, an indicator of pedestrian activity, presented a highly significant effect in the models, based on the sensitivity analysis. The results indicated that 4.5 more stops (one standard deviation) in the roadway segment led to an increment of 60%

in the number of e-scooter trips during the prepandemic period and 70% for the reopening period. This finding suggests that users were highly attracted to traversing segments with more pedestrian infrastructure (in addition to sidewalks) and that this effect increased during the pandemic.

The population density variable was not statistically significant at a 10% level. However, it remained in the model owing to the relevance of this variable in the demand of other modes. The sensitivity analysis also indicated that this variable did not have a high influence in the models. During the pandemic, fewer trips passed through more densely populated residential areas. For example, the sensitivity analysis showed that one standard deviation increment resulted in 25% more trips prepandemic and only 15% during the pandemic. Also, roads in TAZs with larger average household sizes showed fewer trips, but of greater magnitude during the pandemic. This could indicate the effectiveness of stay-at-home and WFH policies in reducing average daily trip counts. Job density had a positive effect on trip counts; the sensitivity analysis indicated that one would expect more e-scooter trips in areas with higher job densities during the pandemic than before. Perhaps this was a result of operational policies of positioning e-scooters in downtown areas where jobs are centrally located, and not necessarily indicative of the effectiveness of WFH policies. Roadway segments in areas with an increase of $40,000 in median income could expect 22% (prepandemic) and 26% (during pandemic) more e-scooter trips, suggesting that a greater number of trips were made in higher-income areas during the pandemic.

The effect of the pandemic on daily e-scooter trends obtained from the regression models differed in certain aspects from the daily mobility trends observed in the Austin region, as shown in Figure 1. Specifically, there were 10% more e-scooter trips in segments with a high number of transit stations, whereas the mobility trend showed a reduction of trips ending at transit stations compared with the baseline. Similarly, the model suggested that there were fewer trips in residential areas, whereas the mobility study suggested higher activity in these areas. However, it is important to highlight that the demand for e-scooters was not directly captured by the trajectory data. The data analyzed in this study corresponded to the observed trips, which were influenced by the device reposition strategy of the company.

Limitations

This study obtained trip and trajectory data from a single provider operating in Austin, TX. Spin has the second-smallest fleet size, accounting for about 6% of the 15,850 devices (*41*). Though the market share by fleet size was small, this provider had unusually high market share by trips during the reopening phase (20% to 60%), owing to the hesitancy of other vendors to restart operations (*34*). Since the availability of a device influences willingness to take a shared e-scooter, this analysis of trip and trajectory data representing user demand for this mode and route choice was inherently influenced by operational decisions (e.g., rebalancing). An absence of trips for a given spatiotemporal combination is not indicative of an absence of demand for shared e-scooters since if there are no devices within a customer's maximum access distance then an alternative mode is chosen or the trip foregone.

Exclusively using trip data potentially ignores valuable research questions, specifically, who used shared e-scooters during the pandemic, was a use change observed, and if so, why? The authors acknowledge these questions and encourage additional research in ensuring equitable access to this mode. Second, the data set of trajectories relies on the assumption that the devices' units are accurately collecting location data. The authors used a filtering approach to remove specific trips that may have biased the results, and suggest research in alternative computer-aided approaches using validated e-scooter data to filter out false data. The use of a road segment count model also ignored routes that used trails, paths, and private parking lots, which are observable in real life and in Figure 2*b*. Nevertheless, most direct routes use roadway or adjacent sidewalk and bike lane infrastructure. The count model of trips by roadway segment will capture these routes.

This study chose a segment-level count model to explain route choice behavior given the difficulty in generating choice sets in discrete choice models for a casual mode oriented for recreational trip purposes. Future work should use a modeling approach with unrestrictive choice sets and use the roadway design variables from this study that explained the changes in roadway segment usage. The models developed in this study did not account for spatial autocorrelation. It is therefore recommended that future research in the topic evaluate spatial count models for overdispersed data. Furthermore, the models did not include weather variables. Research into the topic has found that weather influences e-scooter demand (*27, 42*), therefore, analysis of e-scooter route choice in relation to weather effects is also recommended.

Conclusion

This study examined shared e-scooter trip and trajectory data in Austin, TX, before and during the COVID-19 pandemic. Our data confirmed that average shared e-scooter trip length (in time and distance) increased during the pandemic, and that temporal trends with this mode were largely undisturbed (i.e., increased trips and trip lengths during the weekend compared with weekdays). Unlike prior work, this unique data set included trajectories, which allowed for a finer analysis of route choice preferences before and during the pandemic. We built an NB count model to statistically investigate these route preferences in addition to zonal-level before–during exploratory analyses with maps.

The count model included segment-level built environment variables as well as zonal-level demographic data, including density attributes. A before-and-after pandemic modeling setting was implemented to isolate effects in these periods and to provide a sensitivity analysis comparison. The results suggested that riders may have been more cautious during the pandemic. There were more average daily trips on road segments with lower annual vehicle volume (prepandemic levels) and fewer lanes during the pandemic. Also, more e-scooter trips were taken on roads with pedestrian infrastructure (such as sidewalks and bus stops) during the pandemic than before. Roads with dedicated bike lanes did not play as large a role in route choice, which aligned with the finding that less trafficked roads may not have separated travel and bike lanes. Interestingly, riders made fewer trips in areas with larger household sizes and higher residential densities, which could be related to the effectiveness of stay-at-home and WFH policies in reducing average daily trip counts.

Our analysis suggested that shared e-scooter users are still attracted to sidewalk infrastructure, even though curb use policies often prohibit riding on sidewalks. Adding bike lanes as traffic levels return to prepandemic levels may help to keep scooters off sidewalks and help in attracting e-scooter users to these roads. The recovery for shared modes like public transit has been slow. E-scooter trips take road segments with transit routes, or at least transit stops. Given the need to address first- and last-mile connections, public transit agencies could experiment with free transfer passes to attract riders.

Exploratory zonal-level maps indicated that shared e-scooter demand fell during the pandemic in and around the main university, UT Austin, and to/from nightlife areas. This is partially explained by Spin pausing operations during the initial lockdown phase of the pandemic. There also appeared to be a decline in the number of trips made at parks, though users continued to use park infrastructure (e.g., trails, pedestrian bridges) to travel between places. Transportation officials may overlook the use of parks as active transportation assets. This trajectory data revealed that urban trails do attract e-scooter users, even if these are just leisure trips. Enforcing existing trail etiquette and rules and planning for a mix of trails and traditional bicycle/pedestrian infrastructure could attract many active transportation road users.

Data showed greater e-scooter connectivity during the pandemic between neighborhoods in South Austin (relative to downtown) and between West Campus/UT Austin and the downtown area. A plausible explanation for an increase in these trips is mode switching or the desire for recreation or to shop locally at destinations served by shared e-scooters, as suggested by the decreased daily travel distance observed in longitudinal mobility surveys (*40*). However, this study does not presuppose who these riders are or why they chose to use this mode (i.e., mode shifting analysis) and leaves this research question unanswered.

The results and methods used in this research effort could serve multiple purposes. From the policy perspective, this analysis helps to understand the effectiveness of policies aimed at reducing social contact during the pandemic. Regulations to discourage social gatherings in confined spaces, such as in nightlife districts, appear to have diminished total trips.

From the transportation point of view, this study has provided an analysis of the impact of the pandemic on shared micromobility usage, both spatially and temporally. As vehicle volumes return to (or exceed) prepandemic levels, it is critical to study and reflect on how to encourage riders to return to shared modes, like public transit and micromobility, and incorporate lessons of resiliency into these systems. From the planners' perspective, understanding the route choice of e-scooter users could improve the design of nonmotorized infrastructure, which supports shared micromobility. By improving sidewalk infrastructure and protecting or separating bike lanes from travel lanes, cities could attract more active transportation users.

From a research perspective, this study has shown the usefulness of trajectory data in developing diverse research analysis and providing methods that could be used while also protecting personally identifiable information.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: M. D. Dean, N. Zuniga-Garcia; data collection: M. D. Dean, N. Zuniga-Garcia; analysis and interpretation of results: M. D. Dean, N. Zuniga-Garcia; draft manuscript preparation: M. D. Dean, N. Zuniga-Garcia. All authors reviewed the results and approved the final version of the manuscript.

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ORCID iDs

Matthew D. Dean https://orcid.org/0000-0002-0346-4316
Natalia Zuniga-Garcia https://orcid.org/0000-0002-1538-3599

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