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Patterns and predictors of dockless bikeshare trip generation and duration in Boston's suburbs

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ABSTRACT

The introduction and proliferation of privately-operated dockless bikeshare systems across North America has caught many public planning agencies, who seek evidence to recognize the extent of dockless bikeshare adoption in their communities and its impact on existing transportation systems, by surprise. In this study, we investigate systemwide travel patterns during the first 18 months of a dockless bikeshare program in the Greater Boston region. Specifically, by identifying neighborhood-level predictors of dockless bike access and usage, this study offers insights into the spatial equity-related impacts of this promising active mobility option in Boston's suburbs, which have limited access to the region's decade-old public dock-based bikeshare system. Utilizing spatiotemporal route-level data provided by the sole dockless system operator to model bikeshare trip generation and duration, this study finds that neighborhoods with a higher share of renter-occupied housing and historically disadvantaged populations had less access to dockless bikes while also exhibiting higher rates of bike usage. We conclude that this undesirable finding may be addressed by implementing safeguard policies such as an equitable dockless bikeshare rebalancing scheme.

1. Introduction

Dock-based bikeshare systems in North America have experienced sustained growth in the ten years since becoming a public mobility service, with the addition of privately-operated dockless systems now offering an exciting opportunity to expand bikeshare services into new communities. Each system allows residents, workers, and visitors of the communities they serve with short-term, on-demand access to a travel option that does not require the same monetary costs and responsibilities of personal bike ownership (Xu et al., 2019). Moreover, dock-based as well as dockless bikeshare systems offer communities lacking good public transit service with a sustainable mobility option bearing notable environmental benefits related to traffic congestion and greenhouse gas emissions reduction. Taken together, bikeshare systems offer communities with a viable solution for addressing immediate concerns of transport poverty and disadvantage.

Unfortunately, inequitable access to bikeshare stations—due to unfulfilled systemwide visions for station placement or a lack of supportive low level of traffic stress bike infrastructure—has been evident in some communities. As a result, some public dock-based systems (Smith et al., 2015) provide limited benefits for underserved residents and communities while exacerbating existing social disparities related to transportation access. While recent research and policy actions have sought to help alleviate the equity-related concerns of dock-based bikeshare access (Mooney et al., 2019), growing concerns surround emergent dockless systems where cities lack evidence needed to implement, maintain, and manage the spatial access afforded by redistributing bikes in these privately-operated systems (Hirsch et al., 2019) that may focus more on maximizing trip generation and profit rather than preserving a minimum standard of community access.

This study aims to bolster the limited evidence base regarding spatial equity to dockless bikeshare services by examining how the introduction of a dockless bikeshare system to Greater Boston changed the region's transportation landscape. Beyond summarizing the travel patterns of dockless bikeshare trips in the first year and a half of its operation in Boston's inner-ring suburbs, the objective of this study is to examine the neighborhood-level predictors of dockless bike access and usage. An assessment of how socioeconomic characteristics relate to these separate

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dockless bikeshare outcomes offers insight into the spatial and social equity-related impacts of this promising active mobility option.

2. Literature reviewer

2.1. Bikeshare and social equity

In offering a new mobility option, bikeshare, whether dock-based or dockless, has the potential to benefit members of society who do not have the financial means to own and maintain a private vehicle as well as those who reside within a neighborhood unsupportive of sustainable travel options that would permit them improved access to employment opportunities and essential goods and services (Shaheen et al., 2014; Ricci, 2015; Murphy and Owen, 2019). Unfortunately, an inequitable distribution of docking stations or bikes may restrict the benefits of these services for individuals confronted by transport poverty or who reside in areas of transport disadvantage.

While surveys on the socioeconomic composition of dockless bikeshare users have been scarce, evidence from dock-based bikeshare surveys suggest that significant population segments, especially lower-income residents and people of color, remain underrepresented as system users by producing fewer bikeshare trips (Shaheen et al., 2014; Buck et al., 2013; McNeil et al., 2018). In analyzing station locations to examine social inequity in early American dock-based systems including Boston's Hubway (now Bluebikes), Ursaki and Aultman-Hall (2015) found that white residents were more likely to reside inside a 500-meter buffer of a docking station as were households earning less than $20,000 per year. However, the authors also discovered that the mean percentage of African Americans per block group living inside bikeshare service areas was significantly lower than the percentage residing outside of the service area. Given the understood importance of access to docking stations toward bikeshare service utilization (Saviskas and Sohn, 2015), the disproportionate distribution of bikeshare stations in neighborhoods with more people of color reflects a clear barrier to their participation in bikeshare systems (Smith et al., 2015). Aside from station siting, other identified barriers to dock-based bikeshare system use by a more diverse population include fee structure, payment systems, and rental cost as well as any promotion, outreach, and marketing activities without a lens toward equitable considerations (Howland et al., 2017).

Overall, the users of dock-based bikeshare systems in North American cities tend to be white, non-Hispanic individuals who are employed full- or part-time with higher levels of income and educational attainment (Fishman, 2016; Hosford and Winters, 2018). An internal survey ($n = 233$) of dockless bikeshare users in the Boston suburbs conducted by Lime and the Metropolitan Area Planning Council in June 2019 largely echoed the socioeconomic trends found in surveys of dock-based system users. In the Boston survey, over 70 percent of respondents reported working full time, living in households earning more than $75,000 annually, and having an Associate, Bachelor's, or advanced college degree. Taken together, the literature seems to support the notion that bikeshare has yet to capture high levels of participation from historically disadvantaged populations, despite their promise to help offer greater access to jobs, goods, and services for communities of concern (Qian and Niemeier, 2019).

2.2. Bikeshare trip generation models

Past studies have explored the relationship between socioeconomic and built environment factors measured at a neighborhood level and trip generation rates of dock-based bikeshare systems (e.g., Faghih-Imani et al., 2017b; Noland et al., 2016; Wang et al., 2016). General agreement in these dock-based bikeshare studies points to higher population and employment density along with an increased supply of docking stations and bike-friendly facilities as indicators that are positively associated with demand (Tu et al., 2019). However, those studies to-date that have examined the neighborhood-level predictors of dockless bikeshare demand—some of which are noted in detail below—have largely took place outside of the United States' social and environmental context.

Guidon et al. (2019), studying eight months of transaction data from an electric bikeshare service in Zurich, Switzerland by using a negative binomial model, found population and employment density as well as areas with good public transit access and higher-income residents were positively associated with demand. These findings may indicate that shared mobility services rely on a functioning public transit system, but that the high relative cost of dockless bikes to public transit may make the former a more attractive option to higher-income individuals. Examining one-month of dockless bikeshare data from Shanghai, China by using a generalized additive mixed model following a Poisson distribution, Tu et al. (2019) determined that neighborhoods with greater bus and rail station density had no significant impact on bike activity, while districts with increased roadway density and land use mixing had a significant and positive association. In assessing the environmental determinants of dockless bike trip generation over four months in Singapore, Xu et al. (2019) echoed the prior findings, noting that grid cells with higher residential and employment densities, greater land use mix, more robust road and bike network infrastructure, and better access to public transit stations generated more demand; with transit station proximity appearing to be a first-mile facilitator rather than a last-mile solution. Finally, Mooney et al. (2019) investigated the spatial equity of dockless bike access during a six-month pilot program—with Lime as one of three operators—in Seattle, Washington. Their study findings did not detect significant racial or ethnic disparities regarding dockless bike access but noted that neighborhoods with greater bike availability and shorter idle times between bike rentals tended to have households with higher median incomes and more college-educated residents.

While limited in quantity and varied in context, these studies suggest that some dockless systems may have uneven bike distribution across their service areas (at least in larger urban areas) and that their usage is most frequent in neighborhoods of high density with mixed land uses and multimodal network access that are more economically privileged. This study seeks to strengthen this nascent knowledge base with a longer-term assessment of what socioeconomic and environmental factors are related to dockless bike availability and activity in an American suburban setting.

2.3. Bikeshare trip duration models

While studies of bike speed prediction have incorporated trip duration, the bikeshare literature is sparse on studies that have explicitly modeled the latter travel time outcome (Ghanem et al., 2017). Using data from New York City's dock-based CitiBike system, Faghih-Imani et al. (2017a) compared bikeshare and taxi trip durations to identify origin, destination, and trip attributes predictive of more competitive bike trips. Results of their panel mixed multinomial logit model indicated that improved bike facility access would decrease bikeshare trip duration and that modal competition is the greatest in areas of higher job density. In another study of CitiBike users, Ford et al. (2019) estimated a least squares model of trip duration for commuters cycling to Manhattan's Financial District, finding that distance, arrival time, and demographic predictors of age and gender were significantly associated with bike commute durations. Building on a multiple linear regression model of dock-based bikeshare trip duration in San Francisco, Ghanem et al. (2017) used machine learning techniques to similarly discover that trip distance and time-of-day were strong predictors of travel time. Their Bay Area study also noted the strong predictive power of subscription type, which may be indicative of a cyclist's familiarity with a road network and ability to exert greater power, and several weather-related factors such as temperature, wind, and precipitation. Lastly, Zhao et al. (2015) explored the travel time differences by day-of-the-week and gender for a dock-based bikeshare system in Nanjing, China, finding that males generally experience shorter trip durations for comparable origin–destination pairings and that weekday trips that are less likely to be

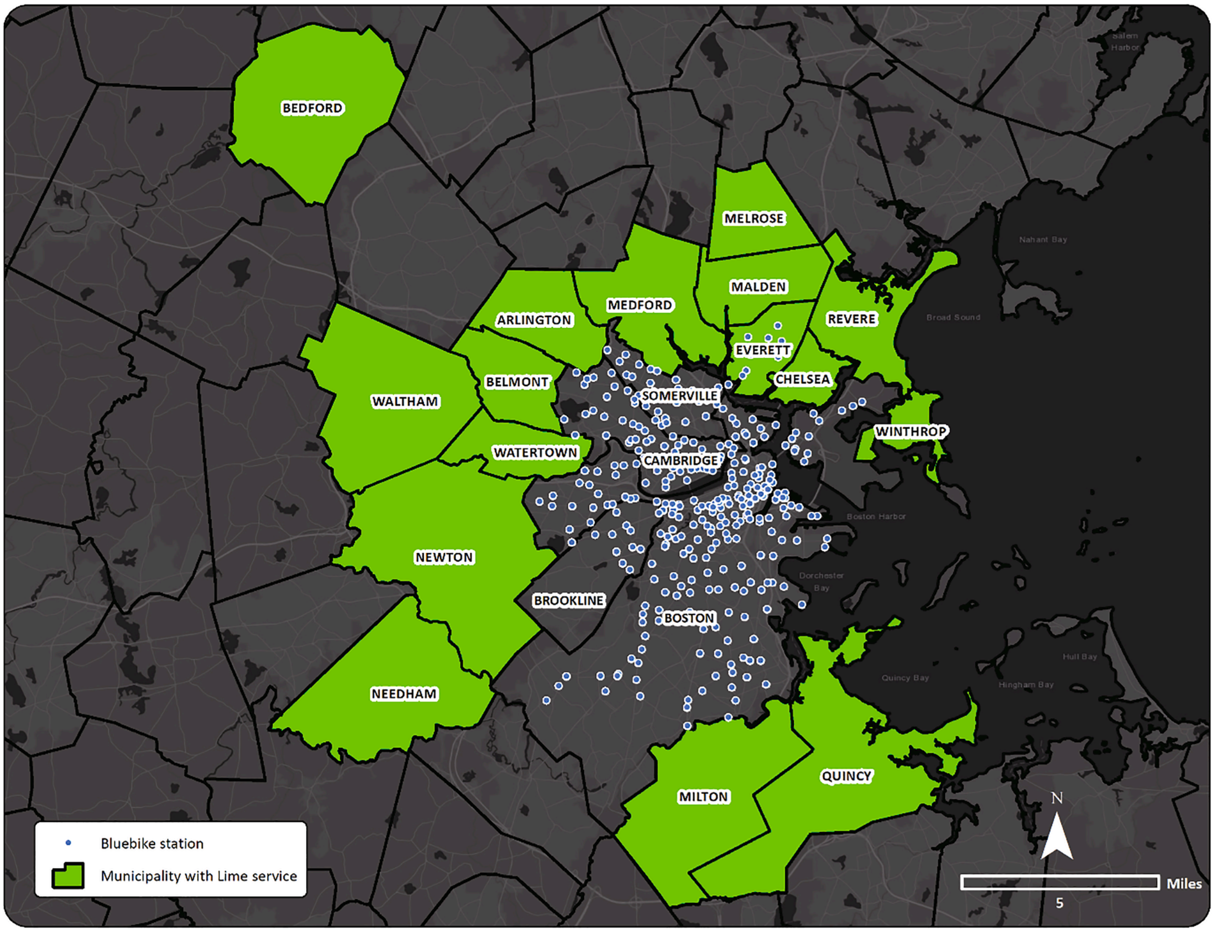

Fig. 1. Municipalities with either dock-based or dockless bikeshare services in the Greater Boston region.

for recreational purposes have lower travel times. These studies demonstrate the significance of individual-level, area-wide, and trip-specific predictors of bikeshare trip duration; however, each of the reviewed studies examined older dock-based systems and lacked requisite GPS data for modeling route-level in addition to neighborhood-level determinants.

3. Methods

3.1. Study area

Lime introduced its dockless bikeshare services to Massachusetts in September 2017 as a pilot program with the City of Malden. Over the next two years, 15 additional municipalities located in the inner core of the Greater Boston region would similarly form a partnership with Lime. Fig. 1 displays the distribution of these dockless bikeshare communities, which notably does not include Boston, Brookline, Cambridge, or Somerville. Due to conditions established in a contract between the Metropolitan Area Planning Council and Motivate, who operates the dock-based bikeshare system (Bluebikes) in the four municipalities, these communities are unable to participate in the regional dockless bikeshare program with Lime. In fact, the City of Everett is the only community with both dock-based Bluebikes and dockless Lime bikeshare service, as the community joined the Bluebikes system in Spring of 2019 under the terms of an updated contract that permitted the simultaneous operation of both bikeshare systems.

3.2. Dockless bikeshare data

Dockless bikeshare data used in this study span in time from April 2018, the conclusion of the Malden pilot and formal expansion into other participating municipalities, through September 2019. Trip-level data for all dockless bikeshare system communities were accessed using Lime's Application Programming Interface (API), which followed the Mobility Data Specification (MDS) format originally created by the Los Angeles Department of Transportation. Data within the provider component of MDS offered both spatial (e.g., trip distance) and non-spatial (e.g., propulsion type) fields analyzed in this study. Trip distance was believed to be the actual on-road distance of the observed trip, as determined by Lime based on collected point locations. Also, of importance to the study design, information regarding the individual Lime cyclist was not provided in the MDS. In all, the unfiltered dockless bikeshare data set comprised upwards of 500,000 trips and 26.5 million GPS points for the 18-month period in which Lime was the sole dockless bikeshare operator in the study area.

As is the case with many publicly operated dock-based systems, Lime provided spatiotemporal information on each trip end. However, unlike dock-based system data, having GPS points detailing the one-half-million dockless bike traces in this data set allowed for the research team to map and analyze the specific routes traveled by system cyclists. To do such, though, the research team undertook a series of steps to handle those GPS points of a lower accuracy rating that produced noise within the data set by placing points in the observed trace that were far from the actual traversed route. Additionally, in the Lime API data set provided for the first 15 months of the sampled timeframe, there were no more than 52 GPS points made available for any given trip; a limitation acknowledged and addressed by Lime for traces recorded in the last three months. A consequence of this artificial cap on GPS points was that segments of some trips were not fully recorded, or in certain instances, multiple successive GPS points recorded identical coordinates, followed

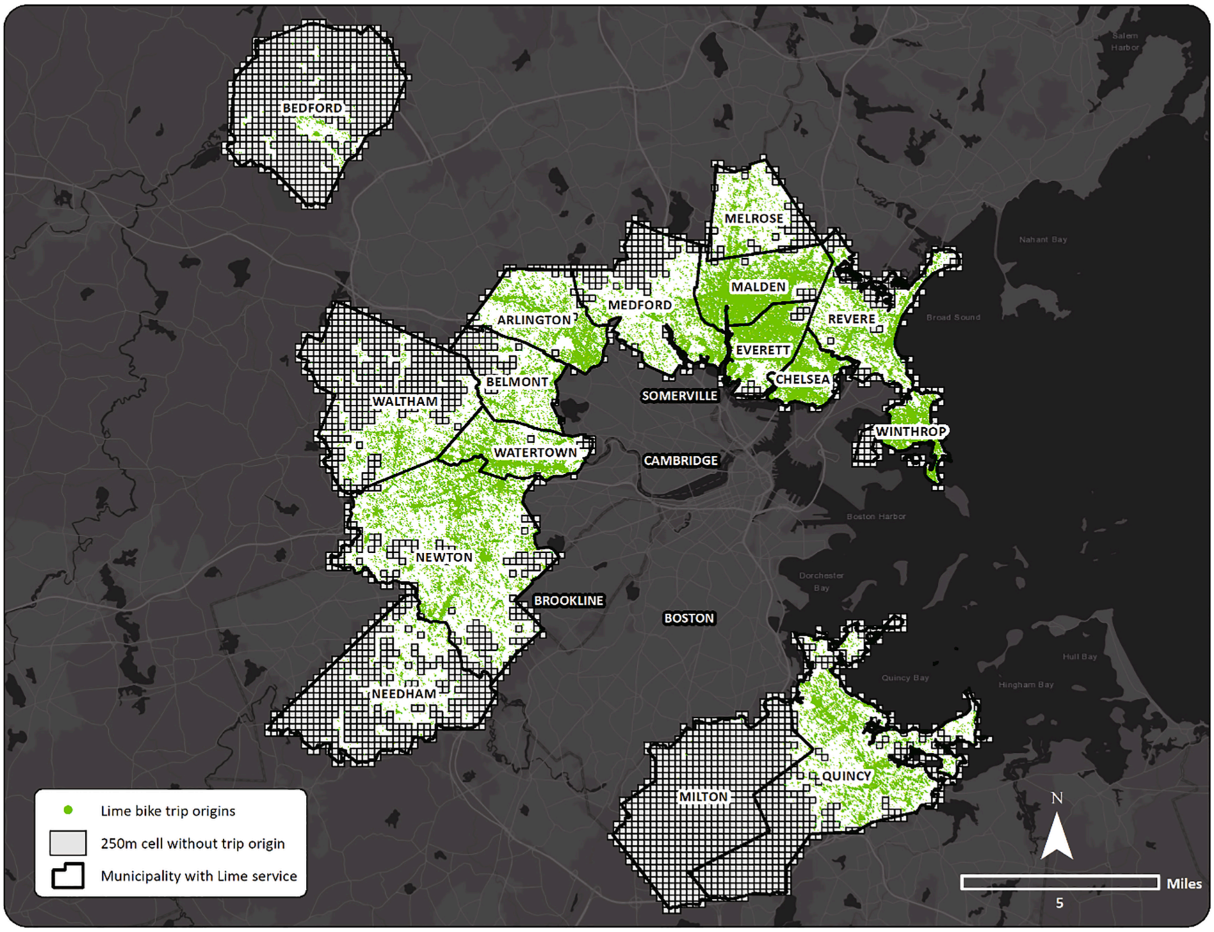

Fig. 2. Boston-area municipalities with Lime dockless bikeshare and trip origin locations from April 2018 to September 2019.

a short time later by a point placed far away. Another shortcoming of the provided data was that nearly one quarter (22.5%) of trips in the raw data contained no intermediate GPS points or recorded trip distance but merely distinct start and end locations. These "zero-distance" trips only offered information on dockless bikeshare trip production and attraction locations, while processes to clean traces with the aforementioned anomalies were pursued to retain as many observed routes as possible.

3.3. Dockless bikeshare data processing

Each trip in the API-retrieved Lime dockless bikeshare data set was provided as a set of raw GPS points—recorded at equal intervals—without the accuracy needed to properly align them to the street network. Therefore, data processing steps were employed to improve the geolocation of GPS points along each trace of an observed route to better align these nodes to the street network. For this study, a method to clean Lime's raw dockless bikeshare data was implemented based on trip durations, distances, origin and destination locations, travel speeds, and the count of recorded GPS nodes.

First, raw data were filtered to remove records identified as outliers or which were missing requisite travel information, records with trip durations of less than one minute or greater than five hours, records with trip distances shorter than 100 m or longer than 20 km, and records with GPS points located outside of the Greater Boston region. There were multiple factors believed to have contributed to the generation of these outliers, including general bike disrepair, malfunctioning GPS unit, Lime user error or indecision (i.e., unlocked and quickly re-locked bike), and the cap placed on the quantity of GPS nodes collected. Yet, after applying these filters, a set of these qualified trips remained compromised by the existence of missing or errant data due to the artificial cap in collected nodes per trace and inaccuracy in GPS devices, respectively, which resulted in some unrecorded portions of a qualified trip.

For cases in which multiple successive GPS points with identical coordinates were followed by a GPS point that was next in the sequence but located far away from the overlapping cluster, a high-speed successive step was produced in the raw data set. The speed of these successive steps was adjusted by removing the extra coincidental points and calculating the travel time interval for the larger step beginning with the timestamp of the first overlapping (and zero-speed) point and terminating with the timestamp of the next unique GPS point in the trace's sequence. An updated speed for this two-node segment was calculated by dividing the reported distance between the two unique points by the observed duration of this larger step. Any such non-continuous route in which the following set of conditions were unmet was filtered out of the sample data set: the newly calculated speed between the successive points elapsed 12 m/second (or 27 miles/hour), the straight-line distance calculated between the two successive and distinct points was greater than 200 m, and the distance of the adjusted link reflected less than one quarter of the trace's overall distance. This process, which improved the quality of Lime's raw route-level data set, produced 424,169 route links associated with a total of 304,102 trips (1.39 links per trip). Only 40 percent of those trips had a single contiguous trace that connected the trip origin and destination, while meeting the three standards concerning small intranodal distances, short time gaps, and reasonable travel speeds. The sample was then reduced further to only account for trips generated in the boundaries of the 16 municipalities with official Lime adoption policies.

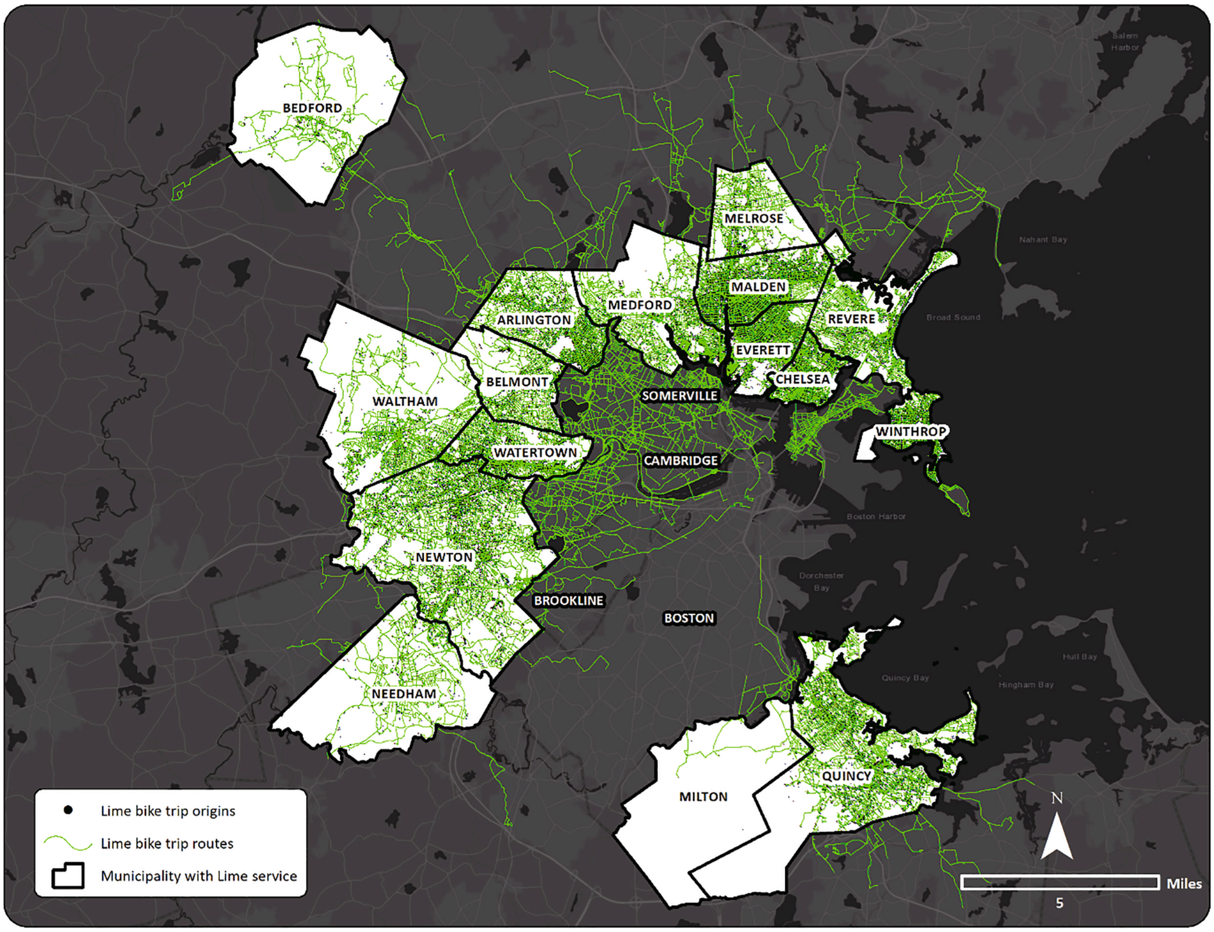

Fig. 3. Boston-area municipalities with Lime dockless bikeshare and trip routes from April 2018 to September 2019.

The remaining route links were then entered into an open-source routing engine, GraphHopper, to assign each link to a specific facility found in the OpenStreeMap (OSM) network. Utilization of a network routing engine for this map matching exercise—rather than simply snapping the GPS points to the nearest network link—was a process necessary to avoid the creation of impossible or unreasonable bike routes. Yet, many observed trips crossed through plazas or parking lots, while other trips traversed sidewalks and pedestrian-only facilities or contraflow on a one-way street; each an action not permitted in the default GraphHopper cyclist profile. In response, this study generated a new cyclist profile that better mirrored the observed travel patterns of Lime cyclists by preventing circuitous routes that would result from routed trips being forced to approach each subsequent GPS point via a legally-sanctioned use of the street network and enabling routed trips to also use the OSM network elements tagged for pedestrian-only uses such as sidewalks on a one-way street. The map matching algorithm utilized a Hidden Markov Model to find the most likely route as determined by the sequenced timestamps of each successive GPS node (Newson and Krumm, 2009). More specifically, for each GPS node, a set of candidate points on the OSM network within a certain radius of each GPS point was computed, with the Viterbi algorithm then used to process the most likely sequence of matched points determined by considering the distances between each GPS node and its candidate points as well as the routing distance between consecutive map matching candidates. Each candidate point was determined by using the GraphHopper routing engine, as were updated routing distances.

3.4. Dockless bikeshare trip generation

By using the 271,058 trip origins in the cleaned Lime API data set, a next analytic step was to examine the count of dockless bikeshare trips generated across the Boston suburbs as a function of the socioeconomic context and built environment near each trip origin. Poisson regression models are the benchmark for analyzing discrete count data by restricting the variance and mean of the sampled data to be equivalent, conditional on a set of predictors (Cameron and Trividi, 1990), and have been estimated in earlier bikeshare trip generation studies (Corcoran et al., 2014; He et al., 2019). Several tests of overdispersion exist to assess whether this implicit assumption of variance and mean equivalence has been met, with any violation of this restriction requiring the estimation of a negative binomial model that relaxes the Poisson assumption. This study employed the standard regression-based procedure for testing this property.

An extension of a Poisson model is the zero-inflated Poisson (ZIP) model, which is a model for count data with excessive zeros and large counts (Lambert, 1992). The ZIP model specification addresses situations where more zeros are observed than would be predicted by a normal Poisson model, with an assumption that the disproportionate count of zeros can be explained by more than one reason. For this study, where dockless bikeshare trip generation counts were aggregated to a system of 250-meter grid cells casted over the Lime service area, a zero could reflect whether a bike was available for use within a given grid cell or the number of times any available bikes in the grid cell were chosen for travel. Thus, the conditional probabilities in this Poisson process can be modeled as (Greene, 2012):

$$Prob(z_i = 0|\mathbf{w}_i) = F(\mathbf{w}_i, \gamma)y \text{ will equal zero}$$

$$Prob(y_i = j|\mathbf{x}_i, z_i = 1) = \frac{exp(-\lambda_i)\lambda_i^j}{j!}y \text{ will be a count variable}$$

In the first Poisson-gamma probability, let z_i denote a binary indicator of bike availability in grid cell i with a set of $\mathbf{w}_i$ characteristics. The second conditional probability offers j as a non-negative value and denotes each y_i as being drawn from a Poisson population with parameter λ_i, which is the expected count of trips generated per grid cell and related to $\mathbf{x}_i$ characteristics.

The grid cell characteristics denoted in the two conditional probabilities above were identical for this study and reflected socioeconomic context and built environment predictors. Socioeconomic characteristics for each grid cell were measured as tract-level indicators derived from the 2014–2018 American Community Survey (ACS) and defined distributions of residents by sex, age, educational attainment, annual household income, and race/ethnicity and their households by tenure and vehicle ownership. A grid cell was given the socioeconomic context of the census tract that was nearest to its centroid. A similar association was made for built environment predictors that were measured at a block group geography and created using ACS data as well as the 2016 Longitudinal Employer-Household Dynamics data set and transit information provided by the Massachusetts Bay Transportation Authority. The contribution of each created predictor to a base trip generation model—with an intercept and categorical factor denoting time elapsed since Lime was authorized to begin operation in the municipality encompassing a grid cell—was iteratively tested using a stepwise process. In constructing the final model, the variable with a p-value less than 0.05 in either the zero-inflated or count model that produced the greatest improvement to the model's loglikelihood was successively added to the base specification, where any variable having a variance inflation factor greater than three being excluded from this forward selection process.

3.5. Dockless bikeshare trip duration

To complement the trip generation results, a second analysis examined the predictors of trip duration by using a subset of 98,738 trips in the cleaned Lime API data set with complete routes and that originated in the study area. Beyond investigating the neighborhood socioeconomic context and built environment characteristics at each trip's origin and destination that predict trip duration, this supplementary analysis also examined the impact of several trip- and route-specific determinants using multiple linear regression. Trip characteristics pertaining to weather were derived using National Centers for Environmental Information data from the National Oceanic and Atmospheric Administration, while seasonal and daily travel period information were created using trip-level timestamps in the Lime API data set. The route-specific trip distance measure—created from applying the GraphHopper routing engine—was also explored in the model specification process, as was the percent of the observed route's distance on low, moderate, and high level of traffic stress facilities (Gehrke et al., 2020).

4. Results

4.1. General travel patterns and descriptive statistics

Within the 16 Massachusetts municipalities that officially launched Lime dockless bikeshare services prior to October 2019, there were 271,058 intra- or intermunicipal trips with a duration of at least one minute. Within this sample, human propulsion powered 163,661 (60.38%) trips, with the remaining trips completed using an electric bike. The City of Malden, which was the first to pilot with Lime in 2017, had the most trips (77,949; 28.76%) within the 18-month study period, followed by Everett (36,630; 13.51%), Newton (29,122; 10.74%), Chelsea (22,078; 8.15%), and Arlington (21,452; 7.91%). The Towns of Milton and Bedford, which are located on the periphery of the study area, had the lowest participation rates of any municipality, with 64 (<0.01%) and 972 (0.36%) trips, respectively. Fig. 2 offers a map of the study area with origin locations for all sampled trips, while Fig. 3 provides a map of the subset of these trips that had a continuously observed route.

Examining temporal characteristics of the study sample, a majority of cycling trips took place during the summer months of June, July, and August (137,389; 53.41%); while, 28,444 (11.06%) trips were performed during the colder winter months of December, January, and February. The day-of-the-week distribution of trips was fairly balanced, with Fridays (42,824; 15.80%) witnessing the highest trip volume and

Table 1
Descriptive statistics for 250-meter grid cells in Boston-area municipalities.

Variable	Mean	St. Dev.	Minimum	Maximum
Lime Dockless Bikeshare Trips	43.16	181.69	0	8120
Human propulsion	46.81	155.32	0	5148
Electric	30.72	87.39	0	2972
Socioeconomic Context				
Sex: Share of male residents	0.48	0.04	0	0.82
Sex: Share of female residents	0.52	0.04	0	0.70
Age: Share of residents <18 years old	0.20	0.06	0	0.46
Age: Share of residents 18–34 years old	0.23	0.11	0	0.79
Age: Share of residents 35–44 years old	0.13	0.03	0	0.30
Age: Share of residents 45–64 years old	0.27	0.05	0	0.55
Age: Share of residents 65 years old or more	0.16	0.05	0	0.33
Education: Share of adults less than Bachelor's	0.30	0.15	0	0.88
Education: Share of adults Bachelor's	0.19	0.05	0	0.36
Education: Share of adults Master's or PhD	0.21	0.10	0	0.50
Race/Ethnicity: White, non-Hispanic	0.71	0.15	0	0.96
Race/Ethnicity: Black/African American	0.06	0.09	0	1.00
Race/Ethnicity: Asian	0.12	0.08	0	0.57
Race/Ethnicity: Latinx/Hispanic	0.05	0.07	0	0.73
Race/Ethnicity: Other distinctions	0.05	0.05	0	0.62
Income: Share of households less than $35,000	0.19	0.11	0	1.00
Income: Share of households $35,000-$75,000	0.21	0.09	0	1.00
Income: Share of households $75,000–150,000	0.28	0.07	0	0.45
Income: Share of households $150,000 or more	0.32	0.16	0	0.68
Tenure: Share of owner-occupied housing units	0.65	0.20	0	1.00
Tenure: Share of renter-occupied housing units	0.34	0.19	0	1.00
Vehicles: Share of households 0 cars	0.04	0.07	0	1.00
Vehicles: Share of households 1 car	0.24	0.12	0	0.71
Vehicles: Share of households 2 cars	0.47	0.12	0	0.78
Vehicles: Share of households 3 cars or more	0.25	0.12	0	1.00
Built Environment				
Persons per acre	8.45	9.12	0	129.55
Jobs per acre	3.89	6.31	0	60.48
Share of retail jobs	0.15	0.19	0	1.00
Retail jobs per acre	0.60	1.22	0	14.93
Share of service jobs	0.59	0.27	0	1.00
Service jobs per acre	2.22	4.22	0	46.82
Share of financial jobs	0.06	0.09	0	0.99
Financial jobs per acre	0.36	1.99	0	59.63
Persons and jobs per acre	12.34	11.58	0	136.27
Jobs-population ratio	2.56	66.45	0	3,706
Balance of retail, service, and financial jobs	0.26	0.25	0	0.91
100-meter commuter rail walk shed	0.01	0.09	0	1.00
100-meter rapid transit walk shed	0.01	0.12	0	1.00

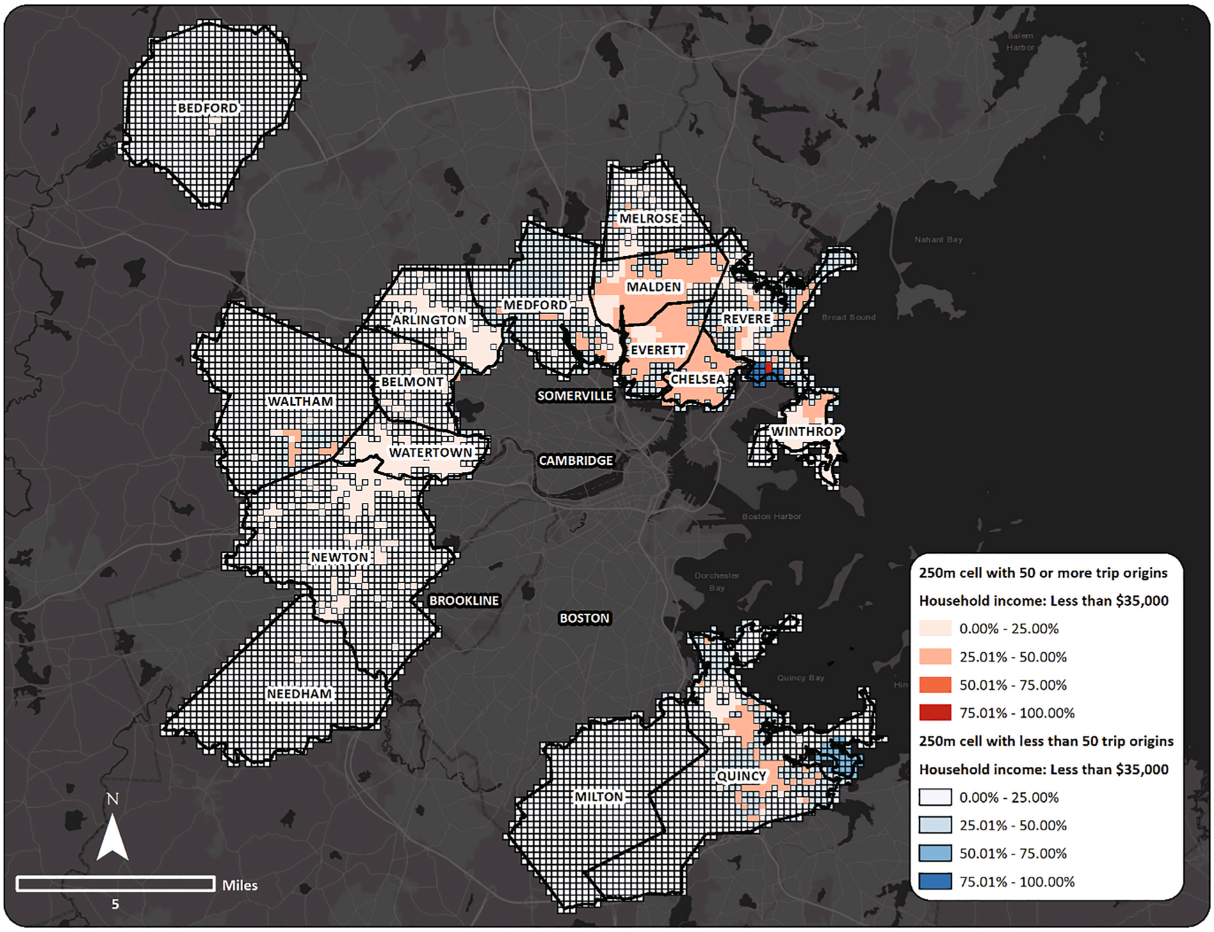

Fig. 4. Lime dockless bikeshare activity from April 2018 to September 2019 and low-income households.

Sundays having the lowest (35,199; 12.99%). Looking at seven daily time periods, Lime bike trips were most popular on weekdays between 10am and 2 pm (73,587; 27.15%), followed by weekends from 2am to 7 pm (61,653; 22.75%), weekday evening peak period (42,705; 15.75%), morning peak period (38,081; 14.05%), weekday mornings from 2am to 6am (27,360; 10.09%), weekend evenings (14,053; 5.18%), and weekday evenings (13,619; 5.02%). The average individual-level cycling trip in the sample lasted over 17 min, while the mean duration for trips on an electric bike was 14 min and 37 s. Grid-level summary statistics for trip duration and trip generation as well as measures describing the socioeconomic context and built environment, which were utilized in the two modeling analyses, are noted below in Table 1.

Fig. 4 and Fig. 5 visualize the spatial distribution of 250-meter grid cells with dockless bikeshare activity thresholds above or below the approximate areawide mean coupled with the share of households in a grid cell with an annual income less than $35,000 and share of racial/ethnic minority people, respectively. In examining Fig. 4, the municipalities of Malden, Everett, and Chelsea have a higher representation of grid cells with above-average dockless bikeshare activity (50 or more trips generated over the study period) and higher shares of low-income households. Revere and Quincy also have areas revealing this association, but also have notable portions of their jurisdictions with high concentrations of low-income households and lower levels of dockless bikeshare trip generation. Turning to the connection between racial/ethnic minority population distribution and dockless bikeshare activity shown in Fig. 5, grid cells in Malden and Chelsea appear to reveal an overall positive spatial association. However, several municipalities including Everett, Quincy, Revere, and Waltham have sets of grid cells with a minority-majority residential population yet a below-average count of originating dockless bikeshare trips.

4.2. *Predictors of dockless bikeshare trip generation*

The results of the zero-inflated Poisson (ZIP) model of dockless bikeshare trip generation counts are shown in Table 2. A decision to estimate a ZIP model with White-Huber standard errors was reached after a base Poisson model with a similar specification—only including a three-level categorical predictor pertaining to months passed since a formal policy was adopted to allow Lime to function in a particular municipality—was found to not fit the data set ($\chi^2 = 6,462.43, df = 6,277$) and underpredicted its number of observed zeroes. A zero-inflated negative binomial model specification was not pursued given that the ZIP model produced a theta value of 0.15. Theoretically, the estimation of a zero-inflated model was supported by the likelihood that a set of 250-meter grid cells were likely to have never had a Lime bike found within their boundaries during the study's timeframe; thus, no dockless bikeshare trip could ever be generated in these geographic units.

Reference to the zero-inflation model where grid cells without a generated bikeshare trip are zero based on the unavailability of a dockless bike offers insight into the distribution of these micromobility options in Boston's suburbs. Grid cells in municipalities where Lime was approved to operate its dockless bikeshare service for seven months to one year experienced a wider distribution of bikes than those grid cells in municipalities with a more recent operations agreement with Lime ($\beta = -0.31, p < 0.01$); underscoring the notion of elapsed time as a requisite for greater network coverage during the first year. Concerning the built environment context, grid cells with a higher population ($\beta = -0.21, p < 0.01$) and job density ($\beta = -0.07, p < 0.01$) were less likely to have bicycle unavailability, an expected outcome. If a grid cell intersected a 100-meter walkshed surrounding a commuter rail station, then the expectation of the cell to not have an available dockless bike

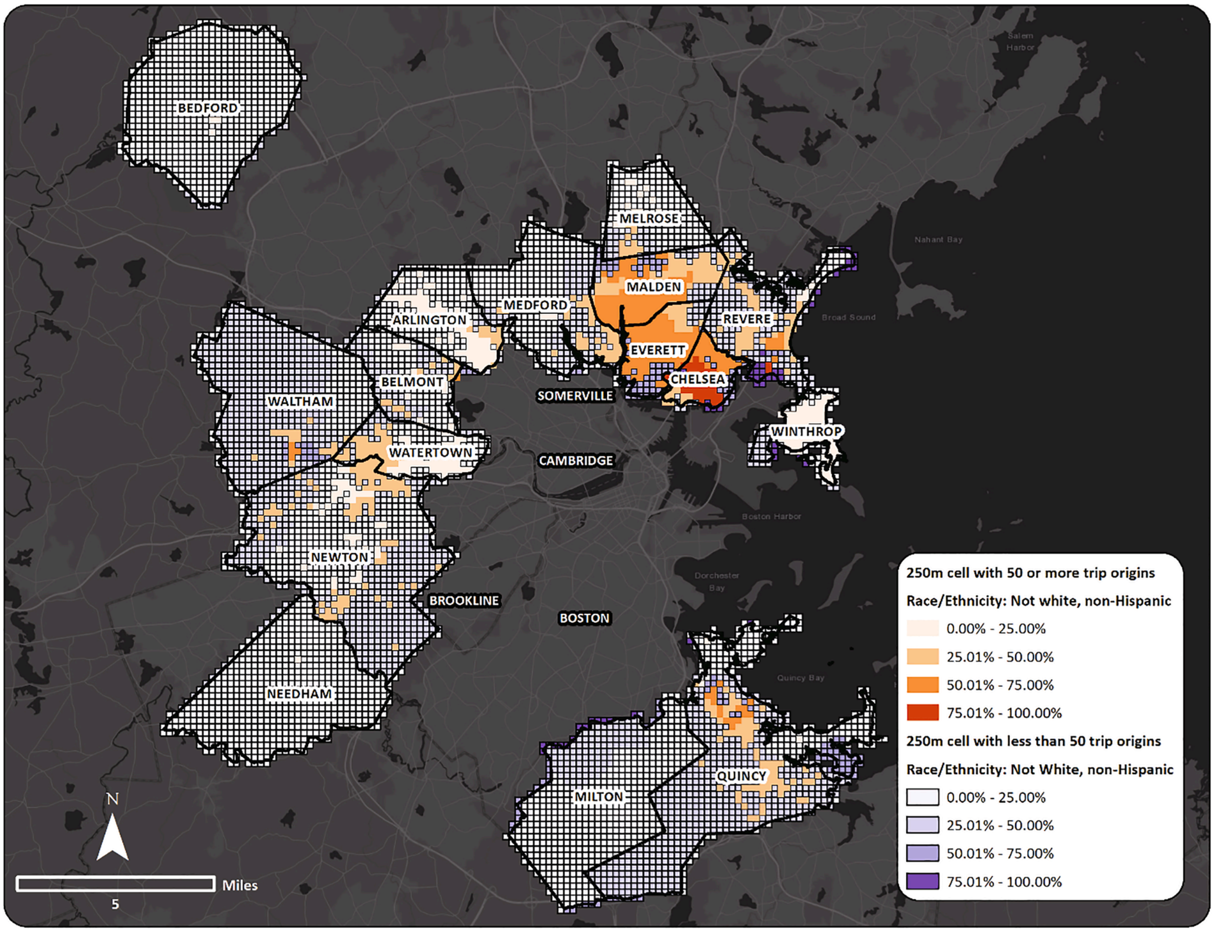

Fig. 5. Lime dockless bikeshare activity from April 2018 to September 2019 and racial minority population.

decreased by a factor of 0.04 ($\beta = -3.16, e^{\beta} = 0.04, p < 0.01$) while holding all other model predictors constant. This finding supports efforts by Lime and local governments to distribute dockless bikes near these suburban stations to provide rail passengers a last-mile option and the likelihood that some dockless bikes are available in these locations because previous cyclists may have used Lime bikes as a first-mile option.

Turning to the socioeconomic predictors in the zero-inflation model, grid cells with a higher share of zero-car households ($\beta = -5.30$, $p < 0.01$) were also less likely to not have an available bike for prospective cyclists, while the opposite condition existed in cells with a higher share of households with three or more vehicles ($\beta = 5.86$, $p < 0.01$). A more surprising outcome was that in grid cells located in census tracts with a higher share of renter-occupied housing, the odds of that grid cell having no dockless bikes available to a prospective cyclist increased by a factor of 1.70 ($\beta = 0.53, e^{\beta} = 1.70, p < 0.05$). This model finding points to a deficiency in the placement (whether behavioral or not) of Lime dockless bikes that capitalizes on their ability to serve as a non-auto mobility option for residents who may have lower economic means to pursue home or car ownership. Comparably, those grid cells within census tracts with a higher share of the residential populace identifying as African American ($\beta = 6.04, p < 0.01$) were also more likely to not have a dockless bike available for prospective cyclists. While these latter two findings are not indicative of any individual but instead the general socioeconomic composition of neighborhood residents in areas with dockless services, the results do emphasize how this new mobility service in the Boston-area municipalities may not have been equitably or most effectively distributed during the initial stages of system expansion.

For grid cells with generated dockless bikeshare trips, the trip count during the first 18 months of service was expected to increase in grid cells where a formal policy was adopted over one year ago ($\beta = 1.06$, $p < 0.01$) when compared to the referent category of six months or less of sanctioned Lime bikeshare service. Other count model results that paralleled findings from the zero-inflated model were also identified. Grid cells characterized by a heightened population ($\beta = 0.02, p < 0.01$) or employment ($\beta = 0.03, p < 0.01$) density as well those 250-meter cells intersecting the 100-meter walksheds around commuter rail stations ($\beta = 1.02, p < 0.01$) were associated with higher counts of dockless bikeshare trip generation. Similarly, if a grid cell intersected the 100-meter walkshed of a rapid transit station, the expected count of dockless bike trips increased over twofold ($\beta = 0.73, e^{\beta} = 2.08, p < 0.01$), given the final ZIP model specification.

Grid cells within the study area with a greater share of renter-occupied housing units ($\beta = 2.19, p < 0.01$) and residents who identify as African American ($\beta = 3.11, p < 0.01$) were also predicted to have higher rates of dockless bikeshare trip generation. Taken together with the zero-inflated model finding that these areas are less likely to have dockless bikes available to its residents, proactive efforts should be made to distribute bikes more widely as model results show that doing so would increase dockless cycling activity across the official Lime service area. Geographic subunits with higher share of households with zero ($\beta = -1.51, p < 0.01$) or at least three cars ($\beta = -2.15, p < 0.01$) were associated with lower levels of cycling activity. The former outcome was an unexpected model result that may be in part due to the greater probability of dockless bike unavailability within cells of tracts with higher shares of zero-car households.

Table 2
Trip generation model results of dockless bikeshare utilization in Boston-area municipalities.

Variable	Coef.	Std. Err.	Sig.
Count model (Poisson with log link)			
Intercept	2.00	0.26	<0.01
Months since Lime policy adoption: 0–6	–	–	–
Months since Lime policy adoption: 7–12	0.14	0.22	>0.10
Months since Lime policy adoption: 13 and above	1.06	0.20	<0.01
Socioeconomic Context			
Race/Ethnicity: African American	3.11	0.66	<0.01
Tenure: Renter-occupied	2.19	0.24	<0.01
Vehicles: 0	−1.51	0.57	<0.01
Vehicles: 3	−2.15	0.62	<0.01
Built Environment			
Persons per acre	0.02	0.01	<0.01
Jobs per acre	0.03	0.01	<0.01
Walkshed: Commuter rail	1.02	0.35	<0.01
Walkshed: Rapid transit	0.73	0.22	<0.01
Zero-inflation model (binomial with logit link)			
Intercept	−0.33	0.19	<0.10
Months since Lime policy adoption: 0–6	–	–	–
Months since Lime policy adoption: 7–12	−0.31	0.11	<0.01
Months since Lime policy adoption: 13 and above	0.02	0.09	>0.10
Socioeconomic Context			
Race/Ethnicity: African American	6.04	0.53	<0.01
Tenure: Renter-occupied	0.53	0.24	<0.05
Vehicles: 0	−5.30	0.68	<0.01
Vehicles: 3	5.86	0.45	<0.01
Built Environment			
Persons per acre	−0.21	0.01	<0.01
Jobs per acre	−0.07	0.01	<0.01
Walkshed: Commuter rail	−3.16	1.00	<0.01
Walkshed: Rapid transit	−0.44	0.37	>0.10
Summary Statistics			
Number of observations	6,280		
−2 log likelihood	−216,854.10		

Table 3
Trip duration model results of dockless bikeshare trips generated in Boston-area municipalities.

Variable	Coef.	Std. Err.	Sig.
Intercept	4.40	0.95	<0.01
Trip Characteristics			
Season: Spring	0.35	0.16	0.02
Season: Summer	–	–	–
Season: Fall	−1.36	0.11	<0.01
Season: Winter	−1.63	0.25	<0.01
Period: Weekday, early morning	−4.20	0.18	<0.01
Period: Weekday, morning peak	−2.10	0.16	<0.01
Period: Weekday, day	−1.51	0.13	<0.01
Period: Weekday, evening peak	−1.19	0.15	<0.01
Period: Weekday, evening	−3.88	0.27	<0.01
Period: Weekend, day	–	–	–
Period: Weekend, evening	−2.65	0.25	<0.01
Daily rain event	−0.44	0.10	<0.01
Daily high average winds	−0.52	0.20	0.01
Electric bike	−3.44	0.11	<0.01
Route Characteristics			
Distance (miles)	9.30	0.95	<0.01
Percent cycled on low Level of Traffic Stress links	4.52	0.15	<0.01
Socioeconomic Context			
Destination: Sex: Share of female residents	6.13	1.56	<0.01
Origin: Age: Share of residents 35–44 years old	−4.49	1.91	<0.01
Destination: Age: Share of residents 35–44 years old	−12.71	2.00	<0.01
Destination: Share of adults less than Bachelor's	5.79	0.39	<0.01
Origin: Race/Ethnicity: Other distinctions	3.48	0.53	<0.01
Destination: Vehicles: Share of households 3 cars or more	−3.57	0.58	<0.01
Built Environment			
Destination: Jobs per acre	−0.02	0.01	<0.01
Origin: Walkshed: Rapid transit	−1.56	0.19	<0.01
Destination: Walkshed: Rapid transit	−2.64	0.22	<0.01
Summary Statistics			
Number of observations	74,914		
Adjusted R^2	0.29		

4.3. *Predictors of dockless bikeshare trip duration*

Table 3 displays the linear regression model results from the subsequent analysis of predictors of dockless bikeshare trip duration. Regarding the socioeconomic context at the trip origin, an increase in the share of residents between 35 and 44 years of age ($\beta = -4.49$, $p < 0.01$) was associated with a decrease in trip duration, while a higher share of residents within a neighborhood who do not identify as White, African American, Asian, or Latinx ($\beta = 3.48, p < 0.01$) was associated with an increased average travel time. At the trip destination, grids cells with an increase in the share of residents between 35 and 44 years of age ($\beta = -12.71, p < 0.01$) or share of households with at least three vehicles ($\beta = -3.57, p < 0.01$) were more likely to experience shorter trip durations. In contrast, dockless bikeshare trips ending in grid cells with a higher share of female residents ($\beta = 6.13, p < 0.01$) or adults without a four-year college degree ($\beta = 5.79$, $p < 0.01$) were associated with longer dockless bikeshare trip durations. In terms of the built environment surrounding either trip end, trips concluding in a neighborhood with a higher employment density ($\beta = -0.02, p < 0.01$) were more likely to be shorter, as were dockless bikeshare trips beginning ($\beta = -1.56, p < 0.01$) or ending ($\beta = -2.64, p < 0.01$) within the walkshed of a rapid rail station.

Turning to modeled route-specific predictors, unsurprisingly, an increase in trip distance ($\beta = 9.30, p < 0.01$) was related to an increase in trip duration. Of greater interest to active transportation planners, an increase in percent of network links along a route classified by a low level of traffic stress ($\beta = 4.52, p < 0.01$) resulted in an increased travel duration. While cyclists who ride along a higher share of bike-friendly facilities may take less direct routes, the association of cycling along these facilities with longer travel times also highlights an increased willingness of risk-adverse cyclists to ride longer durations if routes along safer bike facilities are available. As for trip-specific predictors, dockless bikeshare users who rented an electric bike ($\beta = -3.44$, $p < 0.01$) were more likely to experience a shorter travel time, with trips that occurred on days with any measurable rainfall ($\beta = -0.44$, $p < 0.01$) or average sustained winds above 15 miles per hour ($\beta = -0.52$, $p = 0.01$) also being associated with shorter trip durations. Seasonality and daily travel period were also found to significantly predict dockless bikeshare trip duration. Trips during the first 18 months of dockless bikeshare in Boston's suburbs that took place in the fall ($\beta = -1.36, p < 0.01$) or winter ($\beta = -1.63, p < 0.01$) were, on average, of a shorter duration than trips that occurred during the summer months; whereas, all trips that occurred in a period outside the referent case of weekends from 2am to 7 pm were more likely to have a shorter trip duration.

5. Conclusion

The recent arrival and rise in popularity of dockless bikeshare services in North American cities—with over 200 systems in more than 150 cities providing thousands of bikes for public use (Hirsch et al., 2019)—has surprised many governments who are testing new regulatory models to oversee these for-profit mobility operators. While unique in its unified attempt to help assuage any future tensions between municipalities and this private industry via a regional initiative to select specific vendors and standardize service delivery (Hauf and Douma, 2019), the Greater

Boston region's experience with dockless bikeshare systems remains one faced by social and spatial equity concerns. This study finding demonstrates that there was insufficient access to dockless bikes in the Boston-area municipalities for neighborhoods with a higher share of renter-occupied housing and African American residents, despite the increased likelihood of neighborhoods within this socioeconomic context to be associated with greater dockless bike trip generation. During the 18-month period, Lime redistributed its dockless bikes on a semi-regular basis centered largely on placement in high demand areas; an operator-led redistribution model that may emphasize goals of maximizing trip generation and profit (de Chardon et al, 2016). While access to a regional dockless bikeshare system remains in its preliminary phase in Boston, participating municipalities should look to alternative models in cities such as Seattle who have established requirements to ensure that a minimum share of their fleet is available within identified communities of concern during rebalancing (Hirsch et al., 2019).

More encouraging results of this study found a positive link between the built environment predictors of population and employment density as well as access to commuter rail stations and increased dockless bike access and usage. Coupled with the positive association between rapid transit station access and bikeshare trip generation, the introduction of an expanding dockless bike system in Boston's inner-suburbs appears to be offering a viable active transportation alternative in areas of high demand and further complementing existing non-auto travel options. If corroborated by future individual trip analyses, this finding would be a positive outcome as jurisdictions and privately-owned dockless bike operators seek to create synergistic partnerships around public transit and dockless bikeshare services (Moscholidou and Pangbourne, 2019). In a second promising study finding, neighborhoods with a higher share of zero-car households were positively associated with dockless bikeshare access and trip generation, which points to a prospect for this mobility option to deliver residents—who voluntarily or due to economic circumstance, forego car ownership— a more affordable and healthier travel mode.

In analyzing the first year and a half of dockless bikeshare data in Boston's suburbs, our study offers initial insights into the patterns and trends of its adoption. More specifically, this study estimated a ZIP model to identify the environmental and neighborhood-level socioeconomic indicators of dockless bikeshare system availability and utilization, with a social and spatial equity focus. Beyond our study's contributions, future efforts should look to expand its efforts to help deepen its impact. The predictive power of the dockless bike trip generation model would be enhanced by using built environment measures of network connectivity and land development pattern (e.g., Gehrke and Welch, 2019) that have been found to be significant in existing dock-based bikeshare analyses. Regarding the trip duration analysis, richer insights could be offered by including individual-level attributes, whose exclusion remain a limitation of the provided API data set, rather than a reliance on neighborhood-level socioeconomic context predictors as proxies for the important cycling-related attributes of sex, age, education, race/ethnicity, and income. Third, future analyses of the cleaned Lime API data set should seek to further leverage the GPS traces to identify a more robust set of route-level predictors of dockless bikeshare demand and route choice. To close, while outside our study scope, future research is needed to help identify and address any social equity policy shortcomings related to the provision of dockless bikes to individuals most susceptible to the negative consequences of transport poverty.

CRediT authorship contribution statement

Steven R. Gehrke: Conceptualization, Methodology, Formal analysis, Investigation, Writing - original draft, Visualization. **Bita Sadeghinasr:** Software, Data curation. **Qi Wang:** Supervision. **Timothy G. Reardon:** Resources, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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