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Powering bikeshare in New York City: does the usage of e-bikes differ from regular bikes?

Yingning Xie, Michael Smart and Robert B. Noland

Edward J. Bloustein School of Planning and Public Policy, Rutgers University, New Brunswick, NJ, USA

ABSTRACT

In this study, we investigate the difference between shared electric bicycles (e-bikes) and conventional shared bikes operated by Citi Bike in New York City. We examine differences in usage by examining summary statistics and we develop conditional autoregressive models to examine differences in factors associated with trip generation. These factors include bike infrastructure, subway proximity, area demographics, land use, and elevation. We also control for border effects by identifying peripheral stations. The percentage of e-bike trips fluctuates across hours of the day, with a peak around 3 PM but diminishes during peak commuting hours. We find mostly no significant differences in factors associated with the generation of trips between the two modes. Exceptions include a larger effect on e-bike trip generation when the daytime worker population is larger; other differences are due to the racial composition around the station area, some land use categories, and elevation differentials.

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Bikeshare; e-bikes; trip generation; land use; elevation

Introduction

The Citi Bike bikeshare system in New York City is the largest among more than 60 docked bikeshare systems in the US (US DOT 2022). In 2022, Citi Bike had a fleet of nearly 30,000 bikes, and generated 31 million annual trips from over 1,600 bikeshare stations distributed throughout New York City (Lyft 2023). The introduction of e-bikes to the Citi Bike fleet in 2018 offers the opportunity to compare factors associated with the use of e-bikes and conventional bikes from the same system (Citi Bike 2023).

In this study, we first compare the trip generation of e-bikes and conventional bikes by user type, weekday vs. weekend/holiday usage, and time of day, using descriptive statistics. Then, we examine differences in factors associated with trip generation through spatial regression models, specifically the Negative Binomial Conditional Autoregressive (CAR) models, using a Markov Chain Monte Carlo (MCMC) estimation procedure. This method allows us to estimate the overlap between credible intervals to determine whether coefficient estimates differ between the two modes. Our model is spatial, and we focus on measures of the local area surrounding each bikeshare station, including land use,

CONTACT Yingning Xie yingning.xie@rutgers.edu Edward J. Bloustein School of Planning and Public Policy, Rutgers University, New Brunswick, NJ, 08901, USA

population and demographics, bike infrastructure, subway proximity and relative elevation changes.

While we have few prior hypotheses on expected differences, prior literature on conventional bike share provides some guidance on which factors to include in our model (Noland, Smart, and Guo 2016). We include the percentage of land use types around each bikeshare station as proxy variables to indicate trip ends associated with various trip purposes. Another hypothesis is that there are differences in use by race and ethnicity. We assume that trip generation of e-bikes and conventional bikes are both affected by proximity to bike lanes, bike racks and subway stations within our defined service areas. We extend this by also including an elevation change variable as we expect e-bikes to be used more in hillier areas. We also include a control variable for bikeshare stations on the periphery of the service area.

Background: Citi Bike in New York City

E-bikes were introduced to the Citi Bike system in 2018. These e-bikes can travel at a maximum speed of 18 mph with electric assistance provided only when riders are pedaling. They are classified as Class-I pedal-assisted e-bikes based on the three-tier e-bike classifications in New York City, as opposed to Class-II e-bikes which are throttle-assisted, and Class-III e-bikes which have a higher maximum speed of 28 mph (NYC DOT 2024). Since the legalization of pedal-assisted e-bikes in New York City in 2018, the rapid uptake of this battery-powered travel mode has transformed the city. Privately owned e-bikes, used by delivery workers to transport take-out orders, began to fill the streets. Meanwhile, shared e-bikes operated by Citi Bike have quickly gained popularity among residents and visitors, compared to conventional models (Surico 2022). The growth in e-bike usage is understandable, as the electric assistance feature allows riders to travel longer distances with less effort compared to conventional bikes. Additionally, although New York City is generally flat, there are hillier areas located in Uptown Manhattan and the Bronx where e-bikes are easier to ride than conventional bikes.

Citi Bike has been expanding its fleet and station network. In 2022, Citi Bike had a fleet of nearly 30,000 bikes distributed across 1614 stations; around 20% of these bikes are e-bikes (Lyft 2023). Citi Bike has two main user types: members who pay an annual subscription and casual users who pay for a single ride or for a day. In 2022, member trips made up roughly three-quarters of total rides in the Citi Bike system (Lyft 2023). Prices differ by user type and bike type (Table 1). In 2022, an annual subscription was $185 and provided 45 min of free use for classic bike trips, while casual users paid $3.99 for a single

Table 1. Citi Bike pricing scheme in Sep. 2022.

User Type	Charge Scheme	Classic Bikes	Electric Bikes
Member: $185 Annually	< 45 min		+ $0.15 per minute
	> 45 min	$0.15 per minute for either bike type	
	E-bike Price Cap		$3 cap for rides < 45 min that enter/exit Manhattan
Casual User: $15 daily Pass	< 30 min		+ $0.23 per minute
	> 30 min	$4 every 15 min for either bike type	
Casual User: $3.99 per Ride	< 30 min		+ $0.23 per minute
	> 30 min	$0.23 per minute for both bike types	

ride or $15 for a day pass for 30 min of free use per ride. An additional charge per minute applies for using e-bikes for both members and casual users. Additionally, there is a Reduced Fare Program for Supplemental Nutrition Assistance Program (SNAP) recipients and New York City Housing Authority (NYCHA) residents (Citi Bike 2022).

Existing studies on e-bikes and bikeshare

Advantages and disadvantages of e-bikes

E-bikes offer the user various advantages compared to conventional bikes. E-bikes travel at higher speeds with less physical exertion, enabling users to bike more often, carry more cargo, and travel longer distances more quickly (MacArthur, Dill, and Person 2014), over more challenging topography, in precipitation, or in excessive heat (Heinen, van Wee, and Maat 2010). Due to the ease of riding, e-bikes allow for more diverse trip purposes compared to conventional bikes (Langford et al. 2013), while still being less expensive than cars (Mayer 2020). E-bikes also make cycling possible for people who would not otherwise consider it, including those with physical limitations (Jones, Harms, and Heinen 2016). Scholars have found that e-bikes are used to replace car trips, public transit, walking, and even conventional bikes. Overall, e-bikes increase cycling participation (Fishman and Cherry 2016).

Despite these advantages, e-bikes are still sensitive to weather effects, including high or low temperature, precipitation, and wind (Noland 2021). Additionally, some researchers have interviewed e-bike users and found negative perceptions associated with costs and risks of theft, unwieldiness due to weight, and range anxiety due to battery limits (Popovich et al. 2014). E-bike battery fires in cities such as New York, where privately owned e-bikes are common have caused concerns from both authorities and users, leading to a ban on e-bikes in public housing (Hu 2023).

Shared e-bikes: who uses them and what affects usage?

Shared e-bikes provide short-term bicycle rental to riders but avoid some of the drawbacks of ownership described above, offering a combination of convenience and lower risks of theft (Bachand-Marleau, Lee, and El-Geneidy 2012). Shared e-bikes have been prevalent in Asia and Europe, and are gaining a presence in many US cities. Studies that examined shared e-bikes in the US show that shared e-bikes could substitute for car trips, or increase transit ridership (Fitch, Mohiuddin, and Handy 2020; Martin and Xu 2022).

The adoption of shared e-bikes varies among population groups, which also vary by geography. Outside the US, in Zurich, Switzerland, higher demand for shared e-bikes was observed in higher-income neighborhoods (Guidon et al. 2019). A study in Beijing, China, however, showed that shared e-bike users tend to be young to middle-aged males with lower income and education levels (Campbell et al. 2016). In the US, shared e-bike users are overall similar to regular bikeshare users, who are more likely to be white, male, with higher incomes and education levels (Fishman 2016). In Utah, for instance, most shared e-bike users were middle-aged and used e-bikes for recreational purposes rather than commuting (He et al. 2019). In Philadelphia, however, it was found that e-bikes increase bikeshare ridership more in socially disadvantaged areas (Caspi 2022).

In addition to user profiles, other factors also affect bikeshare usage. High population density, mixed land uses, and proximity to transit stations and bike lanes increase the use of shared bikes (Noland, Smart, and Guo 2019). Bikeshare usage also varies over time, as there are often more trips generated during warmer months, weekdays, and at peak hours (Gebhart and Noland 2014). Furthermore, within a bikesharing system, usage also differs between casual users and members (i.e. those with an annual subscription). Casual riders use bikeshare for recreational purposes more often, while members use bikeshare more frequently for commuting (Buck et al. 2013). Bikeshare also faces barriers, such as lack of infrastructure, and safety concerns (Bateman et al. 2021). While we expect that similar factors affect shared e-bikes, there may be other factors unique to e-bikes, given their ability to travel longer distances and traverse hillier topography.

A few existing studies in the US have compared the use of e-bikes and conventional bikes in small bikesharing systems. Langford et al. (2013) found that bikeshare users prefer e-bikes over conventional bikes, and e-bikes are used for more diverse trip purposes compared to conventional bikes. However, these comparisons were specific to a university campus. In New York City, where the urban environment and user demographics are more diverse, understanding whether people may use shared e-bikes differently from conventional shared bikes could help us better understand the potential of e-bikes as an alternative travel mode.

Previous studies about Citi Bike

Several studies examined the Citi Bike system and reached findings similar to those of other bikesharing systems. Usage is affected by population, land use, bike lanes (Noland, Smart, and Guo 2016), proximity to subway stations (Noland, Smart, and Guo 2019), and favorable weather (An et al. 2019), all generally having a positive effect on Citi Bike usage. An analysis also found that Citi Bike usage is associated with decreased bus ridership in New York City, suggesting substitution effects (Campbell and Brakewood 2017); Another study shows that Citi Bike has been used for last/first mile connections from subway stations during morning and evening peak hours. Members and casual users also use Citi Bike differently, with casual users often starting from recreational areas, while mixed commercial areas attract more subscribers on weekdays (Noland, Smart, and Guo 2019). Nevertheless, most studies that examined Citi Bike have focused on conventional bikes (An et al. 2019; Campbell and Brakewood 2017; Noland, Smart, and Guo 2016; Teixeira and Lopes 2020).

Our study contributes to the literature by investigating the trip generation of shared e-bikes compared to conventional bikes in the Citi Bike system. We address two research questions. First, does the trip generation of e-bikes differ from that of conventional shared bikes? We compare trip counts, average trip distance, and average trip duration by user type and weekday vs. weekend/holiday usage between e-bikes and conventional bikes. Second, are there differences in factors associated with trip generation, such as bike infrastructure, subway proximity, population, land use, and elevation? We estimate spatial regression models to test our hypotheses.

Data and methods

We examine trip generation of shared e-bikes compared to shared classic bikes in New York City. Trip generation, defined as the number of trips originating from each traffic analysis zone – in our case, from each bikesharing station – reflects the travel demand in the vicinity of the station. It is closely linked to the activities individuals intend to undertake and is consequently influenced by population demographics, land use types, and street configurations near the bikeshare station. These factors hold significant policy implications for infrastructure development and land use planning in the area (Mukherjee and Raghuram Kadali 2022). When bikesharing stations are close to each other, they often serve similar population groups and share similar land use types or transportation infrastructure. This frequently results in spatial autocorrelation in regression models, where adjacent observations are correlated with each other.

In our analysis, we first examine summary statistics to compare the number of generated trips of shared classic bikes and shared e-bikes. Then, we use the MCMC-CAR models to control for spatial autocorrelation and identify the differences in the factors that affect trip generation of classic bikes and e-bikes.

Data wrangling

To analyze trip generation and its contributing factors, we compiled data from Citi Bike and multiple sources (Table 2). We downloaded trip data from the Citi Bike website for September 2022. We choose to focus on comparing the effects of certain factors, such as land use, population demographics, and infrastructure, on trip generation between classic bikes and e-bikes, rather than conducting a longitudinal comparison that incorporates the effects of seasonal changes on trip generation. We use trip data from September, a relatively temperate month in New York City, so riding is generally not affected by weather that is too hot or too cold. Since we do not have the demographic data of each user or their trip purposes, we proxy this by using each bikeshare station plus its service area as the analysis unit. We aggregate the trips generated from each bikeshare station. This allows us to analyze bike trips together with zonal data (demographics, land use, etc.) in the service area of each station.

Table 2. Data sources.

Dataset	Provider	Source link
Citi Bike Trip data	CitiBike	https://s3.amazonaws.com/tripdata/index.html
NYC land use	NYC Department of City Planning	https://www.nyc.gov/site/planning/data-maps/open-data/dwn-pluto-mappluto.page
NYC bike routes	NYC Department of Transportation (DOT)	https://data.cityofnewyork.us/Transportation/New-York-City-Bike-Routes/7vsa-caz7
NYC bike racks	NYC Department of Transportation (DOT)	https://data.cityofnewyork.us/Transportation/Bicycle-Parking/yh4a-g3fj
NYC subway stations	NYC Department of Transportation (DOT)	https://data.cityofnewyork.us/Transportation/Subway-Stations/arq3-7z49
Demographic information	Esri updated demographics / US Census Bureau	https://pro.arcgis.com/en/pro-app/latest/tool-reference/analysis/enrich.htm
NYC elevation points	Office of Technology and Innovation (OTI)	https://data.cityofnewyork.us/Transportation/Elevation-points/szwg-xci6

Cleaning and aggregating Citi Bike trip data

The Citi Bike trip data from September 2022 contains 3,507,123 trips generated from 1614 stations. The dataset includes trip start date and time, station name and ID, station latitude and longitude, and user type. The type of bikes, whether classic or electric, is also identified.

We removed outliers, which constituted 3.94% of bike trips, leaving us 3,369,117 valid trips for September 2022. The removed trip records include some 0.24% of bike trips that have no end station information or ended in New Jersey (part of the Citi Bike network). A small number (0.8%) of trips have no identified bike type and were identified as ‘docked bikes’ – an ambiguous term. Additionally, 2.66% of trips are shorter than 1 min, and 0.24% are longer than 3 h. Some stations had their location adjusted very slightly over time; thus to identify the location of the station we used the location data for each bike trip based on the modal longitude and latitude of all trips generated from each station.

After removing outliers, we aggregated trips by start station ID to obtain the count of generated trips for each bikeshare station. Figure 1 shows the bike trip counts distributed throughout the 1614 bikeshare stations in New York City in September 2022. Both classic bikes and e-bikes were observed across almost all stations. Four stations did not have any e-bike trips in that month (Figure 2).

Creating bikeshare station service areas

We created service areas for each bikeshare station using ArcGIS Pro. The service area of a bikeshare station is an associated catchment area surrounding a given bikeshare station. To create the service areas, we first created Thiessen Polygons, which is a geospatial technique that ensures that the station point in this polygon is the closest to any location within the polygon (Esri 2023a). Then, we performed Network Analysis to create facility service areas for each station point, using a ¼ mile walking distance as the threshold – the reasonable distance a typical bikeshare user would walk to the station, as used in previous studies (Noland, Smart, and Guo 2016). We clipped the Thiessen polygons to facility service areas, and used the clipped polygons as our station service areas, which is common practice in previous studies. This approach assumes that the demographics of the service area are strongly correlated with the demographics of the users of that station.

Assigning infrastructure, land use, demographic and elevation data to service areas

Each station service area serves as our unit of analysis and we merged other data to develop our independent variables. We calculated the percentage of each land use type in each service area. There are 11 defined land use types in the NYC data. Roads are not included in this land use dataset. The three residential land use types – one – and two-family buildings, multi-family walk-up buildings, and multi-family elevator buildings – are grouped into one. We also reclassified vacant and uncategorized lands as ‘other land.’

In addition, we used the Enrich function in ArcGIS Pro to obtain the census data in each bike station service area (Esri 2023b). The Enrich function uses the Block-Apportionment method to redistribute demographic variables to input polygons, by assigning values of census block points that contain demographic data to these input polygons (Esri 2022).

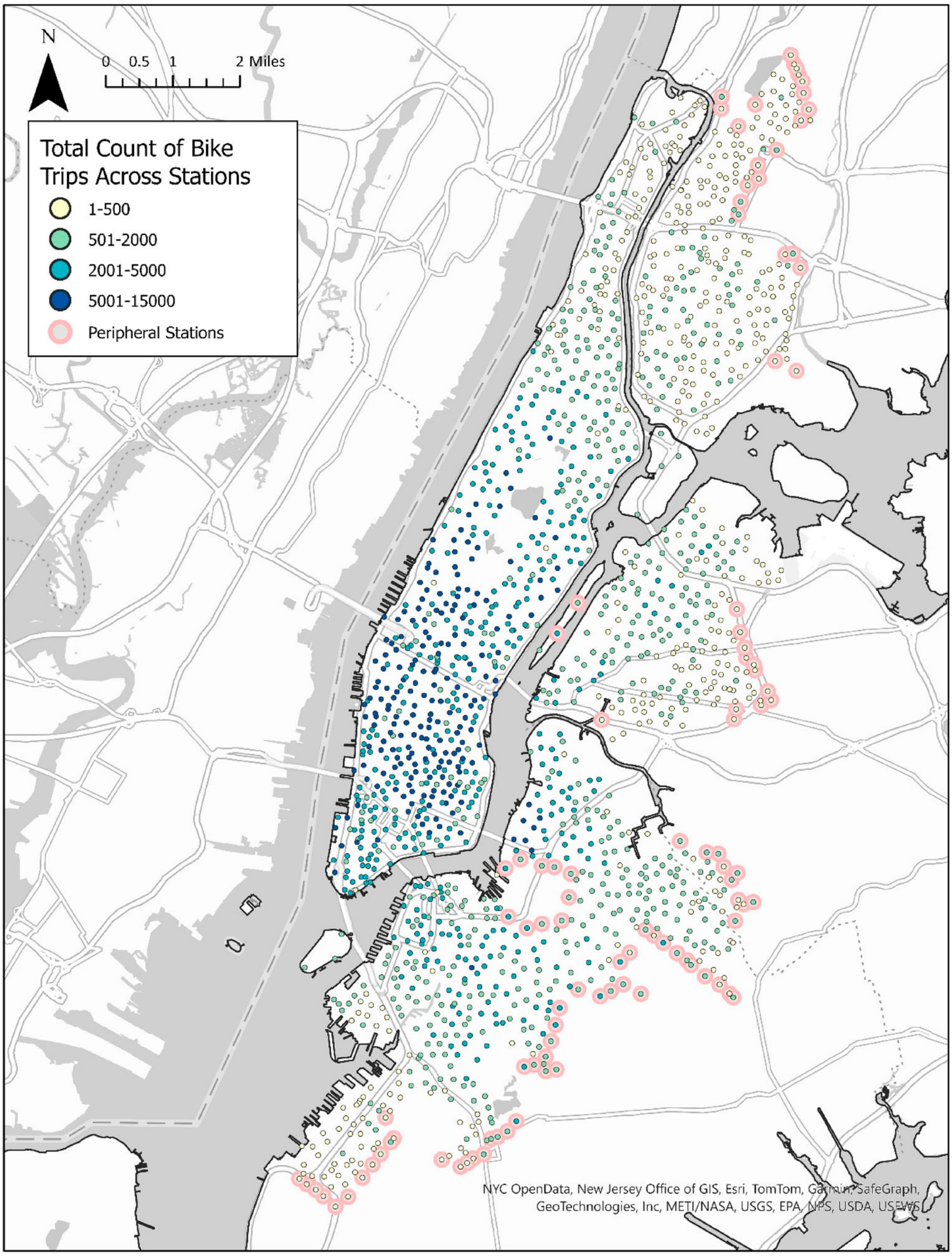

Figure 1. Citi Bike Trip Generation Across 1614 Bikeshare Stations in New York City in September 2022.

We assigned census population of different ethnicities to the service areas, including Hispanic, non-Hispanic White, non-Hispanic Black, and non-Hispanic Asian. We grouped all other non-Hispanic ethnic populations into one category and included the percent of each group in our analysis. Then, the service area polygons are further assigned the daytime worker population (number of occupied jobs in the service area) for 2022.

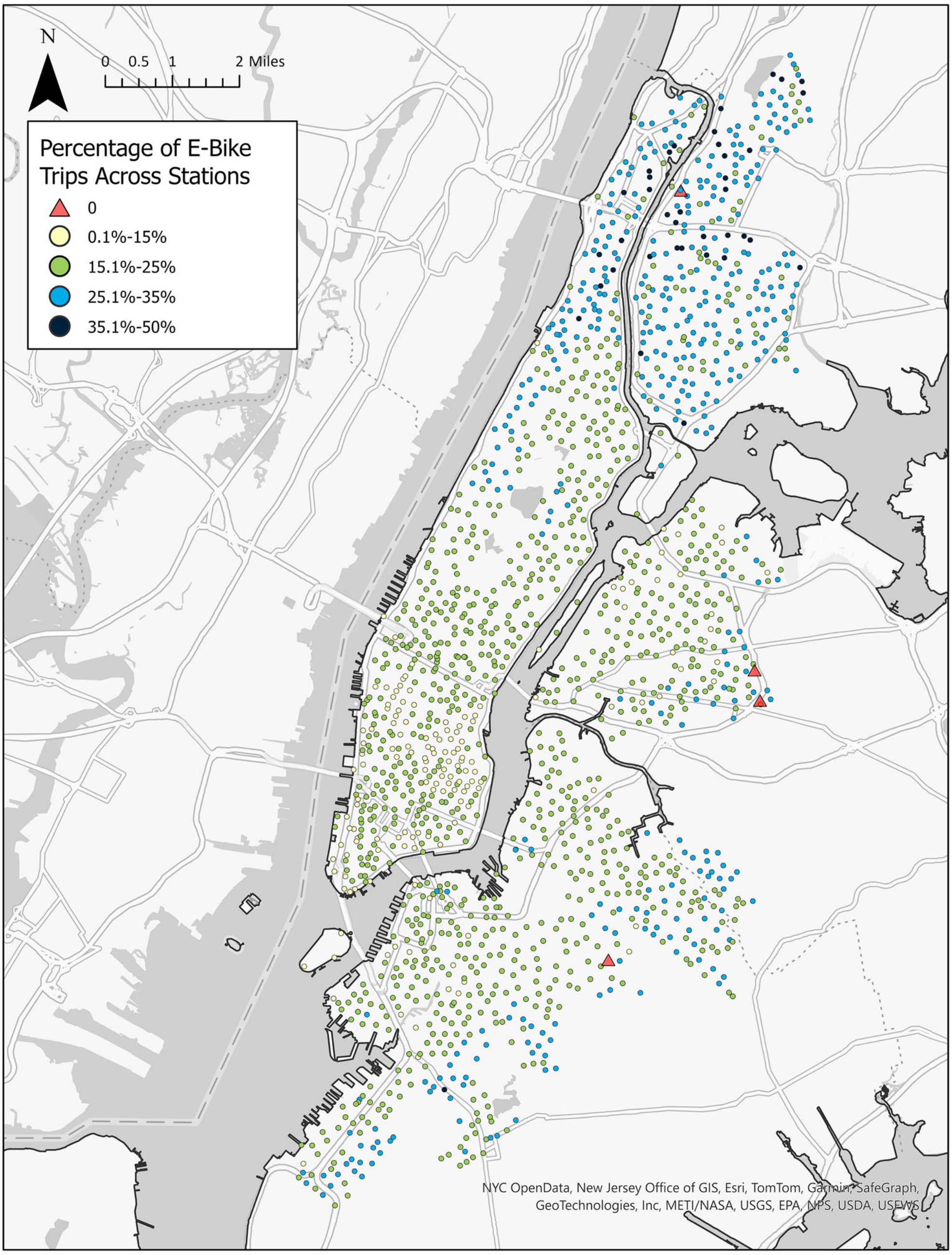

Figure 2. Percentage of E-Bike Trips across 1614 Bikeshare Stations in New York City in September 2022.

For each service area, we also aggregated counts of bike racks and the summed length of bike lanes. We created a dummy variable to indicate the presence of one or more subway stations in the service area.

We created a raster layer with elevation points for New York City and interpolated the elevation data from the surface to station points. We calculated the mean elevation of

Table 3. Summary statistics of 3,369,117 valid bike trips aggregated by 1614 stations in September 2022; with assigned infrastructure, population, land use, and elevation data in the station service areas.

Variables ($N = 1614$ station service areas)	Freq.	Percent	Mean	Std. dev.	Min	Max
Trip counts per station:						
Classic casual trips			376.77	469.83	0	5306
Classic member trips			1312.84	1482.20	0	10652
Classic total trips			1689.61	1895.39	2	12698
Electric casual trips			99.05	106.00	0	1188
Electric member trips			298.77	300.08	0	2122
Electric total trips			397.82	396.77	0	2937
Total trip			2087.43	2275.53	2	14602
Infrastructure in service areas:						
Bike lane length (feet)			1478.98	1194.12	0	9554.14
Bike rack count			12.28	13.53	0	102
Subway station (dummy)	272	16.9%				
Population in service area:						
Daytime worker population%			1720.72	3463.45	0	48459
Hispanic population %			30.17	23.22	0	88.89
non-Hispanic White population %			36.23	27.10	0	89.96
non-Hispanic Black population %			13.83	15.59	0	82.23
non-Hispanic Asian population %			11.59	12.76	0	85.91
non-Hispanic other ethnic population %			1.64	0.50	0	4.62
Land use in service area:						
Residential land %			26.64	17.91	0	76
Mixed land %			10.33	9.81	0	99.58
Commercial land %			7.17	11.92	0	72.43
Industrial land %			3.63	8.88	0	60
Transportation land %			3.08	8.23	0	91
Public facility land %			7.12	8.86	0	71
Recreational land %			6.20	12.98	0	100
Parking land %			1.44	2.73	0	39.22
Other land %			1.99	3.86	0	38
Other:						
Station elevation from the global mean (feet)			0.004	45	−60	209
Peripheral station	103	6.4%				

1614 bikeshare stations in September 2022, and subtracted the mean elevation from the elevation of each station, to create the elevation difference variable which indicates how much the station elevation is higher or lower than the mean elevation.

We also created a dummy variable to account for border effects. There are 103 bikeshare stations that are on the periphery of the bikeshare station network; these mostly border residential areas in the Bronx, Queens, and Brooklyn (Figure 1).

Finally, we merged our aggregated trip data with our data on bike infrastructure, subway proximity, population, land use, and elevation differentials that we assigned to service areas. Summary statistics are provided in Table 3.

Conditional autoregressive (CAR) model with Markov Chain Monte Carlo (MCMC) – estimation

To evaluate the factors affecting trip counts ('generated trips') of classic bikes and e-bikes, we estimated six spatial regression models. Our dependent variables are bike trip counts. We cannot use OLS regression because the trip count data is not normally distributed. As we can see from Figure 1, bike trips are highly concentrated in mid – and lower-Manhattan, with a skewed, Poisson distribution. Yet, we cannot use a traditional Poisson model that follows ‘the law of rare events,’ where most observations are small and constant (Cameron and Trivedi 2013), as the data is over-dispersed – i.e. the mean and the variance of the counts are not equal. This requires us to use a negative binomial regression with a mixture of Poisson-Gamma distribution to account for such over-dispersion (Lord et al. 2013).

We selected our independent variables based on previous literature, which includes a range of variables such as bike infrastructure, subway proximity, land use, population, relative elevation change, and the peripheral location of bikeshare stations (Table 3). We did not include proximity to CBD because New York City has multiple CBDs, including downtown Manhattan, midtown Manhattan, and downtown Brooklyn, which may mitigate the influence of CBDs on trip generation. We examined a correlation matrix for the variables of interest and found the daytime worker population is highly correlated with commercial land uses. To address this issue, we decided to exclude this land use type from our models; therefore it serves as the reference category. For the rest of our variables, the correlation is below 0.5, with most below 0.4, with a variance inflation factor (VIF) below 2. Because most variables are skewed, we log-transformed them.

Our data suggests potential spatial interdependence between neighboring observations. Neighboring bikeshare stations are likely to be similar to each other in trip generation, due to their similarity in factors that contribute to trip generation, such as similar demographic groups, land uses, and street configurations. We tested models without controlling for spatial effects and performed Moran’s *i* test for spatial dependence for each model (Ebdon 1991; Griffith 1987). Our tests show *p*-values smaller than 0.0001 for all the models, indicating strong spatial autocorrelation (Table 4).

To control for spatial dependence, we use the Conditional Autoregressive (CAR) Negative Binomial Regression model that incorporates a spatial effect (Besag 1974). Instead of an explicit spatial lag variable, the CAR model uses an internally estimated spatial parameter that is estimated simultaneously with coefficients (Smith, Goodchild, and Longley 2007). The CAR model incorporates spatial weights between each observation and all other observations, and the weight is created through the Negative Exponential Distance Decay function, where the weight decreases exponentially with distance.

The Poisson distribution is defined as: $y_i \mid \lambda_i \sim Poisson(\lambda_i)$, where y_i is the observed count of events at each observation and λ_i is the mean of the events at each observation. The Poisson regression models the variability in the observed count (y) around the mean (λ). Since our CAR model is a negative binomial regression that incorporates a spatial effect, our mean count of events is defined as $\lambda = \exp(x_i^t\beta+\varepsilon+\phi)$, where x is the independent variable, β is the coefficient, ε is the error term, and ϕ is the spatial random effect, which includes a spatial weights function, $w_{ij} = e_{ij}^{-\alpha d,}$ where d_{ij} is the distance between two zones or points and α is the decay coefficient (Levine 2013).

Due to the complexity of the function when more than one parameter needs to be optimized, the Markov Chain Monte Carlo (MCMC) approach – a Bayesian estimation method – is needed to optimize parameters, instead of a simple Maximum Likelihood Estimation (Goldfeld, Quandt, and Trotter 1966). The Bayesian estimation method allows us to estimate and update the probability of parameters using prior probabilities, although for our model we use a default flat uniform prior $\beta_j \sim U(-\infty,\infty)$. The MCMC algorithm uses an iterative approach to sample posterior distributions based on values of previous samples until reaching an equilibrium state (convergence). In the MCMC

Table 4. Moran's test for spatial dependence.

Moran's test for spatial dependence (H0: Error terms are i.i.d.)						
Model for:	*classic bikes*	*e-bikes*	*classic bike member*	*classic bike casual*	*e-bike member*	*e-bike casual*
chi^2	5259.46	3106.9	5711.77	2255.07	3260.99	1991.5
***p*-value**	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

estimation, a burn-in sample is specified to search for a stable posterior distribution, which will be discarded after convergence and the final results will be summarized based on samples from the remaining iterations (Lord et al. 2013; Miaou 2006).

Unlike point estimates in frequentist statistics, Bayesian inference provides us with a probability distribution of parameter estimates, with a mean coefficient and a credible interval (as distinct from a confidence interval in classical statistics). The credible interval provides an estimate of the probability that the coefficient is within a specified range. This allows us to evaluate the overlap between coefficient estimates of our model with classic bikes versus our model with e-bikes.

We used the software package Crimestat Version 4.02 to estimate our CAR models (Levine 2013). For our two initial models, we used 25,000 iterations and a 5000 burn-in sample. Models by membership type required more iterations to converge. We used 100,000 iterations and a burn-in of 10,000 for e-bike member and casual-user trips, while models for classic member and casual-user trips required 500,000 iterations and a burn-in of 30,000 to reach convergence. We used a negative exponential decay with an exponent of -1 mile to control for spatial correlation. Our constant coefficients did not converge; however our other variables did as confirmed by the Gelman-Rubin (GR) value, which should be below 1.2 for each coefficient, and a value below 0.05 for the Monte Carlo simulation error (MC error). Our models successfully controlled for spatial autocorrelation, as the variable for spatial autocorrelation (*Phi*) is not significant after model convergence.

Results

Comparing trip generation of classic bikes and e-bikes

Trip counts, distance, and duration

We summarize trip counts by bike type, user type, and weekday vs. weekend/holiday (see Figures 3–5). Non-weekdays in our September dataset include weekends and one national holiday, Labor Day (on Monday, 5 September 2022).

In September 2022, among 3,369,117 valid trips, 19% were e-bike trips. Roughly three-quarters (77%) of all trips are made by members, of which 18% are e-bike trips. Casual users make somewhat more of their trips (22%) by e-bikes. A total of 72% of all trips are made during weekdays, and 19% of these are e-bike trips (Figure 3). During non-weekdays, the percentage of e-bike trips is slightly lower (18%). Members ride e-bikes more during weekdays (19% of weekday member trips) than non-weekdays (18% of non-weekday member trips) (Figure 4). Casual users also ride e-bikes more on weekdays (22% of weekday casual trips) and less on non-weekdays (19% of non-weekday casual trips). There is a higher percentage of casual users taking e-bike trips, especially during weekdays.

The generation of trips for members or casual users, during weekdays or non-weekdays also varies by bike type (Figure 5). Casual users made a higher percentage of e-bike

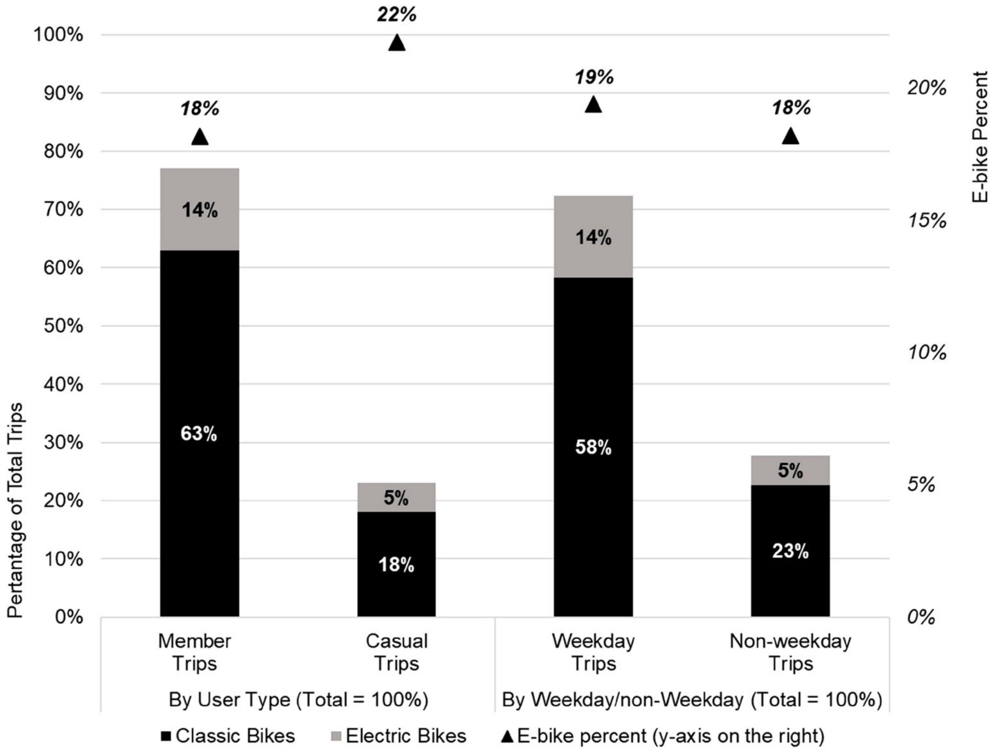

Figure 3. Bike trips in September 2022 ($N = 3{,}369{,}119$), by user type or by weekday vs. non-weekday, for classic bikes and e-bikes (left y-axis), and e-bike percent (right y-axis).

trips (25%), compared to classic bike trips, with 23% of trips made by casual users. The percentage difference mainly comes from casual trips made during weekdays, as 16% of e-bike trips are made by casual users during weekdays, compared to 14% of classic bike trips. For classic bike trips, 72% are made during weekdays, 44% more than non-weekdays (28%). Like classic bikes, e-bikes are ridden more during weekdays (73%) than non-weekdays (27%), making the difference two percentage points larger than that of classic bike trips.

For each trip, we calculate its duration (minutes) by subtracting the trip start time from the trip end time. We also calculate the geodesic distance (meters) of each trip between the start and end station using geometric calculations in ArcGIS Pro. We summarize the distance and duration of trips by bike type, user type, and weekday vs. non-weekday (Figure 6). We found that e-bike trips uniformly have longer distances (between 12 and 23 percent longer) than classic bike trips and the differences are larger for members (20–23%) than casual users (12–14%) but there is not much difference in durations between e-bike and classic bike trips.

Hourly distribution of trips by bike type and user type

We aggregate trips for September 2022 for each hour of the day by user type and calculate the percentage of e-bike trips for each hour (Figure 7). The timing of trips made by members suggests a typical commute pattern with a morning and evening peak. This

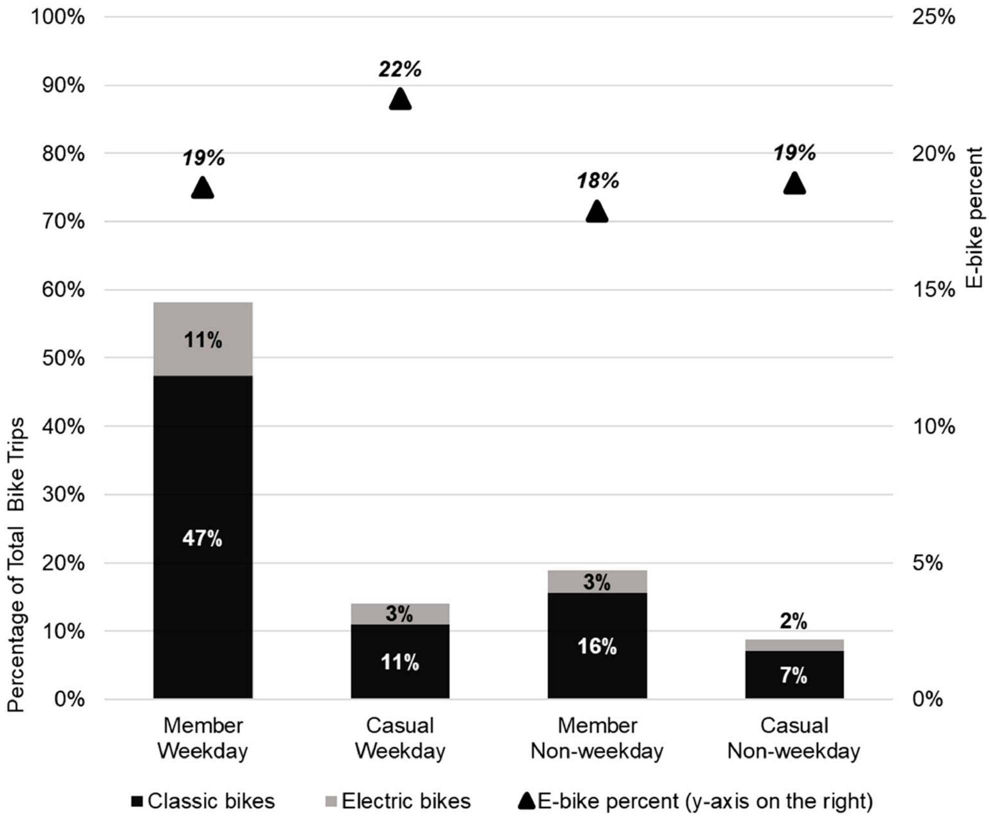

Figure 4. Bike trips in September 2022 ($N = 3{,}369{,}119$), by user type and weekday vs. non-weekday, for classic bikes and e-bikes (left y-axis), and e-bike percent (right y-axis).

is not apparent for casual users. For members, trip counts peak at around 8 AM and 5–6 PM. Casual users show an increase throughout the day, peaking at around 5–6 PM. For casual users, e-bike trips overall constitute a higher percentage of total trips across a full 24 h period, compared to members. For casual users, the percentage of e-bikes has three peaks: between 4–7 AM, around 3 PM, and a smaller one at 8 PM. But for members, 3 PM is the time when the percentage of e-bikes is the highest during the day. The difference in the percentages of e-bike trips between casual and member users is even larger during 4–7 AM.

We compare hourly usage of classic and e-bike trips among members in Figure 8. Member classic bike trips have a morning peak around 8 AM, and an evening peak between 5 and 6 PM. While e-bike trips have similar peak hours, they are flatter. The percentage of e-bike trips peaks at around 3 PM (22%). Then the percentage starts dropping as the evening commute hours approach when classic and total trips peak.

We also compare classic and e-bike trips among casual users (Figure 9), for whom both classic and e-bike trips are at their lowest at 4 AM and keep increasing until the afternoon. While classic bike trips peak at around 5–6 PM, e-bike trips have a much flatter peak from 3 to 5 PM. The percent of e-bike trips drops after 3 PM, when e-bike trips remain stable but classic bike trips are increasing.

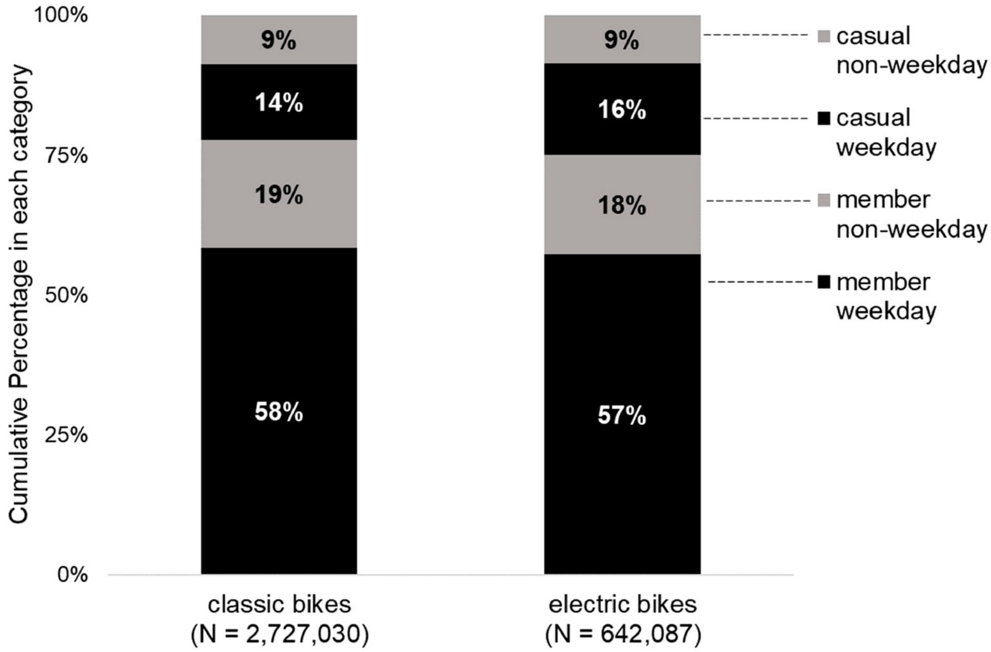

Figure 5. Percentage of bike trips by user type by weekday vs. non-weekday, in total bike trips, classic bike trips and e-bike trips, respectively.

Trip generation models

We estimated a total of six trip generation models for e-bikes and classic bikes to understand the factors associated with trip generation and compare results between the two. For each type of bike, three models were estimated, respectively using total trips, member trips, and casual trips as dependent variables. We present results that compare classic vs. e-bike trips, member vs. casual trips for classic bikes, and member vs. casual trips for e-bikes.

Difference between classic and e-bike trips

Models in Table 5 are for total trips by classic bikes and e-bikes and we test various hypotheses for both. This includes whether e-bikes are less sensitive to elevation change than classic bikes. The unit of our elevation variable is feet (1 foot ≈ 0.3 meter). Since one foot is relatively trivial in elevation change, we interpret its coefficient by the unit of every 100 feet (≈ 30 meters). We also hypothesize that e-bikes are used for different trip purposes, and we include the percentage of land use types and daytime worker population in the service area of each bikeshare station as proxy variables to indicate trip purposes. Another hypothesis is that there are differences in use by race and ethnicity. We use the percentage of each race or ethnicity in the service area in our models, with non-Hispanic White population as the reference group. We assume that the generation of e-bike and classic bike trips are both affected by proximity to bike lanes, bike racks and subway stations within our defined service areas. We hypothesize that the peripheral location of some bikeshare stations also influences trip generation from these

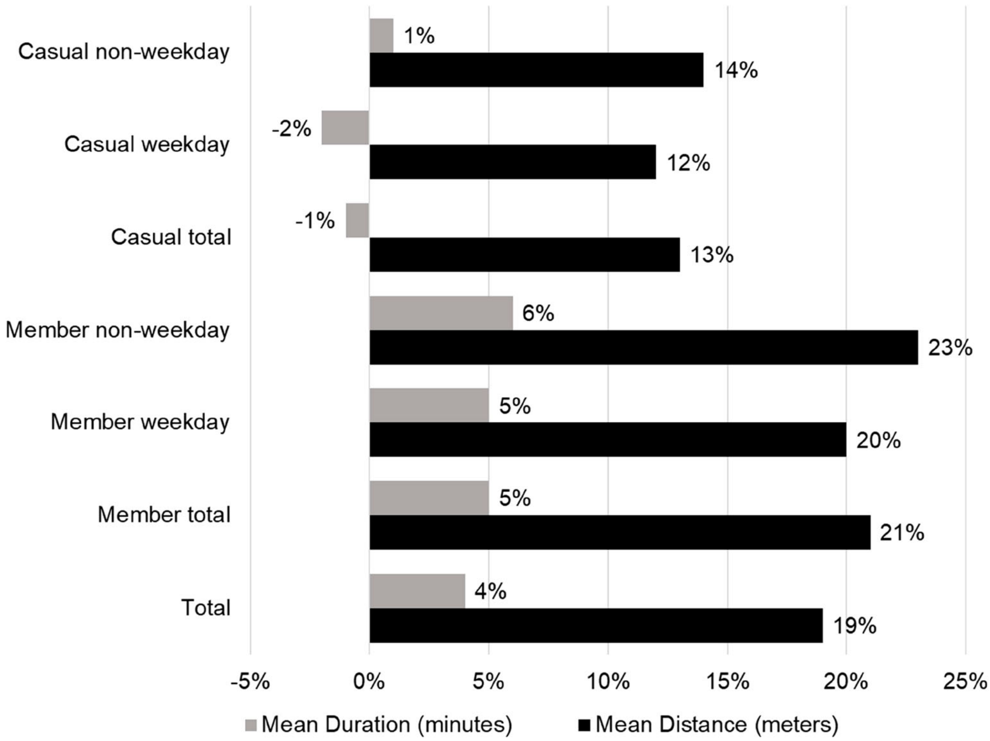

Figure 6. Mean difference in duration (min) and geodesic distance (meters) e-bikes versus classic bikes, by user type, and weekday/non-weekday.

stations. We found that the effects of most variables on classic bikes largely align with previous studies and these variables also have the same directional effect on e-bike trips.

Our models also suggest that what drives e-bike usage does not differ much from what drives classic bike usage. We plot the 95% credible intervals of each independent variable from the two models – classic bikes and e-bikes. We do this by plotting the normal functions of mean coefficients against the unit change of standard deviation from the mean. We mark +/−1.96 standard deviations with dashed lines to indicate the 95% credible intervals. Each plot includes two normal functions – respectively for classic bikes and e-bikes – for the same variable's coefficient. The overlapping area of credible intervals of each plot indicates to what extent the effects of this variable differ between classic bike trips and e-bike trips – the larger the overlapping area, the less likely the difference. A selection of representative plots is shown in Figures 10–15.

Our measures of infrastructure, bike lane length, bike rack counts, and the presence of subways stations, all show positive effects on trip generation for both classic bikes and e-bikes, and these effects are similar for the two bike types (Table 5). Bike lane length increases classic bike trips a bit more than it does e-bike trips. However, the overlap in the 95% credible intervals of the mean coefficients for bike lane length shows little difference between the coefficients (Figure 10).

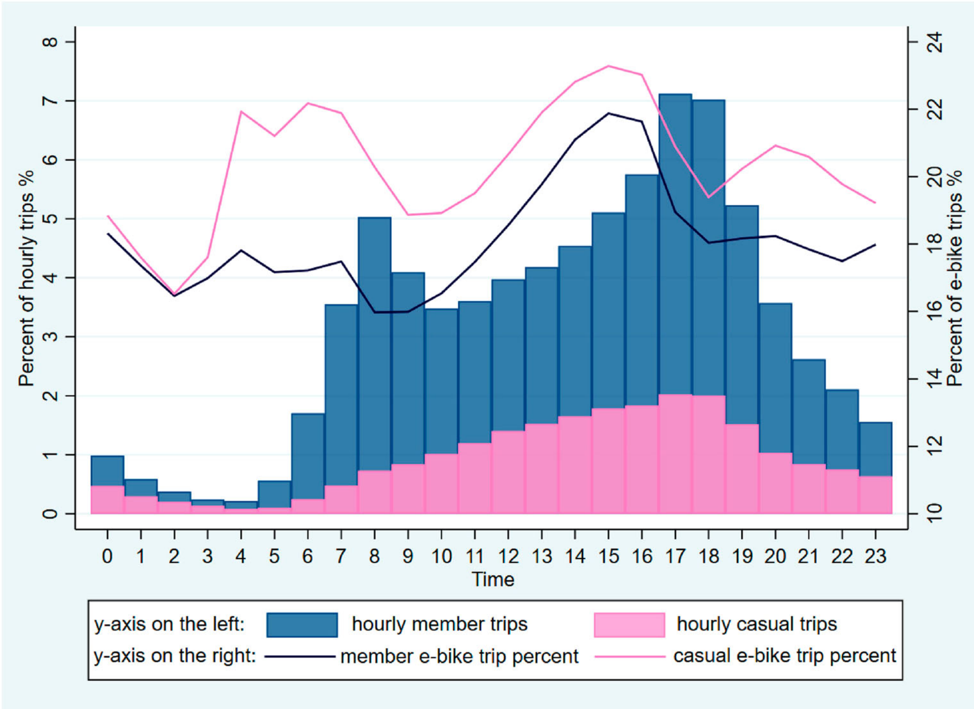

Figure 7. Bike trips in September 2022 aggregated by hour for members and casual users, and e-bike percent ($N = 3,369,119$).

The daytime worker population is positively associated with trip generation for both bike types. In contrast, the higher percentage of the Hispanic population in the service area decreases both classic and e-bike trips. Black, Asian, and other races, all are positively associated with trips. However, the effects of the Black population are not statistically significant for classic bikes, and for e-bike trips, the effects of the Asian population are not statistically significant (Table 5).

Credible intervals for the mean coefficients only partially overlap for our daytime worker population (Figure 11) and Hispanic population (Figure 12) variables. This suggests some differences in the effects of the two variables on classic and e-bikes. The percentage of daytime workers in a service area likely has a stronger positive effect on e-bike trips than on classic bikes. A larger Hispanic population in a service area has a weaker negative association with e-bikes, compared to classic bikes.

Table 5 also shows that higher percentages of residential, industrial, and parking land uses decrease both classic and e-bike trips, although the effects of parking land uses are not statistically significant. Effects of public facility and 'other' land uses, though positive, are not statistically significant either, while mixed and recreational land uses are both positively associated with trips for both types of bikes.

Our plots of credible intervals show there are no major differences in the effects of various land uses on trip generation of classic and e-bikes, especially for residential land use (Figure 13). Thus, we cannot support the hypothesis that trip purposes are meaningfully different for the two bike types. The strongest differences we observe are

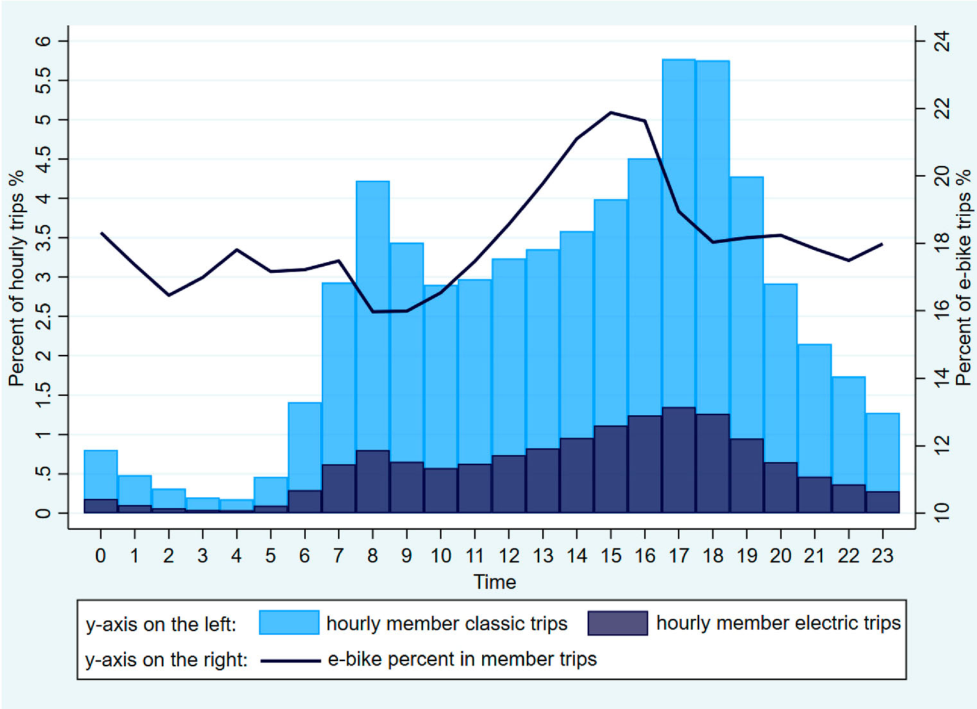

Figure 8. Member bike trips in September 2022 aggregated by hour for classic bikes and e-bikes (N = 3,369,119).

for industrial land use and recreational land uses (Figure 14), which both appear to result in more e-bike trips, though again the intervals overlap considerably.

Elevation is negatively associated with classic bikes. For every 100 feet more compared to the mean elevation of all stations, classic bike trips decrease by a factor of 0.79. This suggests that classic bikes are less likely to take place when trips begin at a higher elevation, which is surprising. Elevation is positively associated with e-bike trips, though not statistically significant. Yet, the smaller magnitude of effects on e-bikes than classic bikes still suggests that e-bikes may be less sensitive to elevation change (Table 5). This is also the largest difference between classic bikes and e-bikes that we found for our trip generation factors (Figure 15).

Finally, we found that relative to other bikeshare stations in the network, stations in the periphery are less likely to generate bike trips, while the negative effects are smaller for e-bikes (Table 5).

Differences between member and casual trips

We examine differences between trips generated by members and casual users as well as how each varies by bike type. Tables 6 and 7 show model estimates. Our infrastructure variables are positively associated with both member and casual trips, for both classic and e-bike trips. Effects do not differ much between members and casual users. However, the presence of a subway station has a larger association with casual users than members. The difference also exists in the models for e-bikes and suggests that casual users are more

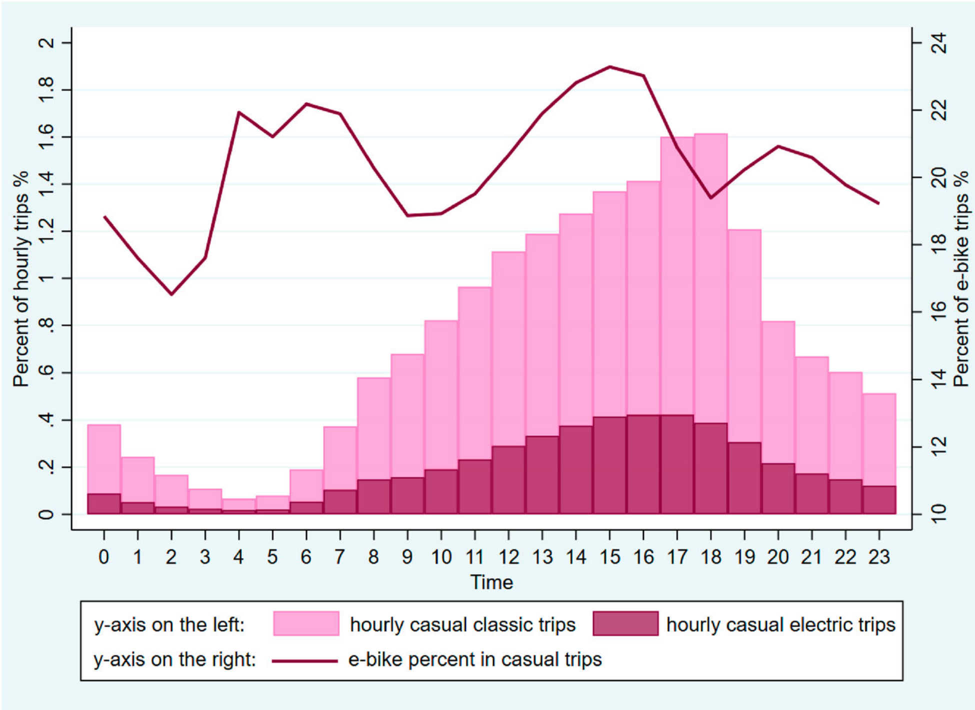

Figure 9. Casual bike trips in September 2022 aggregated by hour for classic bikes and e-bikes ($N =$ 3,369,119).

likely to use shared bikes to connect to the subway than are members, regardless of the type of bike.

When there are more daytime workers near a station, there are more trips generated by members compared to casual users. A similar pattern is found in the usage of e-bikes. Relative to the non-Hispanic white population, a larger percent of the Hispanic population near a station generally decreases bike trips, with a larger negative effect on casual users using classic bikes, compared to e-bike use by casual users. This suggests that the Hispanic population may be more likely to use e-bikes as casual users.

A larger Asian population is associated with more classic member trips relative to casual-user trips. A larger percent of the Black population increases member trips more than casual trips. This indicates that areas with more Asians are more likely to have subscribers riding classic bikes, but those with Black populations tend to be member e-bike users. The population of other races has positive effects in all models. Their effects are the largest on classic casual trips, and the smallest effects on e-bike casual trips.

Land use types have varying effects on member and casual trips, although differences are trivial between classic and e-bikes. Residential land use is the most likely to generate member e-bike trips compared to other trips. Mixed land uses increase member trips more than casual trips but do not differ by bike type. In comparison, recreational land uses increase more casual trips and have the smallest effects on classic member trips.

While effects of elevation vary between classic and e-bikes, they do not differ greatly between member and casual trips. We found that classic member users are the most

Table 5. MCMC-CAR models for classic bike trips and e-bike trips.

Models of total trips by bike type								
Dependent variable ($N = 1614$):	Classic bikes				E-bikes			
Bike trip counts	Mean	Std	*p*-value	G-R stat	Mean	Std	*p*-value	G-R stat
Constant	5.82	0.46	0.00	2.01	4.24	0.32	0.00	1.48
ln (bike lane length) (ln(feet))	0.05	0.01	0.00	1.01	0.04	0.01	0.00	1.01
ln (bike rack count)	0.15	0.02	0.00	1.00	0.15	0.02	0.00	1.01
Subway (yes = 1)	0.13	0.05	0.01	1.00	0.11	0.05	0.02	1.00
ln (daytime worker population %)	0.12	0.02	0.00	1.02	0.15	0.02	0.00	1.03
ln (Hispanic population %)[1]	−0.36	0.03	0.00	1.02	−0.30	0.03	0.00	1.05
ln (non-Hispanic Black population %)	0.05	0.02	n.s.	1.01	0.06	0.02	0.01	1.03
ln (non-Hispanic Asian population %)	0.09	0.02	0.00	1.01	0.04	0.03	n.s.	1.01
ln (non-Hispanic other population %)	0.32	0.05	0.00	1.01	0.23	0.05	0.00	1.02
ln (residential land %)[2]	−0.08	0.02	0.00	1.02	−0.08	0.02	0.00	1.02
ln (mixed land %)	0.17	0.02	0.00	1.01	0.17	0.02	0.00	1.00
ln (industrial land %)	−0.16	0.02	0.00	1.01	−0.13	0.02	0.00	1.00
ln (transportation land %)	−0.02	0.02	n.s.	1.00	0.00	0.02	n.s.	1.01
ln (public facility land %)	0.01	0.02	n.s.	1.01	0.00	0.02	n.s.	1.00
ln (recreational land %)	0.08	0.02	0.00	1.01	0.10	0.02	0.00	1.01
ln (parking land %)	−0.04	0.03	n.s.	1.00	−0.04	0.03	n.s.	1.00
ln (other land %)	0.00	0.02	n.s.	1.00	0.02	0.02	n.s.	1.00
Elevation from mean (per 100 feet)	−0.23	0.00	0.00	1.00	0.03	0.00	n.s.	1.00
Peripheral station (yes = 1)	−0.43	0.08	0.00	1.00	−0.30	0.08	0.00	1.00
Spatial autocorrelation (Phi)	−0.11	0.45	n.s.	1.95	−0.04	0.29	n.s.	1.51
Log-likelihood	−13755.95				−11150.95			
AIC	27553.90				22343.89			
Number of iterations	25,000				25,000			
Burn-in sample	5,000				5,000			

Note:
1. Non-Hispanic White population is used as the reference group;
2. All other land use types excluded from the models are used together as the reference group.
3. n.s. = not significant.

sensitive to elevation, while elevation has the smallest effect on member e-bike trips, although it is not statistically significant for either member or casual e-bike trips. Peripheral stations are also less likely to generate member trips than casual trips.

Discussion

In our analyses, we found that around one in five Citi Bike trips in September 2022 are e-bike trips. Generally, casual users are more likely to use e-bikes than members are. Weekdays have a higher percentage of e-bike trips than non-weekdays. E-bike trips are lowest as a percent of all trips during the 8–9 AM morning peak, while at 3 PM they reach their highest percent usage within the system.

E-bikes are more suitable for travelling longer distances (MacArthur, Dill, and Person 2014), and we found on average, e-bikes travelled 19% farther than classic bikes. The difference is larger for members (21%) than casual users (13%), which may be explained by different trip purposes since members are more likely to undertake commute trips, and commuting trips are generally longer than other trips (Plazier, Weitkamp, and van den Berg 2017). The difference in time duration is smaller than the difference in distance. This is intuitive because e-bikes travel faster than classic bikes.

The hourly distribution of classic bike trips is largely consistent with previous studies in North America, such as in Philadelphia (Caspi and Noland 2019) and Washington DC (Gebhart and Noland 2014), except our analysis also identified the hourly distribution of

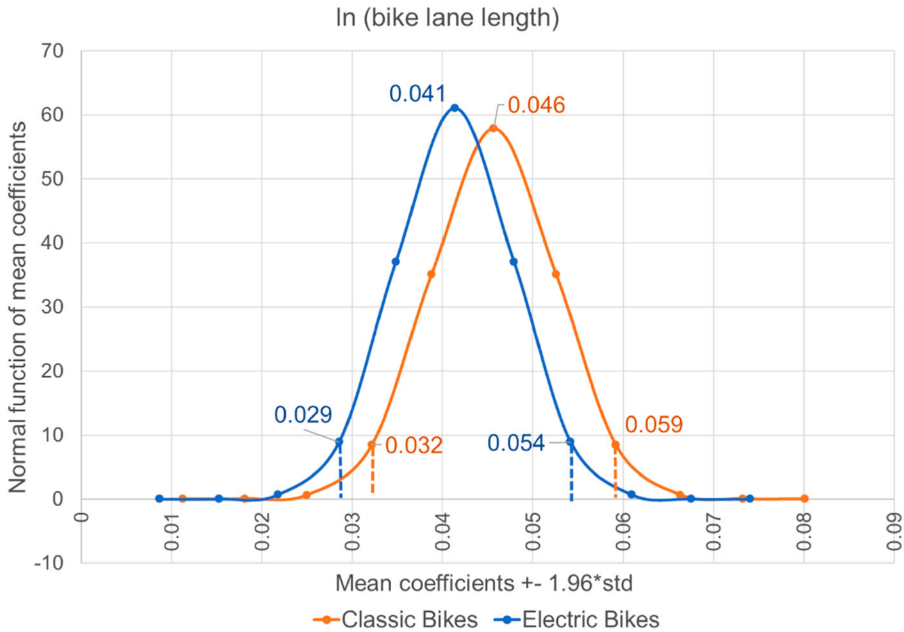

Figure 10. Normal functions of mean coefficients of the bike lane variable, respectively for classic and e-bikes; the 95% credible intervals marked with dash lines at +/−1.96 standard deviation from the mean.

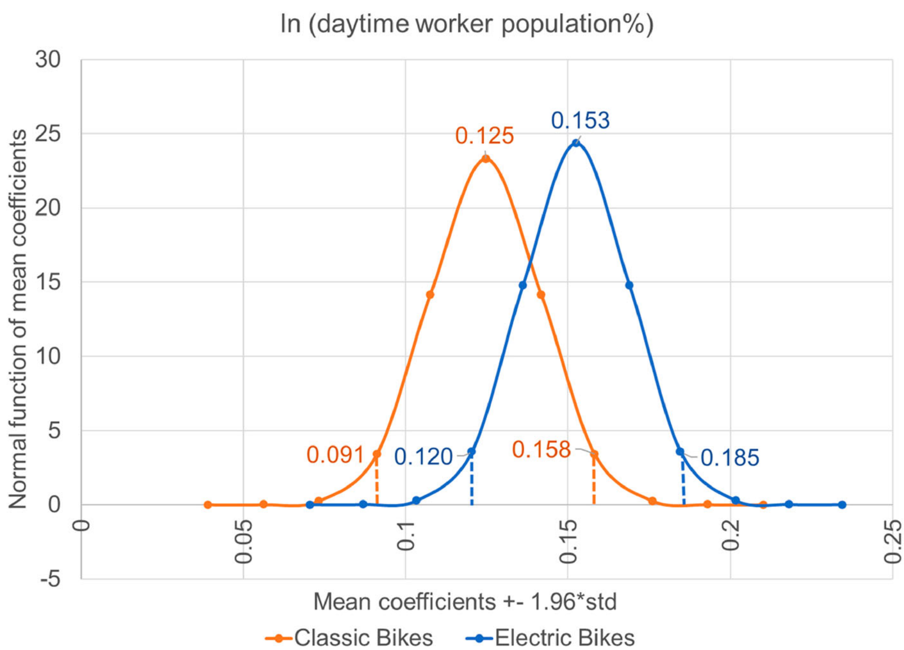

Figure 11. Normal functions of mean coefficients of the daytime worker population variable, respectively for classic and e-bikes; the 95% credible intervals marked with dash lines at +/−1.96 standard deviation from the mean.

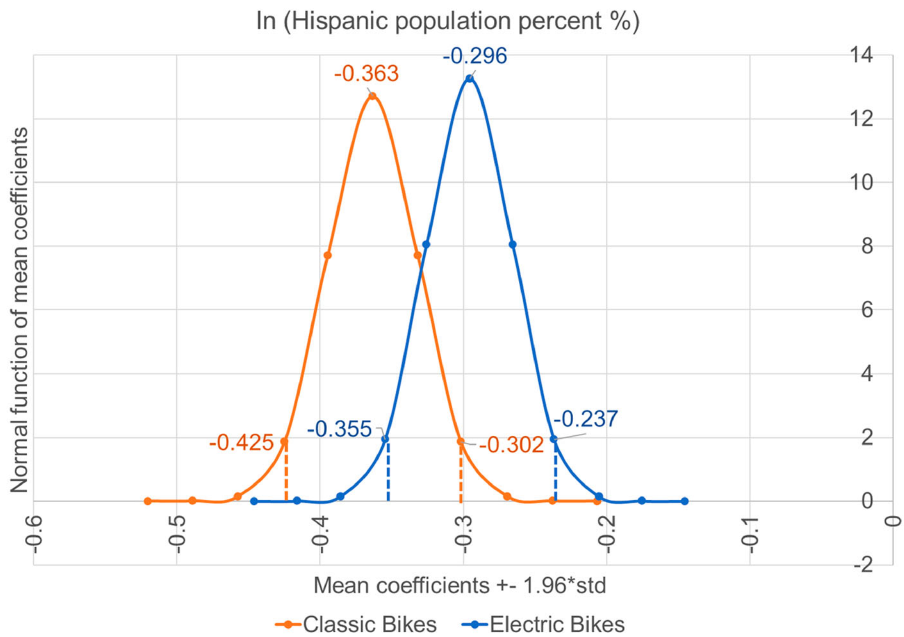

Figure 12. Normal functions of mean coefficients of the Hispanic population variable, respectively for classic and e-bikes; the 95% credible intervals marked with dash lines at +/−1.96 standard deviation from the mean.

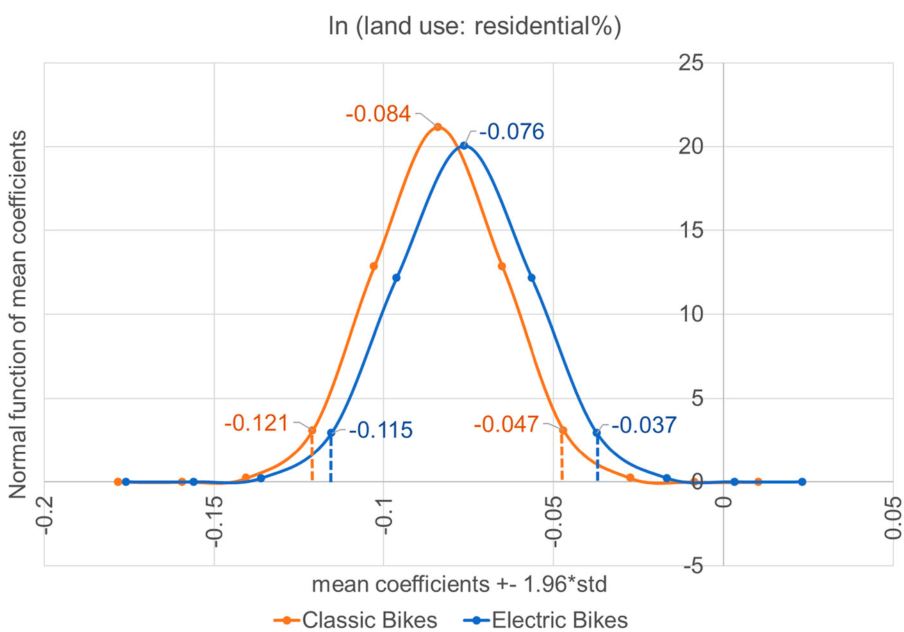

Figure 13. Normal functions of mean coefficients of the residential land use variable, respectively for classic and e-bikes; the 95% credible intervals marked with dash lines at +/−1.96 standard deviation from the mean.

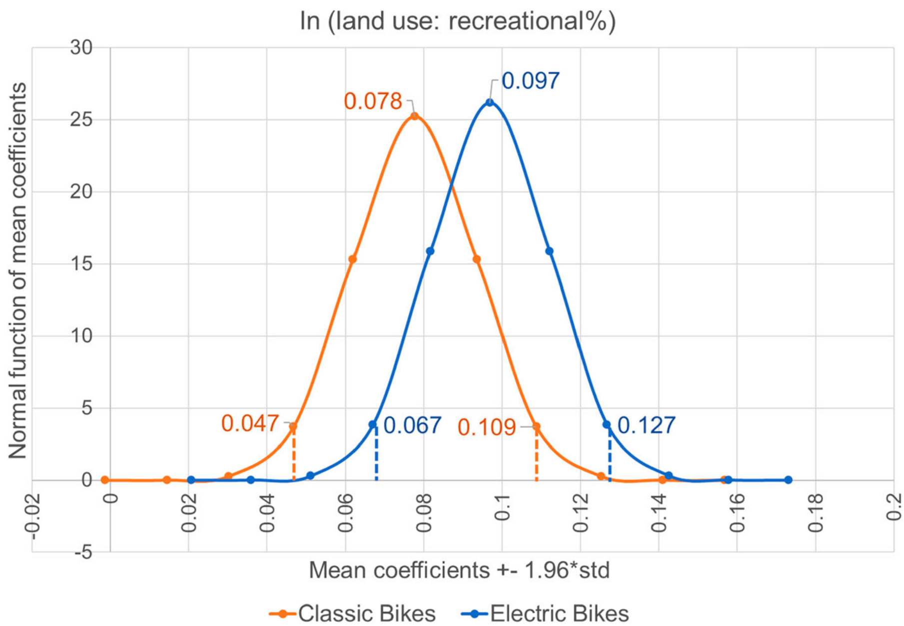

Figure 14. Normal functions of mean coefficients of the recreational land use variable, respectively for classic and e-bikes; the 95% credible intervals marked with dash lines at +/−1.96 standard deviation from the mean.

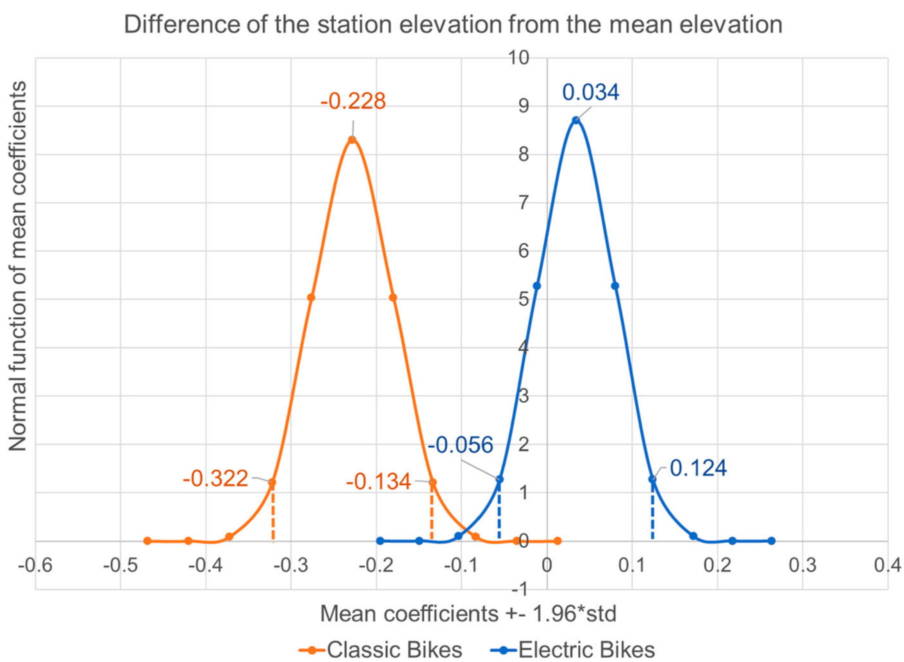

Figure 15. Normal functions of mean coefficients of the elevation variable, respectively for classic and e-bikes; the 95% credible intervals marked with dash lines at +/−1.96 standard deviation from the mean.

Table 6. MCMC-CAR models for member trips and casual trips for classic bikes.

Models of classic bikes by user type								
Dependent variable ($N = 1614$):	Member trips				Casual trips			
Bike trip counts	Mean	Std	*p*-value	G-R stat	Mean	Std	*p*-value	G-R stat
Constant	5.56	0.86	0.00	1.20	4.27	0.33	0.00	1.39
ln (bike lane length) *(ln(feet))*	0.05	0.01	0.00	1.00	0.05	0.01	0.00	1.01
ln (bike rack count)	0.15	0.02	0.00	1.00	0.15	0.02	0.00	1.01
Subway *(yes = 1)*	0.12	0.05	0.02	1.00	0.19	0.05	0.00	1.00
ln (daytime worker population %)	0.13	0.02	0.00	1.01	0.09	0.02	0.00	1.03
ln (Hispanic population %)[1]	−0.37	0.03	0.00	1.02	−0.30	0.03	0.00	1.02
ln (non-Hispanic Black population %)	0.06	0.02	0.02	1.00	0.01	0.02	n.s.	1.01
ln (non-Hispanic Asian population %)	0.10	0.03	0.00	1.00	0.07	0.03	0.01	1.01
ln (non-Hispanic other races population %)	0.29	0.05	0.00	1.00	0.34	0.05	0.00	1.03
ln (residential land %)[2]	−0.07	0.02	0.00	1.01	−0.10	0.02	0.00	1.02
ln (mixed land %)	0.18	0.02	0.00	1.01	0.11	0.02	0.00	1.00
ln (industrial land %)	−0.15	0.02	0.00	1.00	−0.15	0.02	0.00	1.01
ln (transportation land%)	−0.01	0.02	n.s.	1.00	−0.02	0.02	n.s.	1.00
ln (public facility land %)	0.02	0.02	n.s.	1.00	−0.02	0.02	n.s.	1.00
ln (recreational land %)	0.07	0.02	0.00	1.00	0.10	0.02	0.00	1.01
ln (parking land %)	−0.04	0.03	n.s.	1.00	−0.01	0.03	n.s.	1.00
ln (other land%)	−0.01	0.03	n.s.	1.00	0.05	0.03	n.s.	1.00
Elevation from mean *(per 100 feet)*	−0.22	0.00	0.00	1.01	−0.19	0.00	0.00	1.00
Peripheral station *(yes = 1)*	−0.50	0.09	0.00	1.00	−0.19	0.09	0.05	1.00
Spatial autocorrelation (Phi)	−0.22	0.84	n.s.	1.21	0.03	0.33	n.s.	1.46
Log-likelihood	−14982.17				−61393.76			
AIC	30006.34				122829.51			
Number of iterations	500,000				500,000			
Burn-in sample	30,000				30,000			

Note:
1. Non-Hispanic White population is used as the reference group;
2. All other land use types excluded from the models are used together as the reference group.
3. n.s. = not significant.

e-bikes exhibits a slightly different pattern compared to classic bikes. E-bike usage has a much flatter peak for both user types, compared to classic bike trips which have morning and evening peaks for members, and a relatively flatter peak for casual users in the evening. We observe a drop in the percent of e-bike trips during peak commuting hours. This may be due to the limited supply and high demand for e-bikes, which is particularly reflected during peak hours. Another observation is that the percent of casual user trips on e-bikes peaks between 4 and 6 AM. This may be because there is a preference to avoid public transit late at night, due both to less frequent service and fear of crime.

Our modelling results confirm the positive effects of bike lanes, bike racks, and nearby subway stations (Noland, Smart, and Guo 2016; Mateo-Babiano et al., 2016), and demonstrate that these effects are not very different for e-bike trips. A larger percent of Hispanic population is found to be negatively associated with trip generation. Relative to areas that have a larger non-Hispanic White population, those with a larger Hispanic population tend to be negatively associated with trip generation. This suggests that the generation of Citi Bike trips has some disparity in usage, similar to bikeshare systems in other North American cities (Caspi and Noland 2019; Hosford and Winters 2018; Kong and Leszczynski 2022). Nevertheless, we also found that the negative effects are lessmaller for those who ride e-bikes, and smallest for e-bike users who are casual users. This may suggest that e-bikes are more attractive to the Hispanic population than classic bikes, providing a more equitable outcome. Other research has found that shared

Table 7. MCMC-CAR models for member trips and casual trips for e-bikes.

Models of e-bikes by user type								
Dependent variable (N = 1614):	Member trips				Casual trips			
Bike trip counts	Mean	Std	*p*-value	G-R stat	Mean	Std	*p*-value	G-R stat
Constant	3.52	0.76	0.00	1.99	2.76	0.43	0.00	3.03
ln (bike lane length) (ln(feet))	0.04	0.01	0.00	1.00	0.04	0.01	0.00	1.03
ln (bike rack count)	0.15	0.02	0.00	1.00	0.15	0.02	0.00	1.03
Subway (yes = 1)	0.10	0.05	0.05	1.00	0.17	0.05	0.00	1.02
ln (daytime worker population %)	0.16	0.02	0.00	1.01	0.12	0.02	0.00	1.12
ln (Hispanic population %)[1]	−0.31	0.03	0.00	1.00	−0.20	0.03	0.00	1.05
ln (non-Hispanic Black population %)	0.07	0.02	0.00	1.00	0.02	0.02	n.s.	1.02
ln (non-Hispanic Asian population %)	0.04	0.03	n.s.	1.00	0.05	0.02	n.s.	1.07
ln (non-Hispanic other races population %)	0.22	0.05	0.00	1.01	0.20	0.04	0.00	1.08
ln (residential land %)[2]	−0.06	0.02	0.01	1.00	−0.10	0.02	0.00	1.07
ln (mixed land %)	0.18	0.02	0.00	1.00	0.10	0.03	0.00	1.04
ln (industrial land %)	−0.12	0.02	0.00	1.00	−0.15	0.02	0.00	1.01
ln (transportation land%)	0.01	0.02	n.s.	1.00	−0.03	0.02	n.s.	1.02
ln (public facility land %)	0.01	0.02	n.s.	1.00	−0.03	0.02	n.s.	1.01
ln (recreational land %)	0.09	0.02	0.00	1.00	0.10	0.02	0.00	1.02
ln (parking land %)	−0.04	0.03	n.s.	1.00	−0.01	0.03	n.s.	1.01
ln (other land%)	0.01	0.02	n.s.	1.00	0.05	0.03	n.s.	1.02
Elevation from mean (per 100 feet)	0.03	0.00	n.s.	1.00	0.09	0.00	n.s.	1.01
Peripheral station (yes = 1)	−0.38	0.08	0.00	1.00	−0.07	0.09	n.s.	1.01
Spatial autocorrelation (Phi)	0.30	0.75	n.s.	2.03	0.15	0.40	n.s.	2.88
Log-likelihood	−10688.47				−28535.08			
AIC	21418.95				57112.15			
Number of iterations	100,000				100,000			
Burn-in sample	10,000				10,000			

Note:
1. Non-Hispanic White population is used as the reference group;
2. All other land use types excluded from the models are used together as the reference group.
3. n.s. = not significant.

e-bikes increase transit ridership more than classic bikes, and shared e-bikes contribute to increased bus ridership mainly in Census Blocks with lower household incomes (Martin and Xu 2022).

It is not surprising that our models suggest that higher recreational land use is more likely to generate e-bike trips, as e-bikes have been found to be used for recreational purposes (He et al. 2019), and since New York City attracts a large number of tourists. Shared e-bike usage seems to differ from privately owned e-bikes, as the latter has been found to be used more for utilitarian trips (MacArthur, Dill, and Person 2014). We found negative effects associated with residential land use opposite that of previous findings for the Citi Bike system (Noland, Smart, and Guo 2016). Other research on bikeshare has found that commuting was the most common trip purpose across four of North America's largest bikeshare programs (Shaheen, Cohen, and Martin 2013). The COVID-19 pandemic might partially explain the pattern change, as Wang and Noland (2021) identified longer trips and more recreational trips with fewer work-related trips taken in the Citi Bike system comparing data before and after COVID-19 occurred.

We found that elevation has negative impacts on classic bike trips. This may be due to the rebalancing challenges of classic bikes because there are fewer classic bike trips that end at higher elevation stations, which leads to lower supply. The effects are positive for e-bikes, with a smaller magnitude than effects on classic bikes, though not statistically significant. This indicates that classic bikes are less likely to be used, compared to e-bikes when there are elevation differentials. Others have found a similar result and this is not surprising as many users will shun the physical effort in hilly areas (Guidon et al. 2019).

Conclusions

Our study contributes to the existing literature by evaluating differences and similarities between classic and e-bikes within the same bikeshare system in New York City, controlling for spatial effects. Using Citi Bike trip data from September 2022, we compare the trip generation of classic bikes and e-bikes, by user type, weekday vs. non-weekday, and time of day. We model bike trip generation with independent variables for cycling infrastructure, nearby subway stations, population, land use, elevation, and peripheral stations, and compare models by bike type and user type.

Our analysis shows that e-bikes made up around 20% of total bikeshare trips in September 2022. We suspect that some of our findings may be due to an undersupply of e-bikes in the system, leading to unmet demand for e-bikes at certain times of day and at certain stations. While e-bike usage increases when peak hours approach, the fraction of total trips drops during peak hours, possibly implying that demand is not being fully met for a mode with the potential to meet many mobility needs. This is a signal for the bikeshare operator that there is potential to increase the rental of e-bikes if they increase e-bike availability during peak hours by increasing the supply of e-bikes.

Our model results confirm that cycling infrastructure, subway stations, population, mixed and recreational land use contribute to the trip generation of shared e-bikes in New York City. We found no large differences in factors associated with trip generation for e-bikes compared to classic bikes. The one exception is that hillier areas generate fewer classic bike trips compared to e-bikes. Providing cycling infrastructure (both lanes and racks), and placing bikeshare stations near subway stations, in highly populated areas, or near mixed and recreational land uses could encourage bikeshare usage for both types of bikes.

Our findings show that e-bike trip generation is more positively associated with recreational land uses than classic bikes. While this suggests how e-bikes are currently being used, this also means there is a potential for policy makers to encourage more e-bike trips for other purposes, especially commuting. In addition, areas with more Hispanic population are more likely to generate e-bike trips; this suggests a path for policy makers to support Citi Bike expansion to allocate more e-bikes in areas with a higher concentration of minority and disadvantaged groups. While New York City is generally flat with a few hillier areas in Upper Manhattan and the Bronx, our findings still suggest that e-bikes have the advantage of being less sensitive to elevation change. This may be a factor the Citi Bike operator should consider when rebalancing supply.

We do not have GPS data on the routes taken which is needed for a more accurate evaluation of the impacts of elevation. This is one of our limitations. Another limitation common to most prior work is that we do not have information on actual trip purposes and therefore must infer the purpose of trips from land use associations. To facilitate analysis, we also assumed that the demographics of riders in a service area largely match the demographics of those who live in the service area, which may differ from reality. Without access to user information and GPS data, we are unable to evaluate in detail how trip purposes, motivating factors, and trip routes differ between e-bikes and classic bikes.

Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID

Yingning Xie http://orcid.org/0000-0003-0753-3320
Michael Smart http://orcid.org/0000-0003-3739-2725
Robert B. Noland http://orcid.org/0000-0003-0775-0624

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