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Bikesharing, equity, and disadvantaged communities: A case study in Chicago

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ABSTRACT

Bikeshare systems are rapidly becoming more prevalent in metro and micropolitan areas around the world. However, low-income populations, people of color, and transit-dependent households are not highly representative of the bikeshare user's profile. Some bikeshare programs in the United States, such as *Divvy* in Chicago, try to address this equity problem by promoting their systems among low-income communities. Currently, there is limited research estimating bikeshare ridership in these communities and quantitatively analyzing the impacts of financial barriers in disadvantaged areas at the station level. This research fills this gap by analyzing the current utilization of bikeshare systems among disadvantaged populations. The study develops a Negative Binomial regression model to estimate bikeshare ridership using data from Chicago's bikeshare system. The results show that bikeshare stations in disadvantaged communities generate around two-thirds of the average annual trips across all stations. The employment rate plays an important role in increasing bikeshare ridership, especially for disadvantaged areas. Additionally, the research found that the proportion of trips by annual members is significantly lower in disadvantaged communities than in other areas. However, interestingly, residents in disadvantaged communities tend to make longer bikeshare trips once they are annual members. Their dependence on bikeshare systems may result from accessibility improvement (e.g., work commute by bikeshare). Based on all the findings, we discuss planning implications for more socially inclusive and equitable bikeshare systems.

1. Introduction

Bikeshare, as a non-motorized transportation service, is an increasingly prevalent transportation option that offers members access to shared bicycles (NACTO, 2018). In North America, a recorded 35 million bikeshare trips were made in 2017; 25% more than in 2016 (NACTO, 2018). For example, the "*Divvy*" bikeshare system in Chicago has increased total annual trips by almost 50%, from 2.45 million in 2014 to 3.81 million in 2017 (Motivate International, 2018b).

Technology innovations in managing bikeshare systems (BSSs) have progressed from unlocked and untended coin-deposit systems to automated self-serve kiosk systems (Gaegauf, 2014; Shaheen et al., 2010), and recently, dockless (free-standing) systems. Self-serve kiosks and dockless systems achieve a more user-friendly interface and are convenient for unsubscribed users with smartphones and credit cards. In 2016, there were 55 bikeshare systems across the US, with the majority adopting dock-based and self-serve kiosk

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systems (National Association of City Transportation Officials, 2017, pp. 2010–2016). With the introduction and growing prevalence of dockless systems, the numbers of both bikeshare systems and bikes continue to increase.

However, disadvantaged communities are not highly representative of the bikeshare user's profile. Currently, bikeshare systems are trying to expand systems to cover disadvantaged areas and mitigate financial barriers to participation. For instance, "*Motivate*," a for-profit bikeshare company has promoted a five-dollar annual membership program among its operating systems. In July of 2015, *Divvy* launched this particular membership program and named it "*Divvy* for Everyone (D4E)." Two years later, *GoBike* in San Francisco, *Capital* bikeshare in Washington D.C., and *CitiBike* in New York introduced similar programs. All of these programs offer an affordable annual membership fee (five dollars) for low-income populations (Capital Bikeshare, 2018; CitiBike, 2018; Motivate International, 2017b, 2018a). Besides the one-time $5 annual membership fee, *Divvy* also introduced a cash payment system since many residents in disadvantaged communities do not have credit cards (Motivate International, 2017b).

There are plenty of studies analyzing equity issues for bikeshare systems, and identifying the bikeshare user's profile, including the average user's income, at a system level from survey data (Bernatchez et al., 2015; Buck, 2013; Cohen, 2016; McNeil et al., 2017a). Nevertheless, most of these survey studies related to bikeshare equity qualitatively indicate the existence of financial barriers. Another vein of research develops bikeshare ridership estimation models with spatiotemporal and demographic variables. However, these models do not consider the impacts on bikeshare ridership from disadvantaged communities at the station level. Thus, this research focuses on the number, length, and cost of trips made from stations in disadvantaged communities, particularly for trips by annual members. Finally, we discuss the implications of these results and offer planning recommendations to foster a more sustainable and equitable transportation system.

2. Literature review

2.1. Bikeshare ridership

In light of the growth of BSS, operators, planners, and academics have been interested in predicting future usage. To do so, they have developed and applied different methodologies with different temporal scales and resolutions. Some focus on estimates per year or month, usually conducted at an aggregate level. For example, at the beginning stage of implementing a large-scale BSS, Lyon and Paris, France predicted potential bikeshare trip volumes based on demographic and transportation data (Krykewycz et al., 2010). Similarly, to explore the feasibility of a BSS in Philadelphia, researchers created a "Bikeshare Score" to identify areas with a high potential demand to implement the BSS (Krykewycz et al., 2010). The "Bikeshare Score" uses data such as population, job density, proximity to parks, recreation areas and other facilities, and proximity to transit stations. Likewise, Frade and Ribeiro (2014) developed a demand estimation method at the traffic analysis zone level, combining target populations of bikeshare, trip characteristics, and physical characteristics of city paths (e.g., the slope of a road).

In addition to these aggregate models, station ridership prediction research has received increased attention. Rixey (2013) introduced a linear regression model to forecast station-level monthly bikeshare ridership. Vogel and Mattfeld (2011) used time-series analyses to forecast daily and hourly bike demands to support strategic and operational decisions. As the level of analysis becomes more disaggregated, more detailed data is introduced into prediction models. For example, Giot and Cherrier (2014) found that weather forecasts and bikeshare usage within the past 24 h are essential in predicting bikeshare usage per hour. Hyland et al. (2017) developed a hybrid cluster-regression model to predict station-level usage. First, they clustered stations based on the types of trips the station attracted. Then, they found that station-cluster interaction terms significantly improved the performance of the usage prediction model.

With respect to disadvantaged communities, however, previous research has considered income and race as two separate independent variables and has not explicitly evaluated disadvantaged communities. In general, there is a relative paucity of research on station-level usage: the number, length, and cost of trips made from stations in disadvantaged communities, particularly for trips by annual members. Cohen (2016) built a multivariate regression model to estimate bikeshare ridership in low-income communities. The results show that ridership is lower in low-income communities, and could be increased if financial barriers are removed. Cohen's study (2016) did not spatially analyze trip features, e.g., trip duration and trip spending, using trip data from low-income communities.

2.2. Bikeshare finacial barriers for disadvantaged populations

Bikeshare systems have broad benefits, not only at the city level but also for individuals. Many cities around the world have adopted these services and enjoyed considerable environmental and social benefits (Fishman et al., 2014a; Wang and Zhou, 2017). Among their benefits, bikeshare systems provide reduced traffic congestion, improved accessibility, and an environmentally friendly urban transportation option. BSSs also provide benefits in terms of improving physical health, eliminating the maintenance burden of bicycle ownership and bike storage requirements, and reducing the risk of bike theft and vandalism, (Qian and Niemeier, 2019). However, in many cases, disadvantaged populations do not enjoy these broad benefits due to existing cultural and financial barriers, or limited or no availability of bikeshare stations within walking distance (Bernatchez et al., 2015; Cohen, 2016; McNeil et al., 2018; Smith et al., 2015; Ursaki and Aultman-Hall, 2015; Winters and Hosford, 2018). Among these, financial constraints are a primary issue that discourages disadvantaged populations from joining bikeshare programs (McNeil et al., 2017a). Fishman et al. (2012) found that the membership fee is an expense that discourages people, especially those from disadvantaged communities, from using the systems. Moreover, besides the one-time membership fee, users must "pay as you go." A case in London evidenced a decrease in bikeshare usage among low-income areas after the price doubled (Goodman and Cheshire, 2014). Residents living in poverty have limited mobility and accessibility options, mainly because of financial conditions and transit-dependence (often with sub-par quality of service). Financial barriers, to some extent, hinder people from disadvantaged communities from enjoying the accessibility improvements that could be realized through BSSs. However, currently, there is limited research analyzing how much users from disadvantaged areas spend on bikeshare services (e.g., spending habits in relation to BBBs, whether they prefer memberships or pay as you go, price elasticities).

In sum, there are current research gaps in the use of appropriate models to consider bikeshare ridership at the station level, distinguishing station area types (disadvantaged or not), and the magnitude of the financial barrier for bikeshare ridership in disadvantaged communities.

3. Case study and data description

To select an ideal case study city, we invited 16 experts from five different related fields (bikeshare academics, a bikeshare company, metropolitan planning organizations (MPO), bike advocates, and local governments) and asked them to rank potential cities across the available data in terms of usefulness for our study. Finally, we selected Chicago, considering its sizeable urbanized land area (2443 square miles), the proportion of non-white populations (68.3% non-white), and a relatively high percentage of households with no vehicle (27.3%). Chicago also has a large-scale bikeshare system and has shown a determination to address bikeshare equity issues. In 2013, the Chicago Department of Transportation (CDOT) launched the *Divvy* BSS (currently with 581 stations and 6000 bikes), and contracted with *Motivate* to purchase, install, and operate the system (Motivate International, 2017a). In July of 2015, Chicago introduced the "*Divvy* for Everyone (D4E)" program, which provides affordable membership fees to qualifying residents (Motivate International, 2017b).

The *Divvy* bikeshare program provides its database to the public for all *Divvy* bikeshare trips from its inception in July 2013. Every trip record includes trip start day and time, trip end day and time, trip start station, trip end station, and rider type (annual member or day pass user). A day pass user is a rider who purchases a 24-h pass, and an annual member is a rider who purchases an annual membership. If a bikeshare trip is made by an annual member, the trip record will also include the member's gender and year of birth. Since trip records cover trip duration information, the price for every bikeshare trip can be calculated according to the company's pricing structure. By exploring this database, the total number of bikeshare trips and the average charge for trips that originate from or terminate at a particular station can be calculated.

This research required complementary data in addition to *Divvy*'s ridership data. The following paragraphs discuss each of these complementary data sources, while the process of compiling these datasets and descriptive statistics is discussed in the following methodology and result sections.

We included demographic information from the Demographic Census Data, the American Community Survey (ACS) Data, and the Longitudinal Employer-Household Dynamics (LEHD) Database. The United States Census Bureau collects demographic information using surveys across the nation every ten years. The most recent is the 2010 Census, which provides demographic data including population, race, age, and household size, and many other variables at the census block group level. In the selected study area (Chicago), a census block group has approximately 1200 people, and covers 9000 square meters on average. Similar to the Census 2010, the ACS 2014 is a survey program administered by the U.S. Census Bureau. For this study, household income, workforce population, and vehicle ownership data from the ACS were used at the level of census block groups. We estimated the employment rate by dividing the number of employed individuals by the sum of employed and unemployed individuals at the same level. Besides the Demographic Census Data and the ACS data, we also collected job data from the LEHD Database. This dataset provides job data associated with either a home census block or a work census block. The home census block data provides job characteristic data for residents who live in a particular census block, while the work census block data provides job characteristic data for workers who are employed in a particular census block. In estimating bikeshare ridership, we associated bikeshare ridership with job characteristic data to uncover relations between them.

Facility information was from OpenStreetMap and Google Application Programming Interface (API). OpenStreetMap is an open data resource for roads, trails, railway stations, and other traffic networks around the world, built by a community of mappers. It contains geographic information layers for all of the road information in Chicago. The database also contains information about the type of infrastructure, e.g., "vehicle road," "pedestrian way," or "bicycle lane." OpenStreetMap was used to identify all bicycle facilities for the case study. Considering that the data may not be exhaustive, we combined it with another bicycle path map from the Chicago data portal to develop a comprehensive picture of bicycle infrastructure in Chicago. The accuracy of OpenStreetMap has been verified by Haklay (2010). As Google gathers more and more geographic data through its diverse practical projects, it is providing many useful APIs for public researchers. Among these, Google Place API can return an extensive list of places within a specified search radius based on a user's location, as defined by the user. For this research, the numbers of schools, hospitals, grocery stores, and transit (bus and railway) stations were calculated within a certain distance of every bikeshare station. Additionally, the Google Distance API can provide the cycling distance between every pair of bikeshare stations. Using this API, we also estimated the number of other bikeshare stations within a certain cycling distance (e.g., 500 m) for every bikeshare station, since proximity to other stations increases the ridership of a given bikeshare station (Hampshire and Marla, 2012).

As indicated in multiple research papers, safety concerns are an important consideration when selecting travel modes, and are particularly relevant to cycling (Christie et al., 2011; Fishman et al., 2014b; Griffin et al., 2008). This study considered two types of safety issues: bicycle crashes with vehicles, and street crime (violent offenses). For bicycle crashes, Chicago has an online database of crash data from 2009 to 2014, which is maintained by the Illinois Department of Transportation (DOT). The database includes bicycle and pedestrian collisions with vehicles resulting in injuries. Additionally, crime data from a local government portal includes incidents of crimes such as aggravated assault, rape, arson, battery, theft, and other violent offenses. Because land use can affect bicycle trip generations (Barnes and Krizek, 2005; Dill and Voros, 2007), we also collected information on recreation areas such as parks and historic locations from the National Register of Historic Places.

4. Methodology

To accurately estimate ridership, publicly available bikeshare trip data was used, as well as the demographic and spatiotemporal data for every census block group in the study area. First, we conducted a buffer analysis for the existing bikeshare stations and summarized the data for these catchment areas. Then, the bikeshare stations in disadvantaged areas were identified based on demographic information on the catchment areas. After assembling the required data, we estimated an econometric model for annual ridership for each station, and conducted the marginal effect and elasticity analyses. Further, we spatially analyzed annual subscription rates and actual trip charges at the station level within different areas using historical bikeshare trip data. Fig. 1 illustrates the process followed to conduct the analyses.

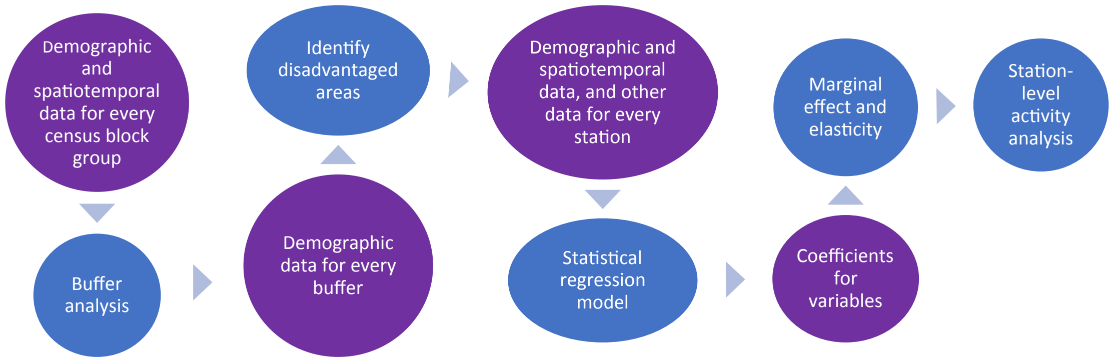


Fig. 1. Analysis process.

4.1. Buffer analysis

According to a Los Angeles study, the average distance for access to a bikesharing station is 400 m (Cohen, 2016). We, therefore, created a 400-meter buffer around each bikesharing station included in this study. Since it is not possible to retrieve direct demographic data (namely, population, income, minority percentage, median age, household number, vehicle ownership, workforce, and employment rate) for the catchment area, the analyses used data for single stations indirectly by compiling the same data in block groups covered by a station's buffer. If a portion of a certain census block falls within the 400-meter buffer, the study assumes a uniformly distributed population in this census block group, and the demographic estimates are weighted proportionally to the amount of the block group within the buffer. For other data (e.g., the number of transit stations in a buffer), the process calculated the total number of places or events, and the total area of parks and historic places within a buffer. All of the data compiled for the stations' buffers are listed in Table 1. There is one variable: the percentage of young populations, which refers to the percentage of the population aged between 20 and 35. People ages 20–35 are reported to be consistently overrepresented as bikeshare users (Buck et al., 2013; Daddio and Mcdonald, 2012; Shaheen, 2012). Thus, we considered the percentage of young populations instead of average age in the later regression analysis since two block groups with the same average age might have different age compositions.

4.2. Identification of disadvantaged communities

While some previous research uses the terminology "disadvantaged" without a precise definition, this work, to avoid misunderstanding and ambiguity, defines the selection criteria for disadvantaged communities. In this research, 'disadvantaged communities' refers to regions where low-income populations and people of color live. To define such communities for this study, we first identified those block groups with a median household income below $50,000 (200% of the federal poverty line for a household with four people) (Jiang et al., 2016; U. S. Department of Health & Human Services, 2016). Then, low, moderate and high thresholds were set using the mean and standard deviation of the percentage of minority populations within each buffer. Table 2 shows the threshold levels for minority populations (Turner et al., 1997).

Finally, the process identified whether a bikeshare station buffer qualifies as a disadvantaged area or not. A buffer was defined as a disadvantaged area if: a) the median household annual income is below $50,000; and b) the percentage of white/Caucasian race is below 41.64%; as shown in Table 2.

Table 1
Summary of key variables considered in the analyses.

Variable	Abbreviation	Description	Source
Dependent			
Total origin trips	O_Trip	Total number of annual bikeshare trips that originate from a bikeshare station	*Divvy* bikeshare system operator
Total destination trips	D_Trip	Total number of annual bikeshare trips that terminate at a bikeshare station	*Divvy* bikeshare system operator
Independent			
System-specific factors			
Station capacities	Capacity	Total number of docks in a bikeshare station	*Divvy* bikeshare system operator
Stations within (x) meters	S_500m, S_1km, S_2km, S_4km	Number of bikeshare stations within (x) meters cycling distance	Google Distance API and *Divvy* bikeshare system operator
Demographic factors (All these factors are summary for a buffer)			
Population	Pop	Total population	Census 2010
Number of households	HH_2010	Total number of households	Census 2010
	Pec_Whi	Percentage of white race (%)	Census 2010
Average age	Ave_age	Average age of population	Census 2010
Percentage of young populations	Pec_young	Percentage of population aged between 20 and 34 years old (%)	Census 2010
Median income	Income	Median household income ($ dollars)	ACS 2014
Low-vehicle households	Pec_01_V	Proportion of households owning or renting 0–1 vehicle (%)	ACS 2014
Labor force	Labor	Total population able to work (workforce)	ACS 2014
Employment rates	Emp_rate	Employed population divided by total workforce population (%)	ACS 2014
Environmental factors (All these factors are summary for a buffer)			
Number of intersections	Int_points	Number of intersections in a buffer	OpenStreetMap
Walk network density	WBN_des	Total length of walkable paths divided by the area of a buffer (meter per 10,000 square meters)	OpenStreetMap
Bike path density	BN_des	Total length of bike paths divided by the area of a buffer (meter per 10,000 square meters)	OpenStreetMap
Number of transit stops	Transit	Number of transit (bus/railway) stations	Google Place API
Number of groceries	Grocery	Number of grocery stores	Google Place API
Number of schools	School	Number of schools	Google Place API
Number of hospitals	Hospital	Number of hospitals	Google Place API
Number of parks	Park_Nm	Number of parks	Chicago Data Portal
Park areas	Park_area	Total areas of parks (square meter)	Chicago Data Portal
Number of historical places	Land_Nm	Number of historical places	Chicago Data Portal
Number of crashes	Crash	Number of bicycle and pedestrian collisions with vehicles resulting in injuries	Illinois Department of Transportation
Number of crime	Crime	Crimes such as aggravated assault, rape, arson, battery, theft, and violent offenses.	Chicago Data Portal

Table 2
Criteria for disadvantaged communities.

Category	Data	Value
Disadvantaged communities	Income	< $50,000 per year
	Percentage of white race (low)	$<$ Mean[1] $-$ 0.5 $\times$ Sd[2] (< 41.64%)
Other areas	Income	Everything else
	Percentage of white race	

Note: 1. “Mean” is the mean of the percentage of white race.
2. “Sd” stands for “Standard deviation.”

4.3. Bikeshare ridership estimation

Bikeshare station ridership is the count of actual trips generated in a station. In statistics, count regression models (e.g., Poisson and binomial) are usually applied to model response variables that are counts. Poisson models, for instance, have a strong assumption that the mean should be equal to the variance. This assumption might present a limitation considering that any new predictor added into a model could change the variance (Agresti, 2013). Alternatively, and considering the potential for overdispersion in origin-destination trip matrices, we also evaluated negative binomial regression models. This study analyzed ridership for trip origins and destinations independently. To straightforwardly uncover the influence of area types (i.e., disadvantaged areas or not), we apply a binary variable to represent them in our model. This is consistent with practices to assess the effect of specific treatments or interventions, for instance, the use of a binary variable for patients with/without treatment when evaluating the effects of a specific medicine (Sterne et al., 2002).

4.4. Marginal effect and elasticity

Marginal effect, also known as average marginal effect, is an index to measure the change of a dependent variable given a unit change in a specific independent variable (Hilbe, 2011). For the count models, we estimated marginal effects for continuous and binary variables separately, considering their different attributes. For continuous variables, the marginal effect for x_k is:

$$M_{x_k} = \frac{1}{N}\sum_{i=1}^{N}\frac{\partial E(y_i)}{\partial x_k} = \frac{1}{N}\sum_{i=1}^{N}\frac{\exp(\widehat{\beta} x_i)}{\partial x_k} = \widehat{\beta_k}\bar{y} \tag{1}$$

where N is the sample size. The marginal effect of a specific variable includes two components: the average of the expected value of the dependent variable ($\bar{y}$), and the estimation for the estimated coefficient corresponding to this variable ($\widehat{\beta_k}$). This is different from ordinary least squares regression, in which marginal effects are identical to coefficients. When the independent variable is a binary predictor, marginal effects are referred to as the average change in the dependent variable as a binary variable changes from zero to one. The formulation is:

$$M_{x_k} = \frac{1}{N}\left[\sum_{i=1}^{N}\left(\exp(x\beta^{'} + \beta_b) - \exp(x\beta^{'})\right)\right] \tag{2}$$

where $\beta^{'}$ and β_b are the coefficients for continuous and binary variables, respectively (Hilbe, 2011). To further understand the influence of a variable, we measured the elasticity of every variable. In contrast to the preceding marginal effects of absolute changes, elasticity is related to the percentage of change of the dependent and independent variables. It is represented as:

$$E_k = M_{x_k} \times \frac{\bar{x}}{\bar{y}} \tag{3}$$

where M_{x_k} is the interpretation of marginal effects defined earlier.

4.5. Trip data analysis

Membership and usage fees are important barriers for disadvantaged communities accessing and using bikeshare systems (Howland et al., 2017; McNeil et al., 2017b). As mentioned, every trip record distinguishes whether the user is an annual member or a day-pass user. This study calculated the proportion of trips made by annual members for every bikeshare station and then associated those subscription rates with demographic information for the catchment areas. In this way, we studied the potential for financial barriers faced by disadvantaged communities.

For the usage fee of a single trip, this study used *Divvy*'s price scheme (Table 3) to estimate each trip's cost with the available trip duration information. Both annual members and 24-h pass holders (hereinafter called "day-pass users") can enjoy unlimited 30-minute free rides. However, after the first 30 min of each trip, the pricing scheme differs between an annual member and a day-pass user. For every additional 30-minute period, a day-pass user has to pay more than an annual member does, which is set as an incentive for more annual members. Estimating the trip costs, and trying to allocate a portion of the annual subscription or the 24-h pass fees to each trip was challenging because *Divvy* does not assign a unique ID to annual members or day-pass users. For trips by annual members, the gender and birth year information is not sufficient to identify individual annual members. For these reasons, it is not possible to know which trips are taken by the same annual member or day-pass user, or to estimate the annual expenditures for a specific individual (annual member or day-pass user). Considering these limitations in the data, we assigned a bikeshare trip to the station from which it starts from or at which it terminates, and estimated the average trip time and expenditure on a single trip for annual members or day-pass users at the bikeshare station level (for both origin trips and destination trips). After estimating the average trip time and costs, we associated the time and costs with the demographic information in the buffer of that station. Interesting findings are reflected through comparisons of the average time and costs between ridership generated (produced or attracted) from stations in disadvantaged and other areas.

Table 3
Price scheme (in dollars) for *Divvy* in 2016.

Trip duration	Annual member	Day-pass user
Base charge	99 per year	9.95 per day
0–30 min	0	0
31–60 min	1.5	2
61–90 min	4.5	6
91 and more min	6 per 30 min	8 per 30 min

4.6. Spatial analyses

To identify if there is a spatial autocorrelation for average trip expenditures and corresponding variances calculated as mentioned, we calculated the Moran's I (Eq. (4)), which has been widely used in spatial analyses (Griffin and Jiao, 2018; Jaller et al., 2017).

Using the Moran's I can help identify spatial correlation on trip expenditures between stations in the neighboring areas. The Moran's I ranges from -1 to 1, where 0 shows random distribution and $-1/1$ shows clustered or dispersed features.

$$I = \frac{N}{W}\frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \tag{4}$$

where N is the sum of stations; x_i is an average trip expenditure or its variance at station i; $\bar{x}$ is the mean value across all stations; W is the sum of the weighted matrix and every element in the matrix is w_{ij}.

Besides the Moran's I, we also visualize exact locations of either high or low cluster values through Hot Spot analysis. The Hot Spot analysis will calculate the Getis-Ord Gi* statistic (Eq. (5)) and indicate where stations with either high or low values cluster spatially. This spatial analysis tool compares an attribute (e.g., average trip expenditure) of a station and its surrounding stations with the expected local value of this attribute; when the difference is statistically significant (e.g., in a 90% confidence interval), this station will be classified as a hot spot.

$$G_i^* = \frac{\sum_j w_{ij}x_j - \bar{x}\sum_j w_{ij}}{\sqrt{\frac{\sum_j x_j^2}{N} - \bar{x}^2}\sqrt{\frac{N\sum_j w_{ij}^2 - \left(\sum_j w_{ij}\right)^2}{N-1}}} \tag{5}$$

where N, x_i, $\bar{x}$, W, w_{ij} are the same as in Eq. (4).

5. Empirical results

This section discusses the results of the empirical analyses in Chicago following the described methodology. First, the spatial distribution of bikeshare stations in areas identified as disadvantaged communities was mapped. Then, we estimated the statistical regression model and conducted the marginal effect and elasticity analyses. Finally, we analyzed bikeshare trip expenditures from stations in disadvantaged communities.

5.1. Bikeshare station distribution

The sample data has 475 observations (based on the available ridership data), which are buffers of 475 bikeshare stations. Using the criteria identifying disadvantaged communities, we identified 99 of the 475 station buffers to be in disadvantaged communities. Fig. 2 shows that the majority are concentrated in western and southern Chicago, where residents tend to be low-income and minority populations. Note that none of these stations (marked with red points in Fig. 2) are in the city's central business district.

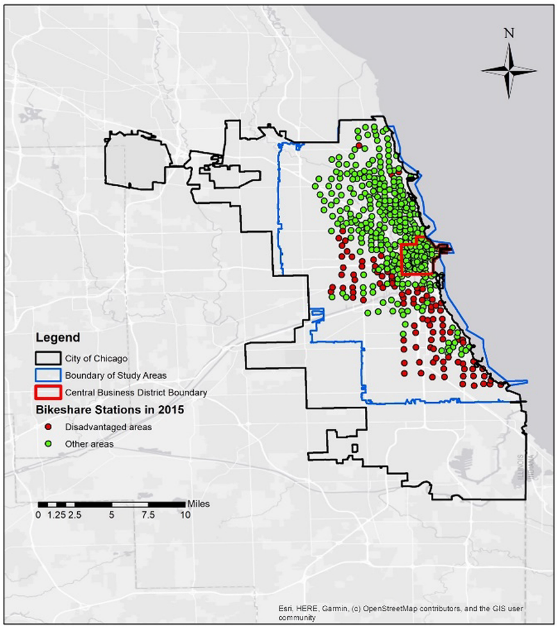


Fig. 2. Distribution of bikeshare stations in Chicago.

5.2. Bikesharing ridership estimation

The descriptive statistics for all variables compiled for station buffers are listed in Table 4. Since the density of the bikeshare stations in Chicago's downtown area is significantly higher than in suburban areas, some buffer areas overlap. However, there are no two buffer areas covering exactly the same block groups. Additionally, the statistic distribution of population or average age in buffer areas (Fig. 3) appears to be normally skewed or normally distributed. Thus, the overlap of buffer data does not affect the effectiveness of the following analyses.

Table 4
Descriptive statistics for all variables.

Variable	Unit	Min.	Median	Mean	Max.	Variance
Total origin trips	Trips/per year	15	4889	7464	89,248	77,690,229
Total destination trips	Trip/per year	17	4822	7464	98,590	81,187,422
Station capacities	Number of docks	11	15	17.69	47	30.48
Stations within 500 m	Number of stations	1	1	1.92	8	1.60
Stations within 1k meters	Number of stations	1	4	4.51	20	13.81
Stations within 2k meters	Number of stations	1	14	16.99	52	122.95
Stations within 4k meters	Number of stations	4	56	53.61	132	718.32
Population	Number of individuals	301	3875	4105.4	12,872	5,022,957
Number of households	Number of households	104	1722	1994.3	8714	2,140,887
White race	%	0.38	59.54	54.38	93.34	649.08
Average age	Years	21.2	32.36	33.07	51.02	18.71
Percentage of young populations	%	14.82	37.75	36.91	70.09	129.5
Population aged 5–9	Number of individuals	3	130	141	775	11,161
Population aged 10–14	Number of individuals	3	99	122	679	9884
Population aged 15–19	Number of individuals	1	149	187	1391	28,436
Population aged 20–24	Number of individuals	13	342	433	1967	108,312
Population aged 25–34	Number of individuals	59	1008	1161	4647	722,303
Population aged 35–44	Number of individuals	29	571	578	1705	104,523
Population aged 45–54	Number of individuals	14	372	424	1506	65,116
Population aged 55–64	Number of individuals	11	282	347	1676	65,971
Population aged 65–74	Number of individuals	9	148	198	1416	35,551
Population aged 75–84	Number of individuals	3	78	107	762	11,908
Population aged 85-up	Number of individuals	0	28	44	367	2627
Median income	$ per year	12,140	66,969	66,904	147,407	840,623,667
Low-vehicle households	%	49.75	80.02	79.73	97.66	105.76
Labor force	Number of individuals	146	2431	2608	9267	2,796,727
Employment rates	%	46.73	92.35	89.86	98.54	54.13
Number of intersections	Number of intersections	7	105	171.3	1513	40,064
Walk network density	Meters per 10,000 square meters	29.7	121.2	128.6	400.2	2307.23
Bike path density	Meters per 10,000 square meters	0	53.22	59.27	195.97	1397.01
Number of transit stops	Number of stops	0	9	10.99	44	53.27
Number of groceries	No. of grocery establishments	0	2	2.48	15	6.80
Number of schools	Number of schools	0	5	6.41	60	59.02
Number of hospitals	Number of hospitals	0	1	4.36	84	122.28
Number of parks	Number of parks	0	1	1.33	5	1.09
Park areas	Square meters	0	5126.9	33723.2	406487.0	4,326,573,869
Number of historical places	Number of places	0	1	2.49	29	16.76
Number of crashes	Number of crashes	3	67	105.4	469	8577.58
Number of crimes	Number of crimes	10	309	483.5	4093	344148.8

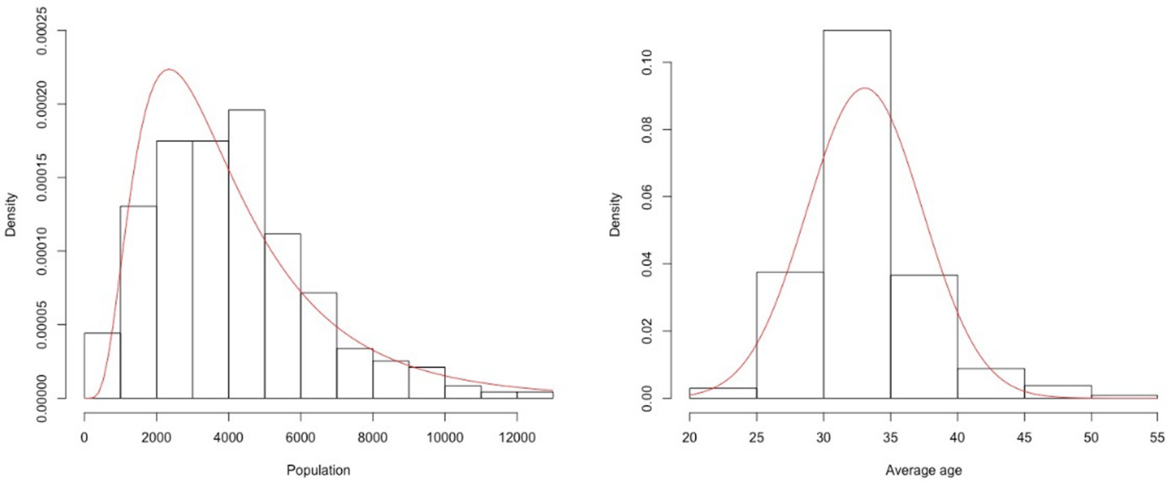


Fig. 3. Frequency distribution of population and average age in buffer areas.

Before the regression analyses, we compared employment-related variables between disadvantaged and other areas. The difference in employment rate between disadvantaged and other areas (Fig. 4) is significant since the p-value of the *t*-test is less than the significant level (alpha = 0.05).

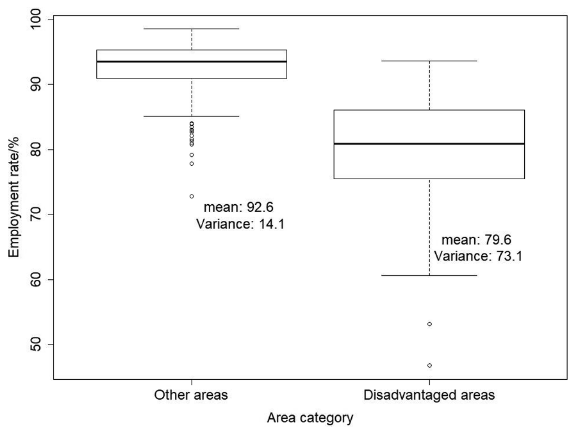
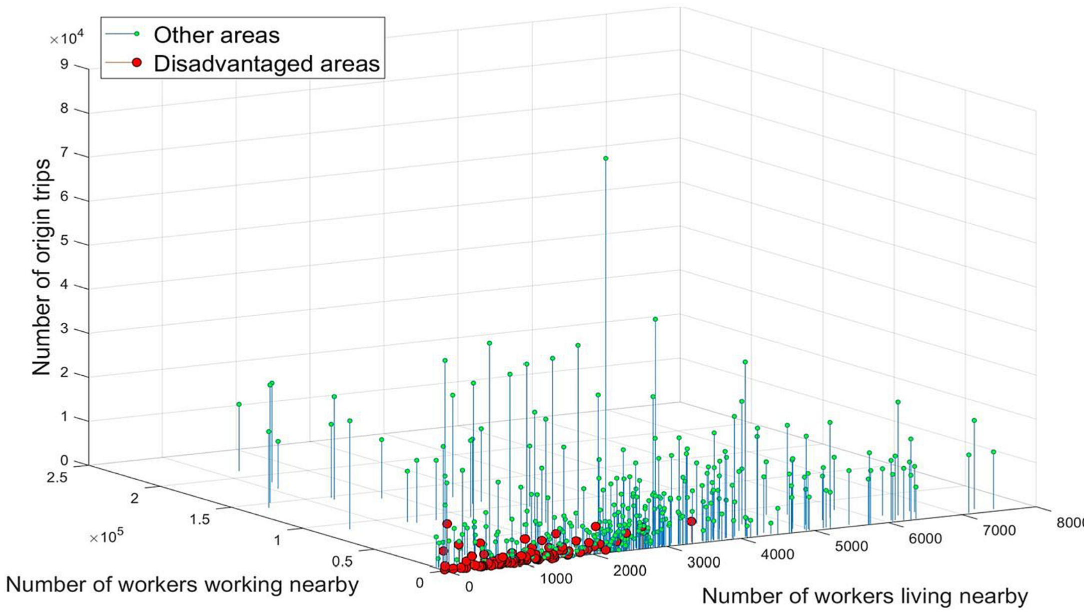


Fig. 4. Boxplot of the employment rate.

To further analyze the relationship between employment and bikeshare ridership, we compare trip productions or trip attractions with workers living and working in each area. The number of workers living nearby refers to the total number of workers who are estimated to live in the buffer (400-meter) of every station, while the number of workers working nearby refers to the total number of workers who are estimated to work in the buffer of every bikeshare station. All of these data related to employment are from the LEHD database, as described in Section 3. Overall, bikeshare demands are greater in an area with either more job opportunities or employed labor force (Fig. 5). It also shows that most disadvantaged areas have a deficit in job opportunities. Thus, bikeshare users in disadvantaged areas may have to reach job locations further away from their residential areas, as compared to bikeshare users in other areas.



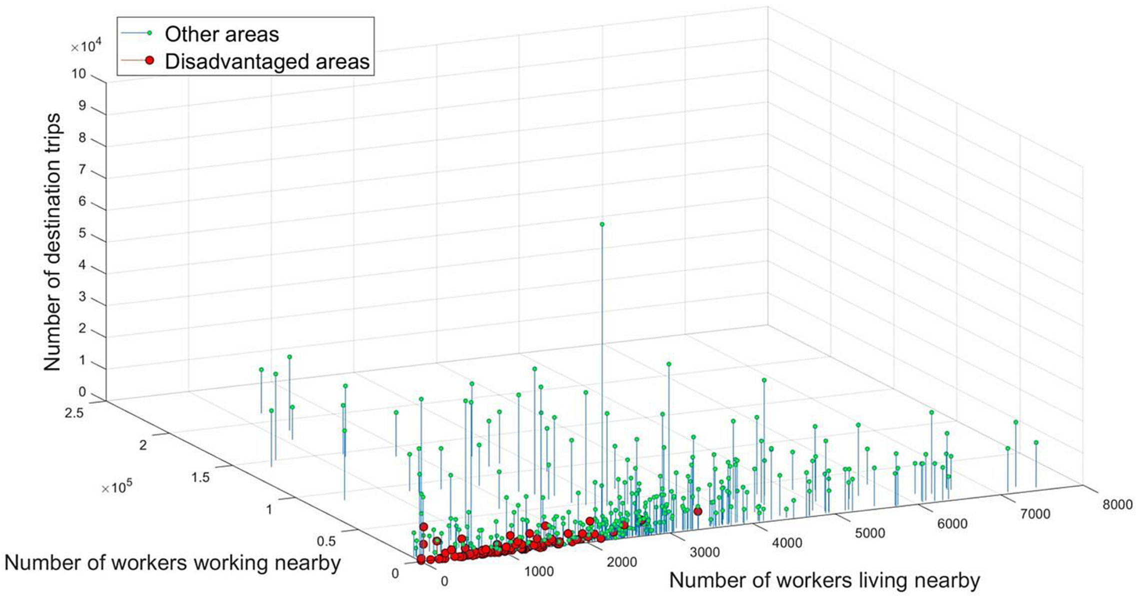


Fig. 5. The number of trip productions/attractions against job data.

As shown in Fig. 5, we can not analyze the relation between trip productions/attractions and job opportunities since there is a limited number of job opportunities in disadvantaged areas. For stations in disadvantaged areas, we focused on the relationship between the worker resident population and bikeshare demand. In areas with fewer than 2000 employees (2000 is set based on the most frequent employee number in disadvantaged area buffers), Fig. 6 shows the relation between workers living nearby and trip productions (or attractions). After testing the correlation between trip productions (or attractions) and number of workers living nearby, the coefficient is positive with 95% confidence (p-value = 1.001e − 06; p-value = 1.485e − 06). The total number of trips increases with the number of workers living near a station. However, disadvantaged areas do not have sufficient employed labor force to support a peak-level trip demand.

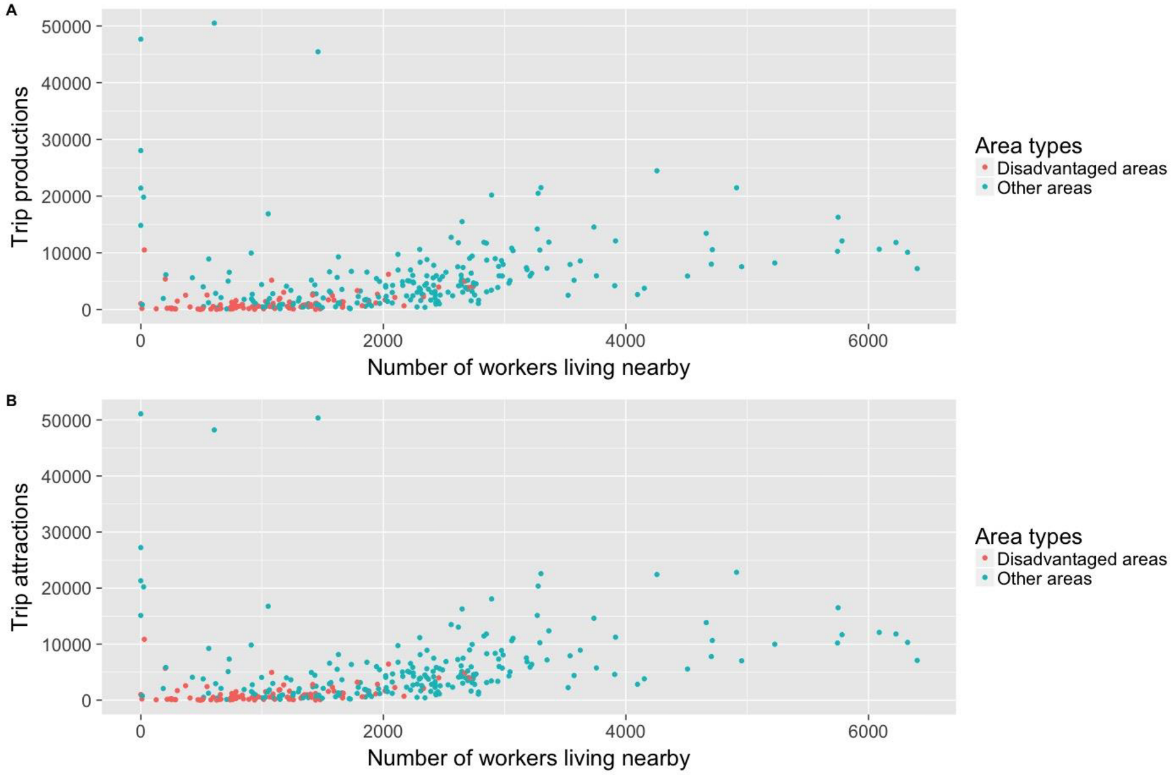


Fig. 6. Number of trip productions or attractions against the number of workers.

After compiling data for Chicago and making some comparisons between disadvantaged and other areas, we estimate the correlation matrix of all the numerical variables. Fig. 7 shows that there are several variable clusters within which variables are highly correlated. For example, population is highly correlated with household number and employment levels. Further, an area with a high percentage of white population tends to be an affluent area.

After estimating the correlation matrix, we conducted our regression analyses. During the model estimation process, we controlled for collinearity, removing statistically insignificant variables, and comparing the model's Akaike information criterion (AIC) index to develop a better model to represent bikeshare ridership. There are several variables that are generally thought to be correlated with trip demand but we chose not to include in the final model. For example, population is highly correlated with labor force and was not selected since work-related variables (e.g., labor force) are very important as reflected by the previous comparisons. The capacity of a station was also removed considering its high correlation with the number of transit stops and bike path density. Besides, the capacity may be increased or decreased by the systems' operators because it is a dynamic decision based on observed bikeshare demand. Thus, in the final regression, capacity is dropped out.

Since we have two dependent variables (productions and attractions) to estimate, Table 5 and Table 6 show the regression results for the two models represented. In Table 5, we conducted the goodness of fit test. The deviance of the NB model (515) is smaller than the 5% critical value (517) for a chi-squared distribution (degree of freedom = 466). However, the deviance for the Poisson model is significantly greater than this critical value. Thus, the NB model is better in terms of fitting the ridership data. Besides, Table 5 shows that the Negative Binomial (NB) model (with AIC = 8899) outperforms the Poisson model (AIC = 9740). The log-likelihood value of the NB model (−4439) is also greater than the Poisson model (−4860). Additionally, the overdispersion parameter in the NB model is 1.917, which indicates that the variance is significantly different from the mean in the sample data. Moreover, among all of the variables in the NB model, labor force, bike path density, park area, transit station number, percentage of young populations, and the number of bikeshare stations within 500 m are significantly important for increasing the number of trips. However, the number of trips will decrease if a bikeshare station is located in a disadvantaged community. Consistent with previous research, we found the percentage of young populations to be statistically significant in predicting bikeshare ridership. McNeil et al. (2017a) found that bikeshare systems are more popular among younger populations. The negative coefficient of station area types (a disadvantaged area or not) indicates the influence of existing barriers to disadvantaged communities enjoying bikeshare. During the estimation process we also evaluated the statistical significance and contribution of interaction terms. However, Tables 5 and 6 show the final regression models, and no significant interactions terms were found.

In Table 6, after testing the goodness of fit, the deviance of the NB model (516) is smaller than the 5% critical value (517) for a chi-squared distribution (degree of freedom = 466). While the deviance of the Poisson model is extremely larger than the critical value. Besides, the regression results for trip attractions (Table 6) also show that the NB model is better than the Poisson model considering the AIC index

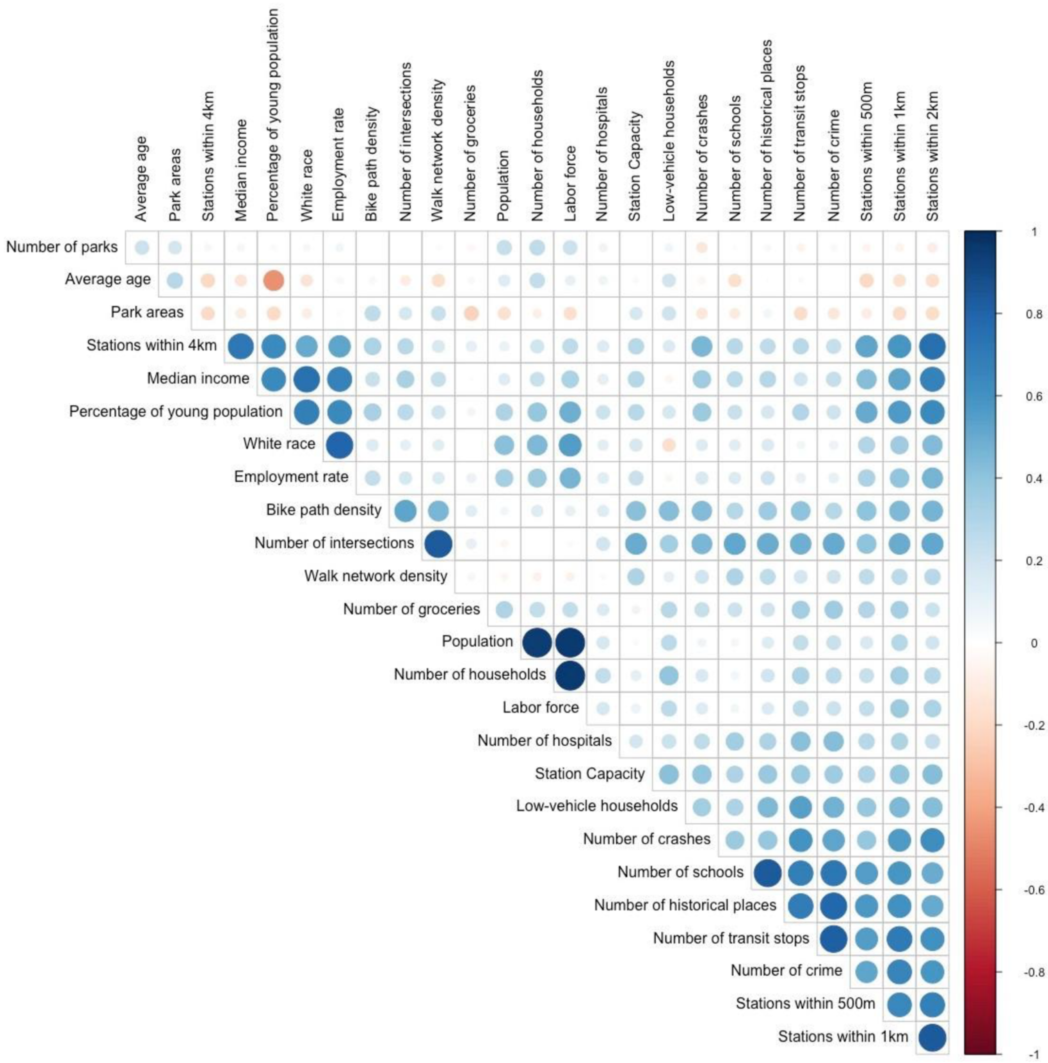


Fig. 7. Correlation matrix of all numerical variables.

Table 5
Annual bikeshare ridership estimation models for trip productions.

Variables	Poisson model		Negative binomial model	
	Coefficient	Significance	Coefficient	Significance
Constant	-1.550×10^{4}	**	-8.315×10^{-2}	
Labor force	3.886×10^{-1}	·	5.455×10^{-5}	*
Employment rate (%)	9.658×10^{1}		7.107×10^{-2}	***
Bike path density	4.959×10^{1}	***	5.212×10^{-3}	***
Park areas	2.672×10^{-2}	***	4.473×10^{-6}	***
Stations within 500 m	5.361×10^{2}		8.750×10^{-2}	*
Percentage of young populations	1.744×10^{2}	***	3.298×10^{-2}	***
Number of transit stops	2.109×10^{2}	***	2.045×10^{-2}	***
Disadvantaged communities	-1.696×10^{3}		-3.082×10^{-1}	**
Overdispersion parameter	1		1.917	
Log-likelihood	−4860		−4439	
AIC	9740		8899	
Deviance	2.14×10^{10}		515	

Significance: 0.0: ***; 0.001: **; 0.01: *; 0.05: ·. Number of observations: 475.

(8909 vs. 9784), the log-likelihood value (−4445 vs. −4882), and an overdispersion parameter of 1.8791.879. All variables–except whether a station is in a disadvantaged–are positively related to the number of attracted trips. Considering the overdispersion phenomenon and a better AIC index, we selected the NB models for production and attraction trips for further marginal effects and elasticity analyses. Also, the coefficients of all dependent variables are similar and consistent between the two models.

Table 6
Annual bikeshare ridership estimation models for trip attractions.

Variables	Poisson model		Negative binomial model	
	Coefficient	Significance	Coefficient	Significance
Constant	-1.626×10^{4}	**	-3.528×10^{-1}	
Labor force	3.776×10^{-1}		5.110×10^{-5}	*
Employment rate	1.079×10^{2}		7.471×10^{-2}	***
Bike path density	4.766×10^{1}	***	5.122×10^{-3}	***
Park areas	2.739×10^{-2}	***	4.415×10^{-6}	***
Station within 500 m	3.433×10^{2}		7.594×10^{-2}	*
Percentage of young populations	1.760×10^{2}	***	3.200×10^{-2}	***
Number of transit stops	2.273×10^{2}	***	2.217×10^{-2}	***
Disadvantaged communities	-1.704×10^{3}		-2.948×10^{-1}	*
Overdispersion parameter	1		1.879	
Log-likelihood	−4882		−4445	
AIC	9784		8909	
Deviance	2.35×10^{10}		516	

Significance: 0.0: ***; 0.001: **; 0.01: *; 0.05: •. Number of observations: 475.

5.3. Marginal effect and elasticity

To gain a deeper understanding of the influence of these variables, we conducted marginal effects and elasticity analyses for the resulting NB models (Tables 7 and 8).

Table 7
Marginal effects and elasticities of the NB model for trip productions.

Variable	Marginal effects	Elasticity (%)
Labor force	0.44	0.24
Employment rate	572	6.89
Bike path densities	42	0.33
Park areas	0.04	0.16
Bikeshare stations within 500 m	704	0.18
Percentage of young populations	265	1.18
Number of transits	165	0.24
Area type (1: disadvantaged areas; 0: other areas)	−2163	–

Table 8
Marginal effects and elasticities of the NB model for trip attractions.

Variable	Marginal effects	Elasticity (%)
Labor force	0.41	0.23
Employment rate	601	7.23
Bike path densities	41	0.33
Park areas	0.04	0.16
Bikeshare stations within 500 m	611	0.16
Percentage of young populations	257	1.14
Number of transits	178	0.26
Area type (1: disadvantaged areas; 0: other areas)	−2080	–

From the perspective of marginal effects, the change of area type from disadvantaged to others will increase annual trips by 2163 on average for productions, and 2080 for attractions. The second greatest impact is from the number of bikeshare stations within 500 m. If the number of bikeshare stations within 500 m of a given station increases by one, there will be a total of 704/611 additional bikeshare trips originating or terminating there. Among the rest of the variables, employment rate can, to a certain extent, significantly affect the number of bikeshare trips. In terms of elasticities, among the other variables, employment rate has the highest

Table 9
Statistics for average trip time (in minutes) per station.

Station type	User type	Minimum	1st quantile	Median	Mean	3rd quantile	Maximum
Disadvantaged	Annual member[1]	6.72/7.14[3]	11.63/11.98	13.16/13.32	13.98/14.21	15.98/15.84	26.78/28.03
	Day-pass user[2]	13.41/16.71	23.17/22.89	27.55/27.97	28.25/29.05	32.16/33.70	51.85/58.63
Others	Annual member	6.87/7.20	10.44/10.36	11.56/11.80	12.06/12.08	13.36/13.50	20.50/22.00
	Day-pass user	16.69/18.22	22.49/21.89	24.36/24.03	25.31/24.95	27.35/27.46	48.65/45.01

Notes: 1. The expenditure for annual members does not include the one-time 9.95-dollar charge.
2. The expenditure for day-pass users does not include the annual membership fee.
3. The left value is for trip productions, and the right value is for trip attractions.

impact. One percent increase in employment rate increases bikeshare trips by around seven percent (6.89% and 7.23%). Among the rest of the variables, the percentage of young populations has the second largest elasticity. A 1% increase in the percentage of young populations will cause a 1.18%/1.14% increase in the total number of bikeshare trip productions or attractions. Although there is no estimated elasticity for the binary variables identifying disadvantaged communities, considering the marginal effect (all other variables remaining constant), a change of 2163 or 2080 is approximately a 29.0% or 27.9% difference when compared to the average of 7464 annual trips (the averages of trip attraction and production are the same) across all stations.

5.4. *Annual subscription rate and trip expenditures by demographic information*

The mean proportion of trips made by annual members is lower in disadvantaged communities (78% for both trip productions and attractions) than in other areas (82% for both trip productions and attractions). To further verify this finding, we conducted a *t*-test to identify if the difference of the mean proportions between disadvantaged areas and other areas is statistically significant. The p-values of the *t*-test are 0.011 and 0.0025 for trip productions and attractions, respectively, which are both less than the significant level (alpha = 0.05). We concluded that the proportion of trips by annual members in disadvantaged areas is significantly less than that of other areas. Previous research has also shown that the odds of membership is higher in wealthy areas (Fishman et al., 2015). Note that, among many barriers, a 99-dollar membership fee is a non-trivial barrier for low-income users. To address this financial barrier, the D4E program in Chicago has helped more low-income people become bikeshare members (Greenfield, 2018). Since we have no access to the demographic information of *Divvy*'s annual members, this study is unable to compare changes, if any, in the demographic profile of users before and after the D4E program. However, Greenfield (2018) reported that D4E membership is much more diverse than standard *Divvy* membership.

Additionally, we analyzed the average trip time and trip costs for each station to understand bikeshare activities in disadvantaged

Table 10
Statistics for average trip expenditures (in dollars) per station.

Station type	User type	Minimum	1st quantile	Median	Mean	3rd quantile	Maximum
Disadvantaged	Annual member[1]	0.00/0.00[3]	0.04/0.04	0.08/0.09	0.14/0.18	0.18/0.15	0.99/1.17
	Day-pass user[2]	0.08/0.17	0.66/0.72	1.10/1.38	1.46/1.59	1.98/2.10	5.55/6.32
Others	Annual member	0.01/0.01	0.03/0.03	0.04/0.04	0.05/0.05	0.06/0.07	0.34/0.58
	Day-pass user	0.00/0.18	0.72/0.69	0.93/0.94	1.04/1.03	1.25/1.29	4.44/3.66

Notes: 1. The expenditure for annual members does not include the one-time 9.95-dollar charge.
2. The expenditure for day-pass users does not include the annual membership fee.
3. The left value is for trip productions and the right value is for trip attractions.

Table 11
Statistics for spatial autocorrelation (Morans I) for average trip expenditures per station.

Station type	User type	Cost ($)	Moran's *I*	Z-score	P-value
Trip productions	Annual member[1]	Average	0.17	9.52	0.00
		Variance	0.09	5.05	0.00
	Day-pass user[2]	Average	0.30	15.78	0.00
		Variance	0.21	11.11	0.00
Trip attractions	Annual member	Average	0.13	7.34	0.00
		Variance	0.05	3.09	0.00
	Day-pass user	Average	0.28	15.16	0.00
		Variance	0.18	9.77	0.00

Notes: 1. The expenditure for annual members does not include the one-time 9.95-dollar charge.
2. The expenditure for day-pass users does not include the annual membership fee.

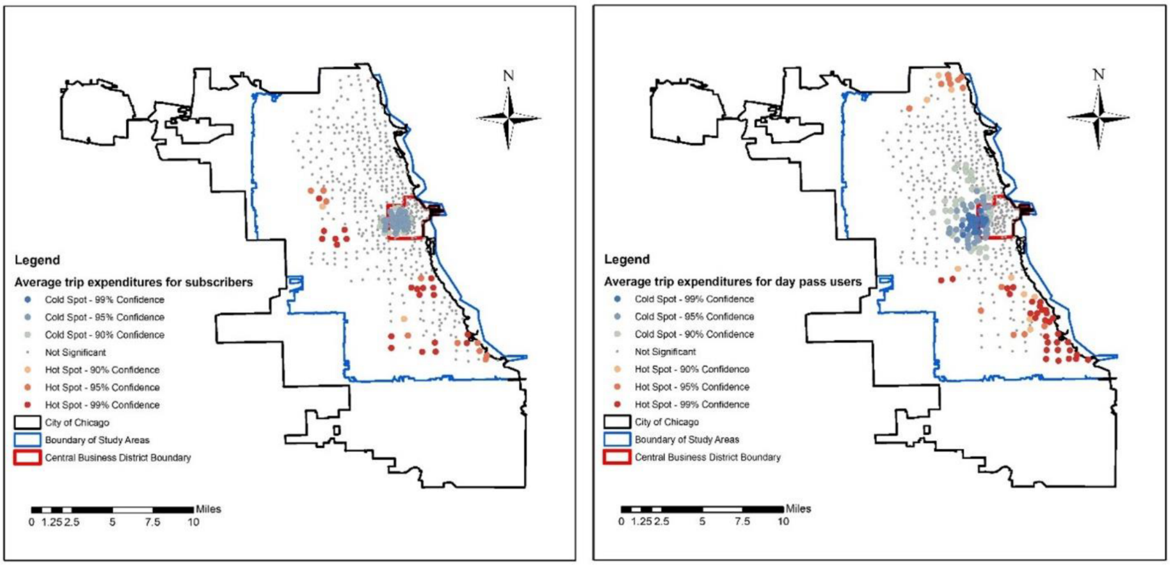


Fig. 8. Hot spot stations for trip expenditures of annual members and day pass users.

and other areas. Tables 9 and 10 show descriptive statistics (e.g., mean and median) for average trip time and trip cost per station. Since there are trips originating from and terminating at each station, we analyzed the average trip time and trip cost per station for originated trips and destination trips, respectively. As mentioned in the previous section, because of a lack of data, we could not allocate the annual membership fee or daily fee across the number of trips a user makes. Consequently, the study estimated average trip costs for every bikeshare station without considering the annual membership fees or daily fees. When calculating the average trip time or cost for each station, we distinguished trips produced or attracted at a station, and separated trips by annual members and day-pass users.

Table 9 shows the differences between annual members and day-pass users, with the former making shorter trips, possibly because of the differences in the use fee scheme (Table 3). However, the average trip time for day-pass users is at least twice that of annual members. If we compare trip time for annual members in disadvantaged and other areas, residents in disadvantaged areas are likely to make longer (time) trips; consequently, they tend to spend more on bikeshare trips than users in other areas. A further *t*-test supports this finding, as p-values are much less than 0.05 for annual members' trips for both trip productions (5.00e − 10) and attractions (4.88e − 11).

Table 10 shows that the average expenditure per trip for annual members is less than one dollar in all areas. Based on the price scheme in Table 3 and the data in Table 9, most annual members ride for less than 30 min. Additionally, annual members in disadvantaged communities spend approximately twice as much per trip as annual members in other areas (0.08 vs. 0.04 dollars for origin trip and 0.09 vs. 0.04 for destination trips) from the perspective of the median value. The maximum of average trip expenditure for annual members is 0.99 dollars in disadvantaged communities for trip productions, which is almost three times that (0.34 dollars) of other areas. To support this finding, we conducted a *t*-test; and p-values are much less than 0.05 for average trip expenditure of annual members trips for both trip productions (2.2e − 16) and attractions (1.03e − 14). Given the price scheme, trip costs, to some extent, reflect trip distances. Thus, users in disadvantaged communities are more likely to make longer bikeshare trips than users from other areas. This phenomenon applies to the trip expenditures of day-pass users.

5.5. Spatial analyses

As there is a statistically significant difference between bikeshare trip expenditures between users from disadvantaged and other areas, we analyzed the spatial patterns of average trip expenditures and corresponding variances. In Table 11, we show the spatial autocorrelation analyses for trip productions and attractions, including the Moran's *I* and corresponding z-value and p-value. As reflected in the spatial autocorrelation analyses, there is a significant spatial clustering phenomenon for trip expenditures across all users' groups, no matter whether for average values or their variances.

After the spatial autocorrelation analyses, we visualized the hot spot by calculating the Getis-Ord Gi* statistic. Since the spatial cluster phenomenon is similar for the trip expenditure of trip productions and attractions, we show the hot spot of average trip (productions) expenditure per station for annual members and day-pass users in Fig. 8. When comparing Figs. 2 and 8, we can see that the stations in disadvantaged areas (mostly located in the south and west of our study area) have significantly higher average trip expenditures than other areas, no matter whether for annual members or day-pass users. The variance of trip expenditures is also higher in disadvantaged areas, which may be influenced by different compositions of trip purposes and limited safe bike paths, leading to more detours.

To further verify whether an annual member user from a disadvantaged area will spend more on bikeshare than a member from other areas will pay, we conducted a statistical test for average trip expenditure per station against the percentage of trips by annual members and area types. As shown in Table 12, a higher proportion of trips by annual members will significantly reduce average trip expenditures per station since annual members are more likely to finish a trip within the free-ride time to save spending. However, if a station is located in a disadvantaged area, average trip expenditure will significantly increase, which is consistent with the spatial analyses and cluster visualization.

Table 12
Statistics for regression on average trip expenditure of annual members per station ($) for trip productions.

Variables	Annual member	
	Coefficient	Significance
Constant	0.2024	***
Percentage of trips by annual members/day pass users (%)	−0.1854	***
Area type (1: disadvantaged areas; 0: other areas)	0.0818	***
Log-likelihood	−521	

6. Discussion

6.1. Slightly less bikeshare trip demand but slightly longer bikeshare trips in disadvantaged areas

First, we notice that bikeshare demand in disadvantaged areas is slightly less compared with that of other areas, which could be related to multiple reasons, e.g., lower employment rate, less bikeshare station density. Among all of these factors, the average marginal effect of employment rate on bikeshare trip number is 586.5 ($586.5 = \frac{572 + 601}{2}$). The difference in the average employment rate between disadvantaged and other areas is 13% (92.6–79.6%), which means that there could be an increase of around 7600 bikeshare trips if the employment rate in disadvantaged areas were as high as in other areas.

The second interesting finding is that the annual subscription rates in disadvantaged areas are lower than in other areas. However, after comparing trip expenditures from different areas from statistical and spatial perspectives, we find that annual members in disadvantaged communities are more likely to make longer bikeshare trips than users from other areas. Average trip expenditure by annual members per station is significantly higher in disadvantaged areas (Fig. 8). This comparison shows that there may exist financial barriers (e.g., membership fee, trip costs) for users in disadvantaged areas. Thus, programs like D4E can motivate bikeshare use in disadvantaged communities. Moreover, the differences in trip length and utilization suggest a need for bikeshare planners to better understand travel mobility needs (e.g., work commute and shopping) in disadvantaged areas and to better address accessibility, and financial barrier issues.

6.2. Insights for developing bikeshare systems in disadvantaged areas

Our research provides quantitative confirmation of the existence of equity problems in the bikeshare industry. For example, previous researchers also found that not enough stations have been provided in disadvantaged areas (Bernatchez et al., 2015; Qian and Niemeier, 2019). Moreover, the employment rates and job opportunities are low in disadvantaged areas, which negatively affects ridership. There are complex historical, policital, and economic reasons behind the lack of opportunities, which are beyond the scope of this paper.

As more and more cities are introducing their own systems, we strongly recommend the use of early-stage promotions of reduced membership fees for low-income and other traditionally disadvantaged populations. Besides, the historical data shows that the maximum trip time for annual members in disadvantaged communities is very close to 30 min, which demonstrates that those populations try to make the most of this subscription benefit without incurring any additional cost. This insight leads to the suggestion of extending the time limit for free rides for annual members from disadvantaged communities. Our analysis demonstrates an important potential role for the public sector in investing in bikeshare access for disadvantaged communities, including partnering with for-profit services. Moreover, city and service providers should strive for better bicycle facility environments and more bikeshare stations in disadvantaged areas.

6.3. Research limitations

This research has some limitations and areas for improvements. The main disadvantage of the bikeshare trip dataset used in this work is that it does not clarify the relationship between bikeshare trips and specific users. The demographic information of users is also unclear. With more detailed demographic information, the analyses could provide more insights into how residents from disadvantaged communities do, and potentially could, use bikeshare to make their travel more convenient. This research measures the bike network density and walk network density using OpenStreetMap data. However, cyclists may use short cuts or potential bike paths, which are not shown in OpenStreetMap. Thus, bike network density could be higher than the calculations in this study.

Moreover, future research could verify the potential impacts of the recommendations made here for improving bikeshare ridership and financial equity issues for residents from disadvantaged communities. Despite these limitations, this research can still provide valuable insight into bikeshare planning, and fills the research gap of analyzing the current utilization of bikeshare systems among disadvantaged populations at a station level.

7. Conclusions and future work

We conducted this research to fill two current research gaps related to bikeshare: ridership estimation in disadvantaged communities, and a comparative analysis on the trip expenditures and trip lengths between members and day-pass-users from stations in disadvantaged communities and other areas. First, we estimate bikeshare trip demand based on a number of key systems and socio-economic variables and calculate the marginal effect of all variables. The estimated NB models provide insight into the impact of socio-economic variables, especially for individuals in disadvantaged communities, that affect their trip productions and attractions. Most importantly, our regression model shows that employment rate has a significant marginal effect, and the greatest elasticity to improve ridership.

Regarding the trip spenditures and length characteristics, three findings emerge from the analyses. First, most bikeshare users tend to make trips of less than 30 min, regardless of whether the trip is located in disadvantaged or other areas. The second result is that the rate of trips made by annual members is lower in disadvantaged areas than in other areas, which may result from multiple barriers that discourage low-income individuals from securing memberships. And related to the previous findings, users from stations in disadvantaged areas tend to make slightly longer (~15%) trips than those in other areas. Access to jobs is among the potential reasons for the longer trips, as they possibly commuter longer distances.

The findings indicate that in addition to increasing the number of stations in disadvantaged areas (and increasing overall density), the development of the supporting infrastructure (e.g., bike lanes), and improving the biking environment (e.g., facility desing), mitigating the impacts of financial barriers could increase accessibility and ridership from disadvantaged areas. For the latter, local governments or bikeshare companies should conduct early-stage promotions of reduced membership fees for low-income and other traditionally disadvantaged populations. Also, extending the time limit for free rides (e.g., 30 min) would be beneficial for bikeshare users from disadvantaged communities. To reduce the equity issues, further research should also analyze the destination choice process from users from disadvantaged communities that can help design a bikeshare network system that provides access to all users.

Finally, economic and financial assessments are needed about stations in disadvantaged communities, to understand their feasibility, especially when provided by private companies. Municipalities should guarantee equitable access to all communities, and develop the mechanisms to incentivize private service providers to sit stations or provide bycicles at these locations, even when they may not be economically viable.

CRediT authorship contribution statement

Xiaodong Qian: Conceptualization, Methodology, Resources, Data curation, Formal analysis, Writing - original draft, Writing - review & editing. **Miguel Jaller:** Conceptualization, Methodology, Resources, Writing - review & editing, Supervision.

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