Modeling Framework for Socially Inclusive Bikesharing Services

By

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DISSERTATION

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Abstract

Bikeshare programs are increasingly popular in the United States and they are an important part of sustainable transportation systems, offering a viable mode choice for many types of last-mile trips. This popularity means that an increasing number of people can enjoy the convenience of cycling and the associated physical health benefits without actually owning a bike (or having access to their own bikes). However, bikeshare systems have not captured high levels of ridership from disadvantaged populations. Many barriers exist that prohibit residents from disadvantaged communities from accessing bikeshare services. These barriers include absence of bikeshare stations within walking distances, lack of financial resources, cultural barriers, and/or unsafe cycling environments. Most of the current research on bikeshare programs focuses on societal benefits (e.g. reducing greenhouse gas emissions by replacing auto trips with bike trips) and bikeshare system management (e.g., bike repositioning between stations). There is some emerging research focused on equity issues in developing bikeshare. However, far less attention has been paid to bikeshare programs' potential benefits for disadvantaged communities and virtually no quantitative research on how to design bikeshare systems to improve access for these populations.

This dissertation work addresses three fundamental bikeshare equity problems. Chapter 2 examines whether bikeshare systems have targeted specific populations, and second, I quantitatively assess the potential for bikeshare systems to provide greater accessibility for disadvantaged communities. The results demonstrate that a well-designed bikeshare system can generate greater accessibility improvements for disadvantaged communities compared to the same system for other populations. Using a newly developed spatial index that combines the potential for increased access to jobs and essential services, the level of bike infrastructure, and

the disadvantaged population shares, I also find evidence that existing bikeshare systems have been specifically designed to target certain populations. The spatial index can be applied to identify potential locations to locate bikeshare stations (dock-based bikeshare systems) or rebalance bikes (dockless bikeshare systems) to address bikeshare equity issues.

In Chapter 3, I extend knowledge about how to estimate bikeshare ridership in underserved communities. This research fills a gap by analyzing the current utilization rates of bikeshare systems among disadvantaged populations. I specify a negative binomial regression model to estimate bikeshare ridership using data from Chicago's bikeshare system (Divvy). The results show that bikeshare stations in disadvantaged communities generate significantly fewer bikeshare trips than stations in other areas. Among the factors influencing bikeshare trips, employment rate has the highest positive marginal effect when considering limited job opportunities in disadvantaged areas. I also find that the bikeshare trip utilization rate differs greatly between annual members and day-pass users from disadvantaged communities. The proportion of trips by subscribers is significantly lower in disadvantaged communities than in other areas. Interestingly, residents in disadvantaged communities tend to make longer bikeshare trips if they are annual members. Based on the findings, I discuss planning implications for a socially inclusive and equitable bikeshare system.

Finally, in Chapter 4, I develop a destination competing model to estimate destination choices and analyze spatial patterns. Here, I show that users in disadvantaged areas are more likely to make bikeshare trips to achieve accessibility improvements, particularly to job opportunities. Members of disadvantaged areas paying annual fees are more likely to travel longer distance to other areas in order to reach additional opportunities. However, these disadvantaged riders are also more sensitive to extra charge after a free ride and that marginal cost for a bikeshare trip will eventually restrict their flexibility in using bikeshare services.

I conclude the dissertation with a review of major findings and suggestions for developing a socially inclusive bikeshare system for both local municipalities and system operators.

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Contents

CHAPTER 1: INTRODUCTION

BACKGROUND AND MOTIVATION

Bikeshare Programs in the United States

Bikeshare systems, offered as a non-motorized transportation service, are a relatively recent transportation strategy that offer members access to a shared bicycle. Users typically pick up a bicycle at a bike-docking station, and return it to any empty dock located near the final destination. The idea originated in a number of European cities (e.g., Amsterdam). With the advent of successful bikeshare systems in Europe, the mode increased in popularity internationally. A lot of US cities have joined the bikeshare trend, including Washington, D.C., New York City, Chicago, and San Francisco. In 2016, there were 55 bikeshare systems across the US, with the majority adopting dock-based and self-serve kiosk systems (National Association of City Transportation Officials 2017, 2010–16).

Between 2000 and 2012, the total number of people in the US who chose to bicycle to work increased by 64%, from 480,000 to 786,000 (McKenzie 2014). With the increase in biking, local governments have taken a growing interest in bikeshare systems, which offer a secure, easy way to make bicycle trips. Most US bikeshare systems are operated by for-profit companies, such as Motivate and B-Cycle. For example, Motivate operates bikeshare systems in the San Francisco Bay Area (CA), Boston (MA), Chattanooga (TN), and Chicago (IL), while B-Cycle runs bikeshare systems in Los Angeles (CA), Philadelphia (PA), Miami (FL). Most of the larger-scale bikeshare systems are located in the western and northeastern US. The average increase in bikeshare trips for Chicago (217%), Washington, D.C. (59%), and New York City (159%) was

145% between March and September 2017. In a survey study conducted in Washington D.C. and Minneapolis-St. Paul during fall 2011 and early 2012, 38% (both Washington D.C. and Minneapolis-St. Paul) of bikeshare trips are going to work or school, following by 21% (Washington D.C.) and 14% (Minneapolis-St. Paul) for entertainment or social activities (S. A. Shaheen 2012).

Equity Problems Faced by Bikeshare Programs

Current bikeshare stations tend to be located in areas with a more affluent and white population. Ricci found that bikeshare tends to attract a particular group of users: male, white, younger, employed, more affluent, more educated and more likely to be already engaged in cycling independently of bikeshare (Ricci 2015). Capital Bikeshare (CaBi) data compiled for users in Washington D.C. also shows that white, high-income users predominate (Buck 2013). Only 19% of annual CaBi members are non-white and only 24% have an annual income less than $ 50,000 (Buck and Buehler 2012). These findings are consistent with Dill's survey investigation (McNeil, Dill, MacArthur, Broach, et al., 2017) and Aultman-Hall's demographic information analysis using bikeshare stations' buffer areas (Ursaki and Aultman-Hall, 2015). Thus, the benefits achieved through bikeshare systems have almost certainly not been extended to disadvantaged communities. As bikeshare systems in the US expand, cities increasingly need to consider how to serve low-income residents and communities of color (Better Bike Share Partnership 2017; Cohen 2016).

Barriers to Bikeshare for Disadvantaged Communities

The barriers to increasing bikeshare access to disadvantaged communities can be categorized into four main groups: safety concerns, physical, financial, and bicycle culture barriers. Safety concerns, considered one of the biggest barriers to bicycling, includes road safety

(Fishman et al., 2014; Griffin et al., 2008; Christie et al., 2011), vulnerability to street crime (McNeil, Dill, MacArthur, Broach, et al., 2017), and bicycle theft (Lusk et al., 2017). Additionally, with a lower percentage of insurance coverage, residents from disadvantaged communities are more worried about the safety issue when bicycling on roads (Mattson, 2012). The financial barrier refers to membership and usage fees (Fishman, Washington, and Haworth, 2012; Howland, 2017), and lack of a credit card (Fishman, Washington, and Haworth, 2012; Howland, 2017; Goodman and Cheshire, 2014). Physical barriers include the absence of docking stations within walking distance (Bernatchez et al., 2015), unavailability of bike helmets (Fishman, Washington, and Haworth, 2012), and lack of bikeshare real-time information (Fishman, Washington, and Haworth, 2012; Stewart, Johnson, and Smith, 2013). Cultural barriers include the attitude in disadvantaged communities that bikeshare systems are for high-income, educated people and tourists (Bernatchez et al., 2015; Stewart, Johnson, and Smith, 2013; Nina Hoe, 2015). For general bicycle, cost and limited bicycle infrastructure are important barriers for low-income populations (Barajas, Chatman, and Agrawal, 2016; Ylitalo et al., 2016).

RESEARCH OBJECTIVES

Although there is a fair degree of understanding of the barriers to bikeshare use, far less attention has been paid to quantifying bikeshare's potential to provide accessibility improvements for disadvantaged communities. There is also not a well-accepted evaluation framework to identify priority areas for implementing bikeshare for disadvantaged communities. Finally, there is a relative paucity of research in bikeshare ridership forecasting in disadvantaged areas. A review shows that the ridership prediction models do not consider over-dispersion in bikeshare ridership data, and the limited knowledge regarding use of bikeshare by disadvantaged populations further constrains forecasts.

This dissertation research addresses these research gaps using multiple quantitative methodologies. To be more specific, this work develops an index to suggest priority areas in which disadvantage populations can be better served considering potential accessibility improvements. I also applied historical bikeshare trip data to calibrate a statistical regression model and a destination competing model.

RESEARCH SIGNIFICANCE

The following significant contributions result from this research:

1) I quantitatively extend current knowledge in bikeshare equity studies. Most of the traditional equity studies in bikeshare are survey studies. This research combines spatial analysis, statistical regression, and a destination-competing model to analyze the current bikeshare system siting and bikeshare trip features in disadvantaged areas.

2) I translate model results to practical suggestions on eliminating bikeshare barriers for disadvantaged communities. These suggestions cover guidelines for planning bikeshare systems as well as for relocation or rebalancing bikes in managing systems.

3) I also develop a novel methodology to analyze equity problems that can be applied to other transportation modes, e.g., shared rider and autonomous vehicles. I introduce an evaluation framework to identify if a specific transportation service is biased in targeting served populations. Importantly, I integrate accessibility into the evaluation process.

DISSERTATION STRUCTURE

The chapters in the dissertation are organized as follows. Chapter 2 discusses bikeshare programs' potential to provide greater access to jobs and essential services for disadvantaged communities. In this chapter, I use two case study cities (Chicago and Philadelphia) to first, examine whether bikeshare systems have targeted specific populations, and second, to quantitatively assess the potential for bikeshare systems to provide greater accessibility for disadvantaged communities. The results demonstrate that a well-designed bikeshare system can generate greater accessibility improvements for disadvantaged communities than the same system would produce for other populations. Furthermore, I suggest a newly developed spatial index that combines the potential for increased access to jobs and essential services, the level of bike infrastructure, and the disadvantaged population shares. The spatial index can be applied to identify potential locations to locate bikeshare stations (dock-based bikeshare systems) or rebalance bikes (dockless bikeshare systems) to address bikeshare equity issues.

Chapter 3 introduces the research analyzing current utilization rates of bikeshare systems among disadvantaged populations. This study develops a negative binomial regression model to estimate bikeshare ridership. The results show that bikeshare stations in disadvantaged communities generate significantly fewer annual trips than stations in other areas. Additionally, among the factors influencing bikeshare trips, employment rate has the highest positive marginal effect considering the limited job opportunities in disadvantaged areas. Furthermore, the research analyzes the bikeshare trip utilization between annual members and 24-hour pass users from disadvantaged communities. Interestingly, residents in disadvantaged communities tend to make longer bikeshare trips if they are annual members. Based on the findings, I discuss planning implications for a socially inclusive and equitable bikeshare system.

Chapter 4 presents the research estimating bikeshare destination choices for vulnerable populations. I develop a destination competing model to estimate destination choices and analyze spatial patterns of parameters in this model. I find that accessibility improvements, especially toward job opportunities, are likely to lead to more bikeshare trips in disadvantaged areas. Annual members from disadvantaged areas are more likely to travel longer distance to other areas in order to reach more services. However, these disadvantaged populations are more sensitive to extra charges after a free ride and that the marginal cost for a bikeshare trip will restrict their ability to use bikeshare services.

The last two chapters conclude the dissertation by giving an overview of the contributions and a discussion of future research needs.

CHAPTER 2: HIGH IMPACT PRIORITIZATION OF BIKESHARE PROGRAM INVESTMENT TO IMPROVE DISADVANTAGED COMMUNITIES' ACCESS TO JOBS AND ESSENTIAL SERVICES

INTRODUCTION

Bikeshare programs are increasingly popular in the United States and they offer an important alternative mode choice for many types of last-mile trips. Bikeshare systems have not captured high levels of ridership from disadvantaged populations, but there is some evidence that current bikeshare systems have specifically targeted certain populations to ensure sufficiently high demand for profitability. Far less attention has been paid to bikeshare programs' potential to provide greater access to jobs and essential services for disadvantaged communities. I use two case study cities (Chicago and Philadelphia) to first, examine whether bikeshare systems have targeted specific populations, and to second, quantitatively assess the potential for bikeshare systems to provide greater accessibility for disadvantaged communities. The results demonstrate that a well-designed bikeshare system can generate greater accessibility improvements for disadvantaged communities than the same system would produce for other populations. Using a newly developed spatial index that combines the potential for increased access to jobs and essential services, the level of bike infrastructure, and the disadvantaged population shares, I also find evidence that existing bikeshare systems have been specifically designed to target certain ridership. I find that locating stations in proximity to disadvantaged communities has the potential to increase household access (by bike and by bike-to-transit) to jobs and essential services and can close accessibility gaps between mobility constrained populations and critical services. The spatial index can be applied to identify potential locations to locate bikeshare stations (dock-based bikeshare systems) or rebalance bikes (dockless bikeshare systems) to address bikeshare equity issues.

LITERATURE REVIEW

Bikeshare usage tends to be highly correlated with a variety of factors, including population density (Buck & Buehler, 2012; Krykewycz, Puchalsky, Rocks, Bonnette, & Jaskiewicz, 2010), income (Rixey, 2013), race (Rixey, 2013), education (Rixey, 2013), weather conditions (Li, Zheng, Zhang, & Chen, 2015), and adjacency to bike lanes (Buck & Buehler, 2012). Among the aforementioned factors, it is worth noting that the proportion of the nonwhite population has a negative correlation with ridership (Rixey, 2013). To date, as a way of ensuring profitability, private bikeshare companies tend to target populations more likely to use their services: male, white, younger, employed, affluent, educated, and those more likely to already be engaged in cycling, independent of bikeshare (McNeil, Dill, MacArthur, Broach, & Howland, 2017; Ricci, 2015). For example, Washington DC's Capital Bikeshare (CaBi) demographics indicate the predominant users are white and of higher income (Buck, 2013). Only 19% of annual CaBi members are non-white and riders with an annual income of less than $50,000 make up only 24% of members (Buck, 2013).

The absence of bikeshare stations within walking distances is a barrier for users of the system (Bernatchez, Gauvin, Fuller, Dubé, & Drouin, 2015) and the siting of stations is the most critical feature of designing a system. A variety of methodologies have been applied in the literature demonstrating ways to optimize the placement of bikeshare stations (García-Palomares, Gutiérrez, & Latorre, 2012; Lin, Yang, & Chang, 2013; Martinez, Caetano, Eiró, & Cruz, 2012;

Romero, Ibeas, Moura, Benavente, & Alonso, 2012). Most of these use objective functions with operational costs and/or service levels (measured by the availability rate and coverage of the respective origins and destinations) as inputs. In practice, bikeshare stations are usually placed in areas with high attraction rates (e.g. shopping centers, transit stations) and/or near sidewalks that are adjacent to bike lanes (Burden & Barth, 2009). Noted barriers to the siting of bikeshare stations include safety, weather, topography, membership registration process, and the unavailability of bike helmets (Fishman, Washington, & Haworth, 2012; Fishman, Washington, Haworth, & Mazzei, 2014).

The aforementioned barriers for general users are only a subset of the barriers faced by disadvantaged communities. First, there is a cultural divide that arises as many residents of disadvantaged communities mistakenly believe that bikeshare is a transport mode solely for high income, highly educated individuals and tourists (Bernatchez et al., 2015; Hoe, 2015; Stewart, Johnson, & Smith, 2013). The lack of financial resources such as credit cards, and additional costs such as membership fees also inhibit the active use of bikeshare systems in disadvantaged communities (Fishman et al., 2012). Furthermore, unsafe cycling environments near or adjacent to living areas can impede the popularity of bikeshare in disadvantaged areas. Of all of the barriers for disadvantaged communities, anxiety over safety issues stands out as most significant (Christie et al., 2011; Griffin, Wilson, Wilcox, Buck, & Ainsworth, 2008; McNeil, Dill, MacArthur, Broach, et al., 2017).

Even when the barriers to cycling are low, there is little empirical data on the cycling behavior of residents in disadvantaged communities. This research can draw a few conclusions based on correlations with certain types of trip making activity that have been studied. McDonald (2008) found that children from low-income and minority groups, particularly

African-Americans and Hispanics, are potentially more likely to use active travel modes to attend school than whites or higher-income households when considering the combined effect of household income, vehicle access, distance between home and school, and residential density. Given this information, it is reasonable to conclude that there may be a strong likelihood for children in low-income and minority groups to use cycling as a primary mode to school. Additionally, McNeil et al. found that low-income African American residents are more likely to use bikeshare for recreation and/or exercise as opposed to utilitarian trips (McNeil, Dill, MacArthur, Broach, et al., 2017).

For bikeshare systems to prove useful to disadvantaged communities, the way in which they are designed must shift from operationalizing systems that target certain demographics to designing systems that target gaps in accessibility. In order to create high impact bikeshare systems in such communities, it is necessary to account for the complexities of how disadvantaged populations currently access jobs and essential services, while also acknowledging that the actual travel behavior forming the basis for these trips is constrained by factors that have not been well studied.

This research presents a new method for identifying how bikeshare systems might be spatially allocated to better serve low income and minority households. Using this new index, this research tests the hypothesis that existing bikeshare systems have been specifically designed to target certain ridership. This research then goes on to show that locating stations in proximity to disadvantaged communities has the potential to increase household access (by bike and by bike-to-transit) to jobs and essential services. This research demonstrates that appropriately sited bikeshare facilities can close the accessibility gaps between mobility constrained populations and the critical services upon which they depend.

CASE STUDY CITIES AND DATA DESCRIPTION

Case Study Cities

This research recruited 16 experts from five different fields (bikeshare academics, a bikeshare company, metropolitan planning organizations (MPO), bike advocates, and local government) and asked them to rank 34 candidate cities across the available data in terms of usefulness for our study. The data for all 34 candidate cities are in the Appendix (Table 24 and Table 25). Using their observations, I selected Chicago and Philadelphia for this analysis. These cities offer interesting similarities and contrasts in terms of size, location and funding.

In 2013, the Chicago Department of Transportation (CDOT) launched the Divvy bikeshare system (currently 581 stations), and contracted with Motivate to purchase, install, and operate the system (Motivate International, 2017a). Divvy acquired start-up federal funding from efforts aimed at promoting economic recovery, reducing traffic congestion and improving air quality. Funds were also provided from the City's Tax Increment Financing program. In July of 2015, Chicago also introduced the "Divvy for Everyone (D4E)" program, which provides affordable membership fees to qualifying residents (Motivate International, 2017b).

Indego, owned by the City of Philadelphia, was planned and managed by the Office of Transportation & Infrastructure Systems. A Philadelphia-based business that specializes in bikeshare launch (i.e., Bicycle Transit Systems) operates and maintains the bikes and the technology platform, which is provided by B-Cycle (City of Philadelphia, 2017). Indego started in 2015 and currently has 105 bikeshare stations, approximately one-sixth of the number of Chicago stations. Indego is in the early stages of development and Philadelphia made a concerted effort to learn from other bikeshare systems before launching (Scola, 2014). One of the critical aspects Indego considered prior to launch was the issue of social equity. Andrew Stober from the Mayor's Office of Transportation and Utilities in Philadelphia pointed out that areas outside of the business core are an important part of a new bikeshare system (J. Mcdonald, 2015; Scola, 2014). As a result, at the same time the program started, Indego implemented a reduced membership fee plan for low-income residents that includes a new cash payment option for its users (Hamilton, 2015; Indego Bikeshare System, 2017; People for Bikes, 2015; Wikipedia, 2017).

In addition to both systems' station location data in two case study cities, the study employs the following demographic and facility data.

- **Demographic Census Data:** The United States Census Bureau collects demographic information using surveys across the United States every ten years. The most recent one is the 2010 Census and provides demographic data including population, race, age, and household sizes, and many other variables at the census block group level in 2010.
- **American Community Survey (ACS):** Similar to the Census 2010, the ACS 2014 is another survey program administered by the U.S. Census Bureau. The ACS 2014 captures the changes taking place in communities throughout the United States in 2014. This study uses household income and vehicle ownership data from the ACS at the level of census block groups.
- **Longitudinal Employer-Household Dynamics (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 (job types and earnings) for residents who live in this census block, while the work census block data provides job characteristic data (job types and earnings) for workers who are employed in this census

block. This study uses the total number of jobs available in every census block groups for later analysis.

- **OpenStreetMap:** 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 the road information in Chicago and Philadelphia. The database also contains information about the type of infrastructure, e.g., “vehicle road,” “pedestrian way,” or “bicycle lane”. This study used the data to identify all bicycle facilities for the case cities. Considering that the data may be not exhaustive, I combined it with another bicycle path map from the local data portals to develop a comprehensive picture of bicycle infrastructure in Chicago and Philadelphia. The accuracy of OpenStreetMap has been verified by Haklay (2010).
- **Google Map Places application programming interface (API):** As Google gathers more and more geographic data through its diverse practical projects, the company provides many useful APIs for public researchers to gain access to these geographic data. Among these, Google Place API can return an extensive list of places within a specified search radius based on a user’s location. When using this API, users can define the types of places they want to search. In this research I calculated the number of schools, hospitals, grocery stores and transit (bus and railway) stations within a census block group.

METHODOLOGY

Identifying Disadvantaged Populations

In this research, the term "disadvantaged populations" refers to people of color, low-income households, and transit-dependent households. Demographic information (population, race, median household annual income, and number of household vehicles) were assembled for both Chicago and Philadelphia from the 2010 Census. For the purposes of this analysis, African-American, American Indian, Alaska Native, and Asian were classified as minorities. The percentages of minority populations were then calculated for every block group in both Chicago and Philadelphia. The median household annual income and number of household vehicles were also assembled at the census block group level. I assumed that the ratio of household income and household vehicle ownership levels are approximately the same for every block within a block group.

Three criteria were used to designate block group disadvantaged populations: median household income, percentage of minority population, and the percentage of households owning 0-1 vehicles. This research first identified those block groups with a median household income below $25,000, the federal poverty definition for a household with four people ($24,600) (U.S. Department of Health & Human Services, 2016). Thresholds of low, moderate and high were set using the standard deviation and the percentage of minority population and percentage of households owning 0-1 vehicles within each block group. Our approach to setting threshold levels for percent population and number of vehicles is similar to the approach used by the North Central Texas Council of Governments (NCTCOG) in their "Bicycle Need Index" (Table 1) (Turner, Hottenstein, & Shunk, 1997). Disadvantaged areas in Chicago are defined as a census block group with: a) a median household annual income below $25,000; b) percent of minority populations over 60.9%; and c) percent of households owning or renting 0-1 vehicle over 77.9% (Table 1). In Philadelphia, in a similar way, a disadvantaged area is a location with median household annual income below $25,000, percent of minority populations over 70.7% of, and percent of households owning or renting 0-1 vehicle above 84.9%.

Table 1 Classification of disadvantaged populations.

Data	Level	Value	
Percentage of minority race[1]/households owning or renting 0-1 vehicle[2]	High	Percentage > Mean + 0.5×SD[3]	
	Moderate	Mean - 0.5×SD <= Percentage <= Mean + 0.5×SD	
	Low	Percentage < Mean - 0.5×SD	
Classification	**Data**	**Chicago**	**Philadelphia**
Disadvantaged	Income: below the poverty line	< $ 25,000 per year	
	Percentage 1[1]: High	> 60.9%	> 70.7%
	Percentage 2[2]: High	> 77.9%	> 84.9%
Other	Income	Everything else	
	Percentage 1		
	Percentage 2		

Note: 1. "Percentage of minority race" is abbreviated as "Percentage 1";
2. "Percentage of households owning or renting 0-1 vehicle" is abbreviated as "Percentage 2";
3. "SD" stands for "Standard deviation".

Bicycle Infrastructure

I relied on mapped bicycle infrastructure data from both the OpenStreetMap[1] and the local government data portals[2]. The bicycle paths in this research include exclusive restrictive paths, exclusive paths, and some paths tagged bicycle friendly in OpenStreetMap. Note that the bicycle path network is a subset of road networks; this means I restricted the cycling route

[1] This database contains all the road information for a selected area (https://mapzen.com/data/metro-extracts/). In the database, there are a tag for a single path. For example, a path may be tagged with "pedestrian way".

[2] Chicago government data portal (https://data.cityofchicago.org/Transportation/Bike-Routes/3w5d-sru8) and Philadelphia open data resource (https://www.opendataphilly.org/dataset/bike-network).

options, which, in turn, causes an interesting finding in our accessibility analysis that I discuss later.

I calculated the total length of bicycle infrastructure (including designated bicycle routes, bicycle-pedestrian shared paths, and on-street bicycle paths) falling within each block group. Next, bike path density was calculated for every block group as the length of the bike path within the block group divided by the block group area. Using the bicycle infrastructure density, I organized block groups into high, moderate, and low levels using the same threshold approach discussed earlier. As noted earlier, areas with a high level of bike infrastructure will be considered as high potential locations for disadvantaged populations to safely cycle for recreation and/or exercise. Considering the importance of bicycle infrastructure for disadvantaged populations to make a bikeshare trip, I use the density of bicycle infrastructure to identify potential areas for bikeshare.

Accessibility Analyses

Opportunities and travel time are two important components in any accessibility analysis. I use opportunities to refer to low-wage jobs (earning $3333/month or less[3]), grocery stores, hospitals, and schools. Jobs data were taken from the Longitudinal Employer-Household Dynamics (LEHD) database. I mapped essential services using the Google Map application program interface (API), which returns a large inventory of places (grocery stores, hospitals, and schools) within a specified search radius (Figure 1, Figure 2, and Figure 3).

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[3] This job data is from LEHD. This database divides jobs by income per month. There are three categories: 1) $1250/month or less; 2) $1250/month to $3333/month; 3) greater than $3333/month. This work chose the first two categories and defined them as low-income jobs.

Figure 1. Distribution of grocery stores in Chicago and Philadelphia.

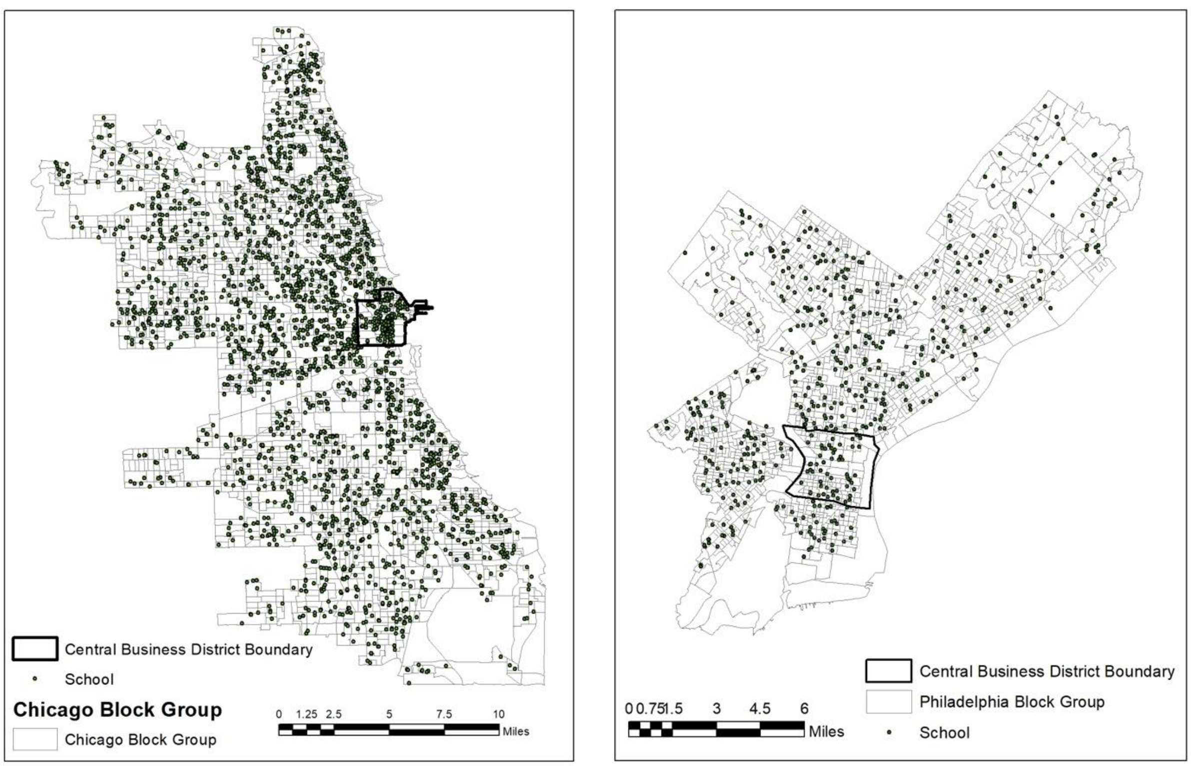

Figure 2. Distribution of schools in Chicago and Philadelphia.

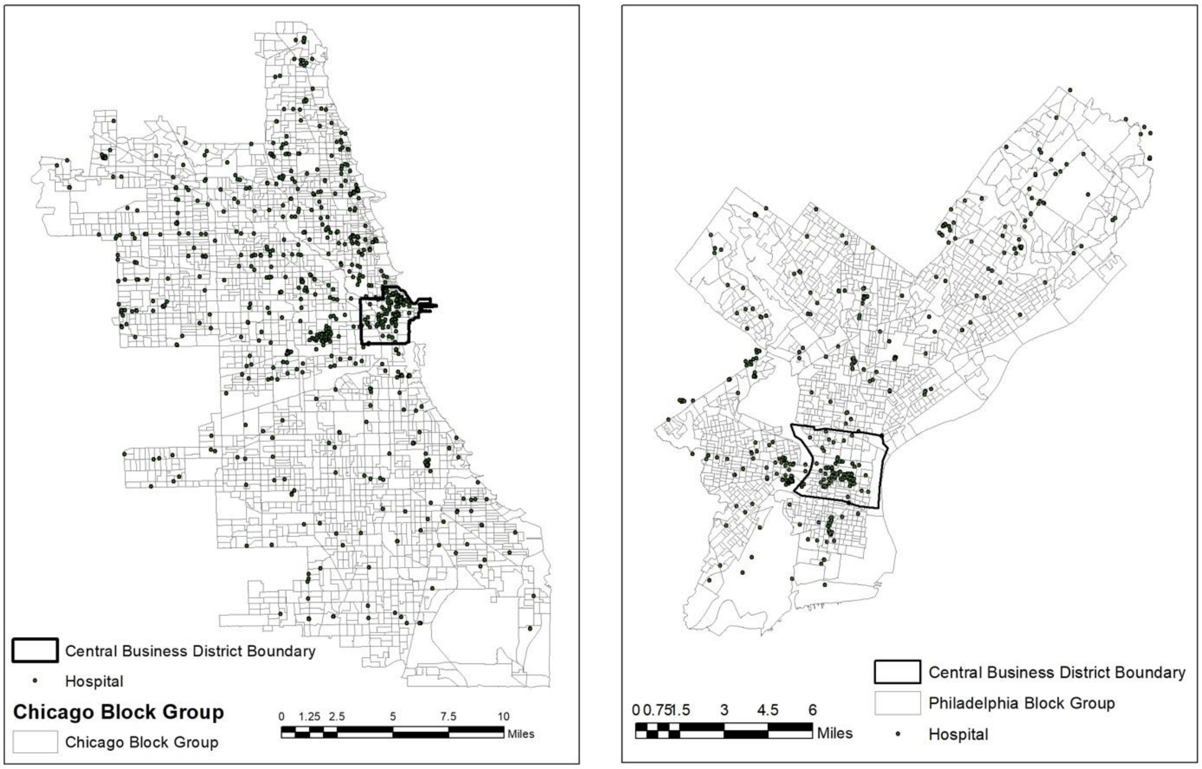

Figure 3. Distribution of hospitals in Chicago and Philadelphia.

I measured the change in accessibility under two scenarios (Figure 4). First, I assumed that the pedestrian system is used both alone and in conjunction with transit, and then I measured accessibility assuming access to bikeshare. In each scenario, the accessibility is calculated using the shortest time by comparing the two options. For the second scenario, I assumed that bikeshare is available in residential areas, transit stations, and destinations for services in our analysis areas. I also assumed that people are able to access the bikeshare system regardless of location or time. Thus, the walking time to get access to bikeshare stations is ignored in the second scenario. In this way, I can identify where bikeshare systems can produce the greatest benefits (accessibility improvements) when compared to the walk mode.

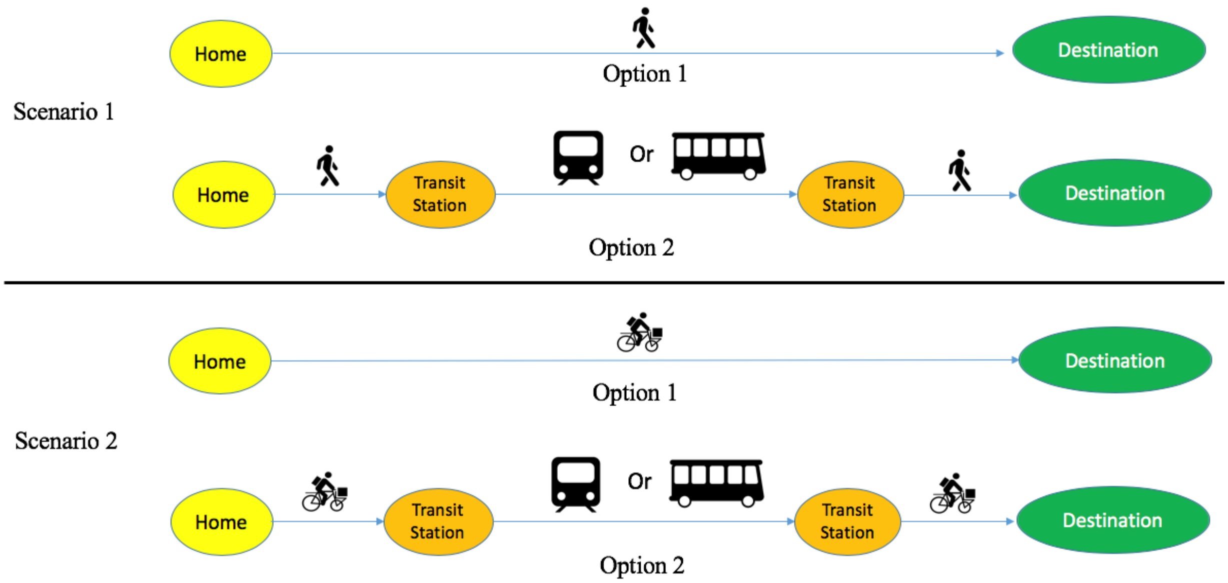

Figure 4. Traffic mode choices in two scenarios.

I calculated travel times assuming typical walking and bicycling speeds (walk speed of three miles per hour and bike speed at ten miles per hour (Salon & Handy, 2014)). Travel times for public transit network in each of the cities are calculated using data in the General Transit Feed Specification (GTFS) format, which is created by local transit providers. The GTFS data provide spatially and temporally explicit information on transit routes, stops, and schedules and can be incorporated into a GIS framework, making it reasonably straightforward to determine access via travel along the transportation network. Note that I restrict the travel time by transit by the schedule of transit services. Thus, a person may not have access to an opportunity if there is no transit service available at the time they want to start a trip and walking to another block group is not allowed (within the specified time allocation). This feature will cause some block groups with zero accessibility in scenario 1 and infinite accessibility improvements (scenario 1 vs scenario 2). It is important to also note that the trip purposes of bikeshare users vary (Buck et al., 2013; McNeil, Dill, MacArthur, & Broach, 2017). Job commute is reported to be the main purpose followed by shopping/recreation, school, medical care, and other purposes (McNeil, Dill, MacArthur, & Broach, 2017). In Equation 1, I assigned different weight factors to different opportunities based on the percentages of trip purpose from survey results by (McNeil, Dill, MacArthur, & Broach, 2017).

I measured accessibility in the standard way using Hansen's formula in Equation (4) (Liu & Zhu, 2004),

$$A_i = \sum_{j=1}^{N} O_j e^{-\beta t_{ij}} \qquad (1)$$

where A_i is the accessibility of block group i, O_j is the sum of opportunities (jobs, transit stations, grocery stores, hospitals, and schools with different weight factors) available at block group j, and N is the total number of blocks that block group i has access to within a specific time threshold; β is an empirically-derived dispersion parameter (Fotheringham, 1981) and t_{ij} is the travel time between block group i and block group j. I divided block groups into high, moderate, and low levels based on accessibility improvements using the same threshold approach discussed earlier.

Identifying Priority Areas

I developed a new index to identify locations where bikeshare stations have a high potential to increase accessibility for disadvantaged communities. I classified each census block group into four different categories based on the quantiles of the levels of served populations, levels of bike infrastructure, and level of accessibility improvement (Table 2). “Very high priority for bikeshare stations” refers to locations below each threshold established for disadvantaged populations, high level of bike infrastructure quality, and high potential for increased job and essential services access via bikeshare. “High priority for bikeshare stations” covers areas that have disadvantaged populations, have a high or moderate level of bike infrastructure, and provide a high or moderate potential to increase accessibility. “Intermediate priority for bikeshare stations” is a location with other populations that have a high or moderate level of bike infrastructure or potential to increase accessibility. The last category, “high priority bikeshare and bike infrastructure combined need areas,” reflects locations having disadvantaged or other populations, a low bike infrastructure quality, and a moderate to high potential for increased job and essential service access via bikeshare.

Table 2 Categories classification based on quantiles of three measures.

Category	Disadvantaged areas		Level of bike infrastructure			Potential for increased job and essential service access		
	Yes	No	High	Moderate	Low	High	Moderate	Low
A	✓		✓			✓		
B	✓			✓		✓		
	✓		✓				✓	
	✓			✓			✓	
		✓	✓			✓		
C		✓		✓		✓		
		✓	✓				✓	
		✓		✓			✓	
D	✓				✓	✓		
	✓				✓		✓	
		✓			✓	✓		
		✓			✓		✓	

Note:
A: Very high priority for bikeshare stations
B: High priority for bikeshare stations
C: Intermediate priority for bikeshare stations
D: High priority bikeshare and bike infrastructure combined need area

RESULTS

Disadvantaged Populations

In both Chicago and Philadelphia, block groups with a median household annual income of less than $25,000 are largely, but not completely, coincident with block groups having minority population percentages greater than 50% (Figure 5 and Figure 6). Additionally, households tend to have fewer vehicles as we move toward the central city areas (Figure 7). Philadelphia has slightly more block groups (12.2%) and also a larger population (10.2%) falling into the disadvantaged category compared to Chicago (9.0% of block groups and 7.8% of total population) (Table 3). There were not any block groups identified as disadvantaged within the central business district (CBD) of Chicago. Two block groups within the Philadelphia CBD are classified as low income, people of color, and limited accessibility areas (Figure 8).

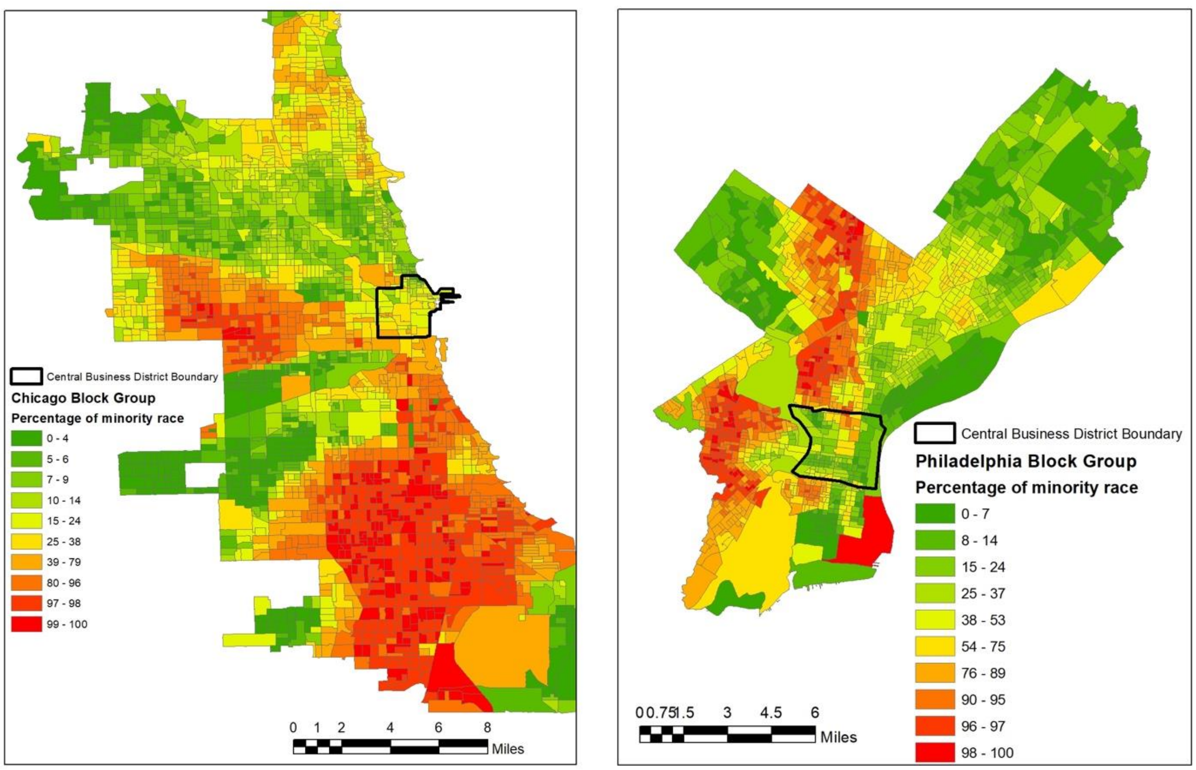

Figure 5. Percentage of minority population.

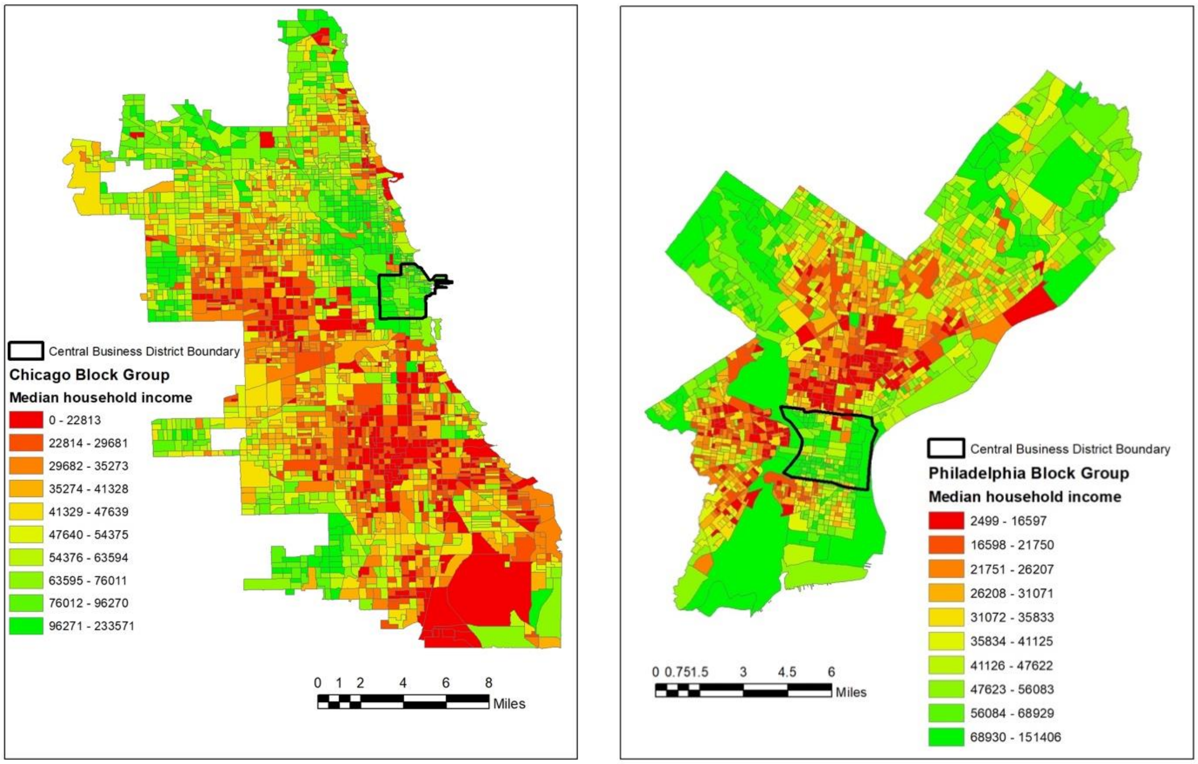

Figure 6. Median household income.

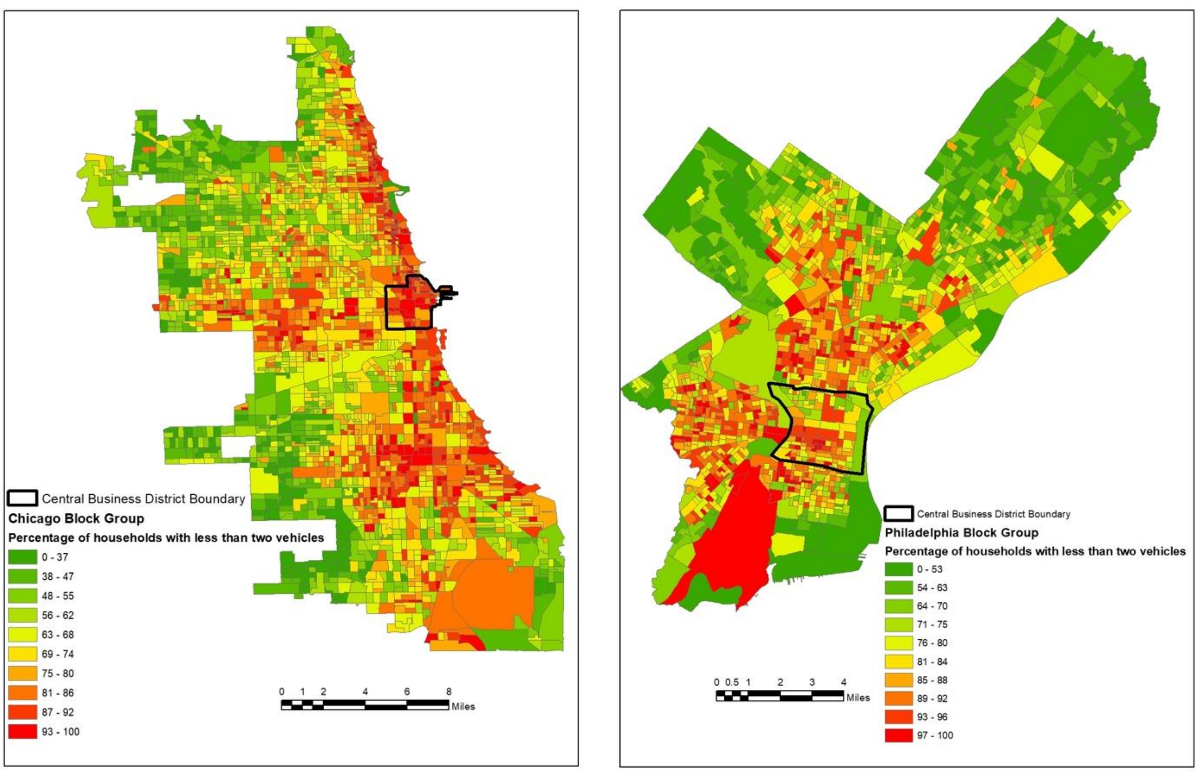

Figure 7. Percentage of households with less than two vehicles.

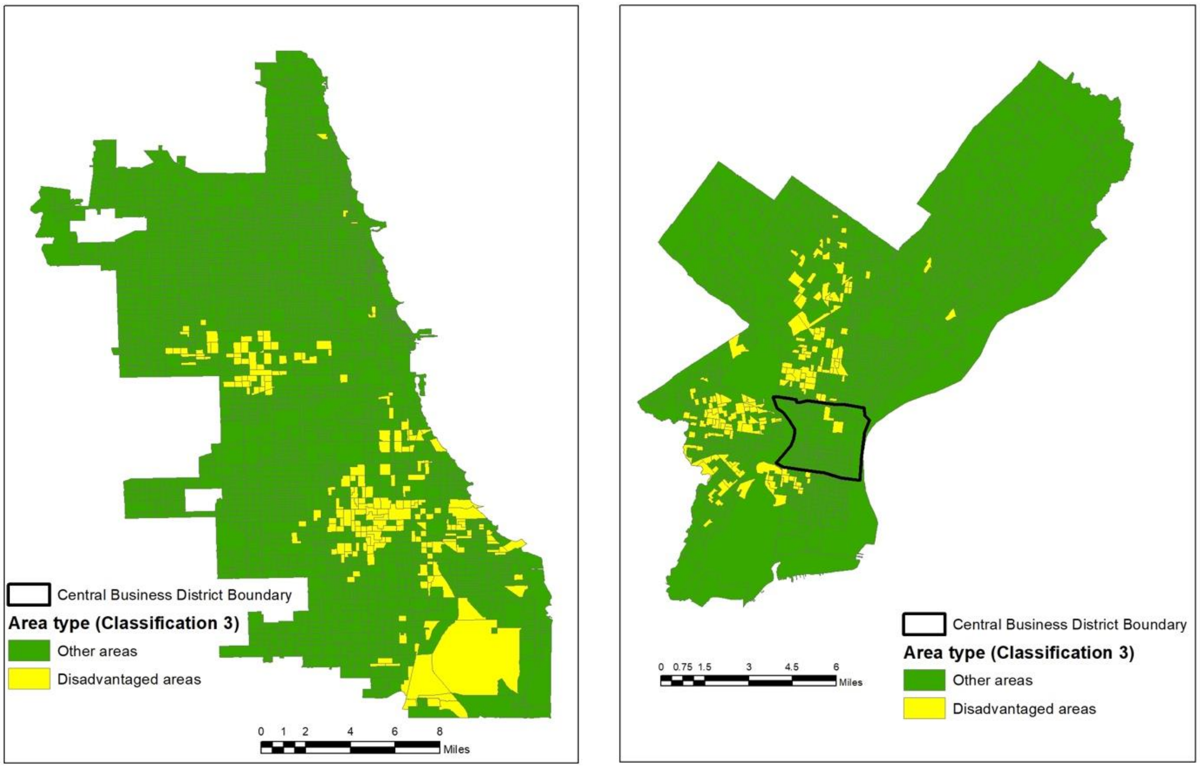

Figure 8. Distribution of disadvantaged areas.

Table 3 Number of block groups and population in different levels of served populations.

Classification	Chicago		Philadelphia	
	Block group	Population	Block group	Population
Disadvantaged	207 (9.0%)	222887 (7.8%)	163 (12.2%)	158103 (10.2%)
Others	2082 (91.0%)	2646668 (92.2%)	1173 (87.8%)	1393670 (89.8%)
Total	**2289[1]**	**2869555[2]**	**1336**	**1551773**

Note: 1. The unit is a block group;
2. The unit is one person.

Since I arbitrarily assign thresholds for minority race and household vehicle ownership, I also conducted a sensitivity analysis with four different thresholds for classification (Table 4). Our initially assigned thresholds are represented in Classification 3. Smaller thresholds obviously result in greater numbers of block groups or population segments as disadvantaged (Table 4).

The number increase of disadvantaged population or block groups also becomes smaller when the thresholds become bigger (see below, classifications 1 to 5). The reason is that the income threshold stays fixed (below $25,000 per year). Based on the proportion of disadvantaged population and block groups, I determined that our initial thresholds were reasonable (Classification 3). If we observe the spatial distributions of disadvantaged block groups under different classifications (Figure 9), the number of disadvantaged areas expands, but still concentrate in specific areas (in the west and south of Chicago or in the west and north of Philadelphia).

Table 4 Sensitivity analysis for disadvantaged population classification

Classification	Threshold	Chicago	Philadelphia
1	Income: < $25,000 P1[1]: >M[3] + SD[3] P2[2]: >M + SD	BG[3]: 128 (5.6%) Pop[3]: 131900 (4.6%)	BG: 66 (4.9%) Pop: 60898 (3.9%)
2	Income: < $25,000 P1: >M + 0.75×SD P2: >M + 0.75×SD	BG: 179 (7.82%) Pop: 190782 (6.6%)	BG: 116 (8.7%) Pop: 111893 (7.2%)
3	Income: < $25,000 P1: >M + 0.5×SD P2: >M + 0.5×SD	BG:207 (9.0%) Pop: 222887 (7.8%)	BG: 163 (12.2%) Pop: 158103(10.2%)
4	Income: < $25,000 P1: >M + 0.25×SD P2: >M + 0.25×SD	BG: 236 (10.3%) Pop: 252301 (8.8%)	BG: 191 (14.3%) Pop: 185413 (11.9%)
5	Income: < $25,000 P1: >M P2: >M	BG: 263 (11.5%) Pop: 280268 (9.8%)	BG: 224 (16.8%) Pop: 223158 (14.4%)

Note: 1. "Percentage of minority race" is abbreviated as "P 1";
2. "Percentage of households owning or renting 0-1 vehicle" is abbreviated as "P 2";
3. "M", "SD", "BG", "Pop" stand for "Mean", "Standard deviation", "Block group", "Population", respectively.

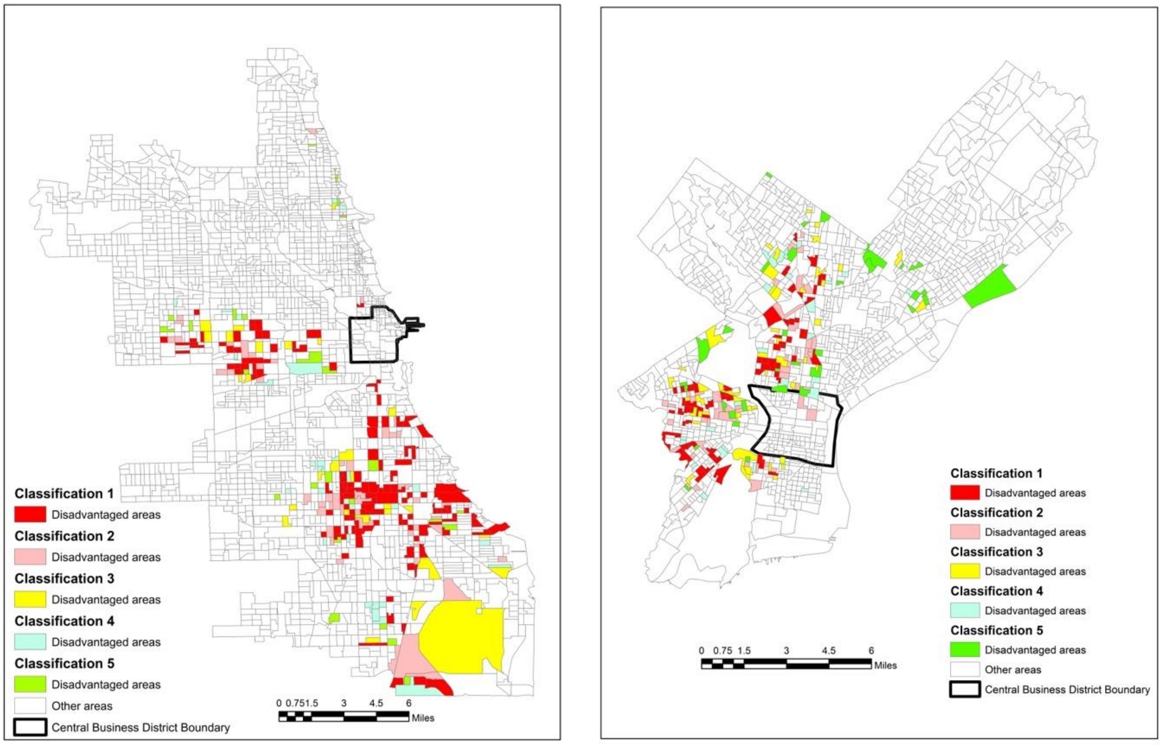

Figure 9. Distribution of disadvantaged block groups under different classification.

Bicycle Infrastructure

The quantiles for bicycle path densities across all block groups are shown in Table 5. I divided block groups into different levels of bicycle infrastructure using the same threshold process used to identify disadvantaged communities (Table 5). Philadelphia has fewer block groups (22.7% in Chicago vs. 19.2% in Philadelphia) and less population (23.6% in Chicago vs. 18.7% in Philadelphia) identified as having a high level of bicycle infrastructure (Table 6). From the ArcGIS map (Figure 10), the areas with the highest bicycle infrastructure density tend to be almost exclusively in the CBD areas. As might be expected, I find limited bicycle path coverage in suburban areas (Figure 10 and Figure 11).

Table 5 Statistics for bicycle path density within block groups.

Quantile		Chicago	Philadelphia
25%		0[1]	0
50%		15	12
75%		33	32
Maximum		215	220
Mean		22.3	22.8
Standard deviation		28.0	32.1
Threshold	High	> 36.3	> 38.8
	Moderate	8.3 <= and <= 36.3	6.7 <= and <= 38.8
	Low	< 8.3	< 6.7

Note: 1. The unit is meter per 10000 square meters.

Table 6 Number of block groups and populations at different levels of bicycle infrastructure.

Level of bicycle infrastructure	Chicago		Philadelphia	
	Block group	Population	Block group	Population
High	520 (22.7%)	676942 (23.6%)	256 (19.2%)	290386 (18.7%)
Moderate	852 (37.3%)	1101726 (38.4%)	525 (39.3%)	636828 (41.1%)
Low	917 (40.0%)	1090887 (38.0%)	555 (41.5%)	624559 (40.2%)
Total	**2289**	**2869555**	**1336**	**1551773**

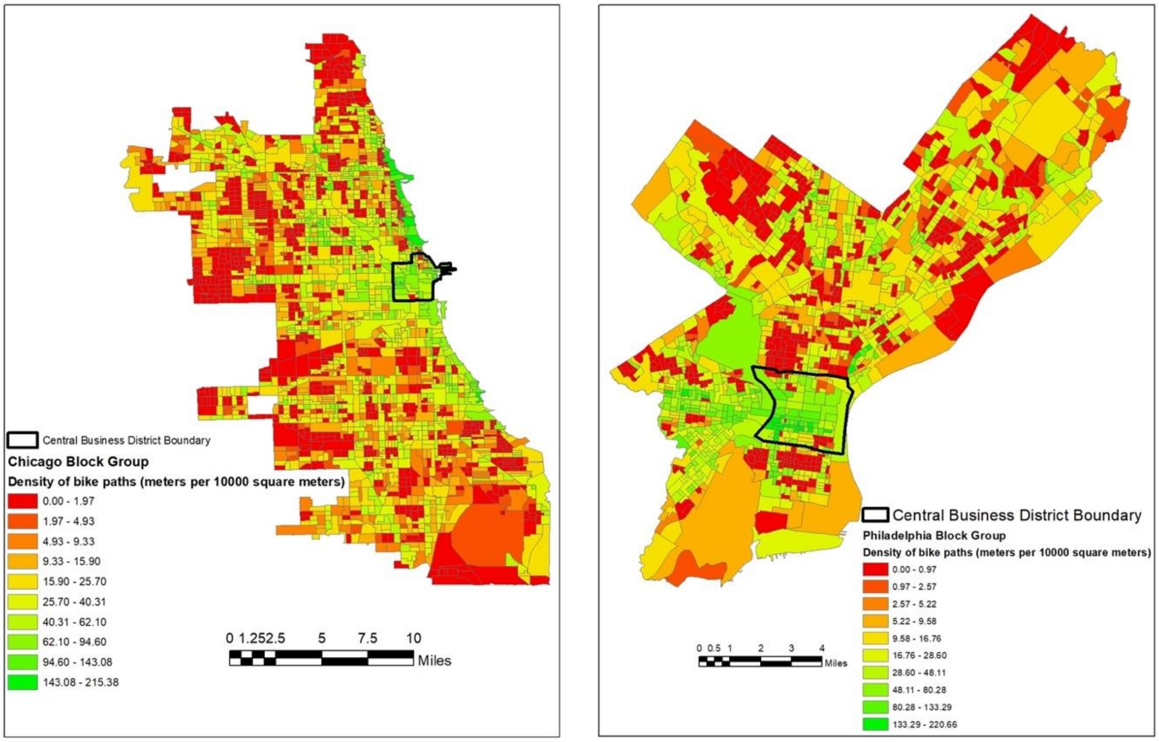

Figure 10. Density of bike path.

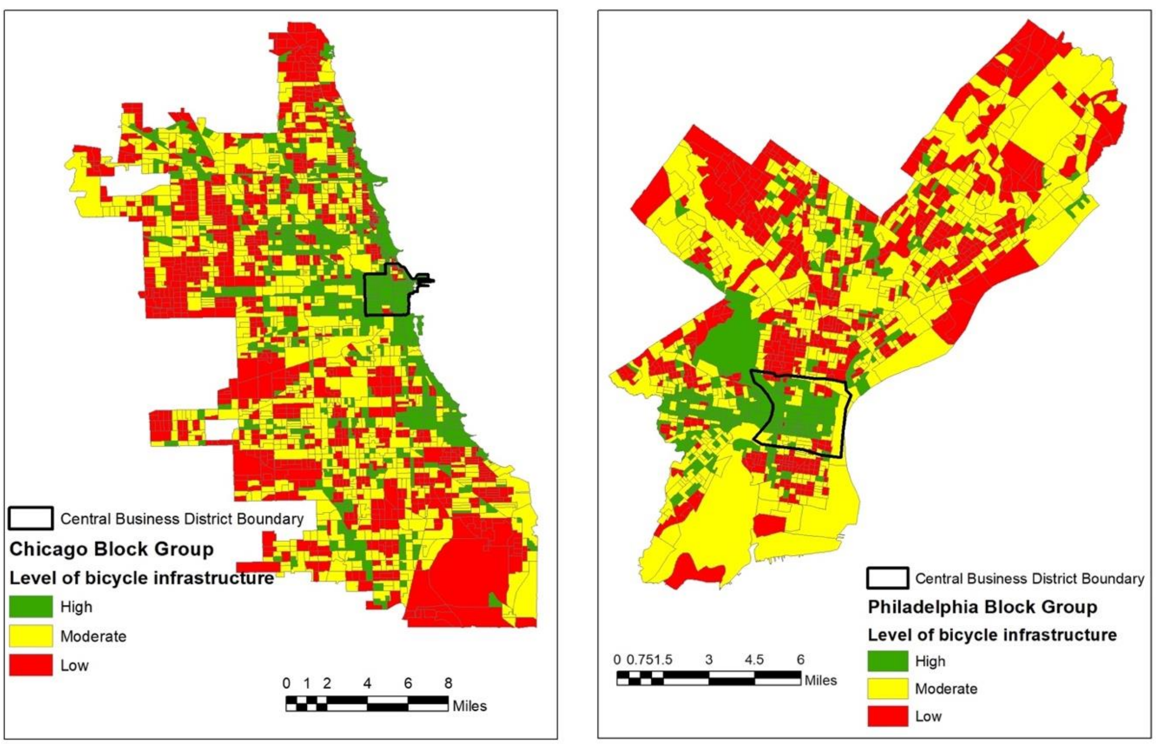

Figure 11. Distribution of block groups at different levels of bicycle infrastructure.

The relationship between the level of served population and the availability of bicycle infrastructure (as expressed by the density of biking facilities) is shown in Table 7 and Table 8. In general, greater population and larger numbers of block groups in disadvantaged communities have a low level of bicycle infrastructure compared to other areas in both Chicago and Philadelphia. However, there are still some disadvantaged block groups (2.0% in Chicago and 3.1% in Philadelphia) located in areas with sufficient bicycle infrastructure. Most of these areas are adjacent to parks where there are numerous bike paths for exercise and recreation. In Philadelphia, this pattern is even more obvious. (Figure 8 and Figure 11). Here, most of the disadvantaged communities in the west of the central business boundary in Philadelphia are located in areas with high levels of bicycle infrastructure. If we consider just the proportion of block group, 25.4% (3.1% out of 12.2%) in disadvantaged areas have high-levels of bicycle infrastructure, while only 18.3% (16.1% out of 87.8%) of block groups in other areas do, taking Philadelphia as an example.

Table 7 Distribution of block groups.

Level of bicycle infrastructure	Area type			
	Disadvantaged areas		Other areas	
	Chicago	Philadelphia	Chicago	Philadelphia
High	46 (2.0%)	41 (3.1%)	474 (20.8%)	215 (16.1%)
Moderate	77 (3.4%)	53 (4.0%)	775 (33.8%)	472 (35.3%)
Low	84 (3.6%)	69 (5.1%)	833 (36.4%)	486 (36.4%)
Total	207 (9.0%)	163 (12.2%)	2082 (91.0%)	1173 (87.8)

Table 8 Distribution of populations.

Level of bicycle infrastructure	Area type			
	Disadvantaged areas		Other areas	
	Chicago	Philadelphia	Chicago	Philadelphia
High	51808 (1.8%)	40080 (2.6%)	625134 (21.8%)	250306 (16.1%)
Moderate	85374 (3.0%)	51054 (3.3%)	1016352 (35.4%)	585774 (37.7%)
Low	85705 (3.0%)	66969 (4.3%)	1005182 (35.0%)	557590 (35.9%)
Total	222887 (7.8%)	158103 (10.2%)	2646668 (92.2%)	1393670 (89.8%)

Accessibility Improvement

When calculating the accessibility values, the choices of β and the maximum travel time in Equation 1 are important. I also conducted sensitivity analyses for both β and the maximum travel time (Figure 12). As reflected in Equation 1, the absolute value of accessibility of scenario 1 or 2 becomes greater with the increase of the maximum travel time and drops with the increase of β, which are also shown in Figure 12. The average accessibility improvement is significantly greater when the maximum travel time is smaller. This makes sense because access to some opportunities in scenario 2 can be achieved within a constrained time compared to no opportunities in scenario 1. I set the value of β equal to 0.5 based on our sensitivity analysis and set the maximum travel time equal to 10 minutes to avoid unrealistic accessibility improvements.

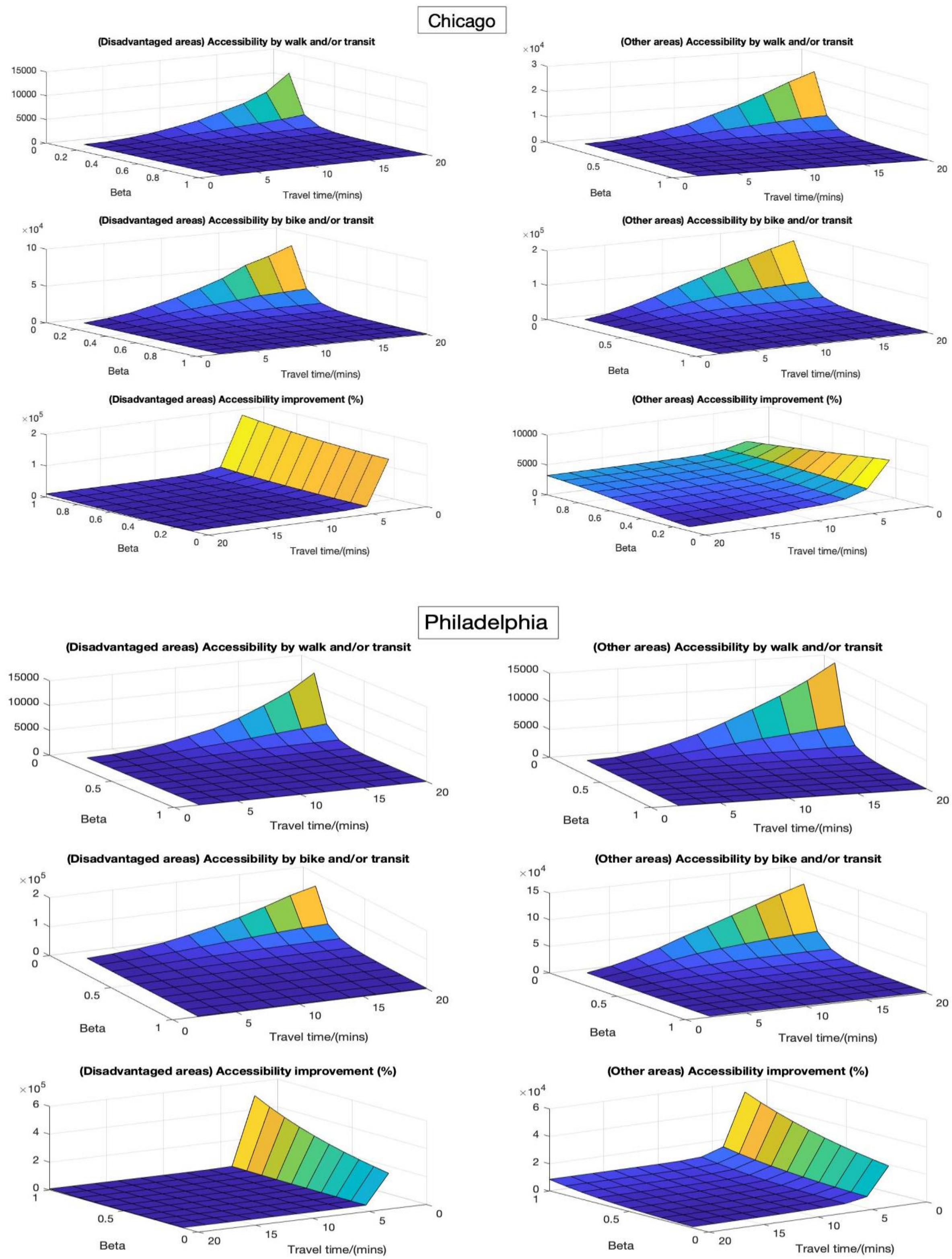

Figure 12. Sensitivity analyses for average accessibility improvement for different groups.

After setting β and the maximum travel time, I can examine the accessibility values for disadvantaged areas and other areas in detail. Histograms of the calculated accessibility values for each scenario for both disadvantaged areas and other areas (Figure 13) indicate that some areas show no accessibility improvement. This is the result of limited bicycle infrastructure in these areas. That is, for areas with limited bicycle paths, negative accessibility improvements (-100%) can be observed.

The histograms of accessibility values for scenario 1 and 2 suggest that disadvantage areas tend to have smaller absolute accessibilities compared with other areas, especially in Chicago. However, when comparing the accessibility improvements that would result from bikeshare service, block groups in disadvantaged areas experience greater accessibility improvements. To compare the distributions of accessibility improvements in two types of areas, I applied the Kolmogorov-Smirnov test, which is a general nonparametric method for comparing two samples (Massey Jr, 1951). The K-S test suggests that the distribution of accessibility improvements in disadvantaged areas is approximately equivalent to other areas (Chicago: D = 0.069 and p-value = 0.31; Philadelphia: D = 0.075 and p-value = 0.40). Even though these two distributions are similar based on the K-S test, we still can observe increased number of block groups in disadvantaged areas with improved accessibility in the tail of the distribution.

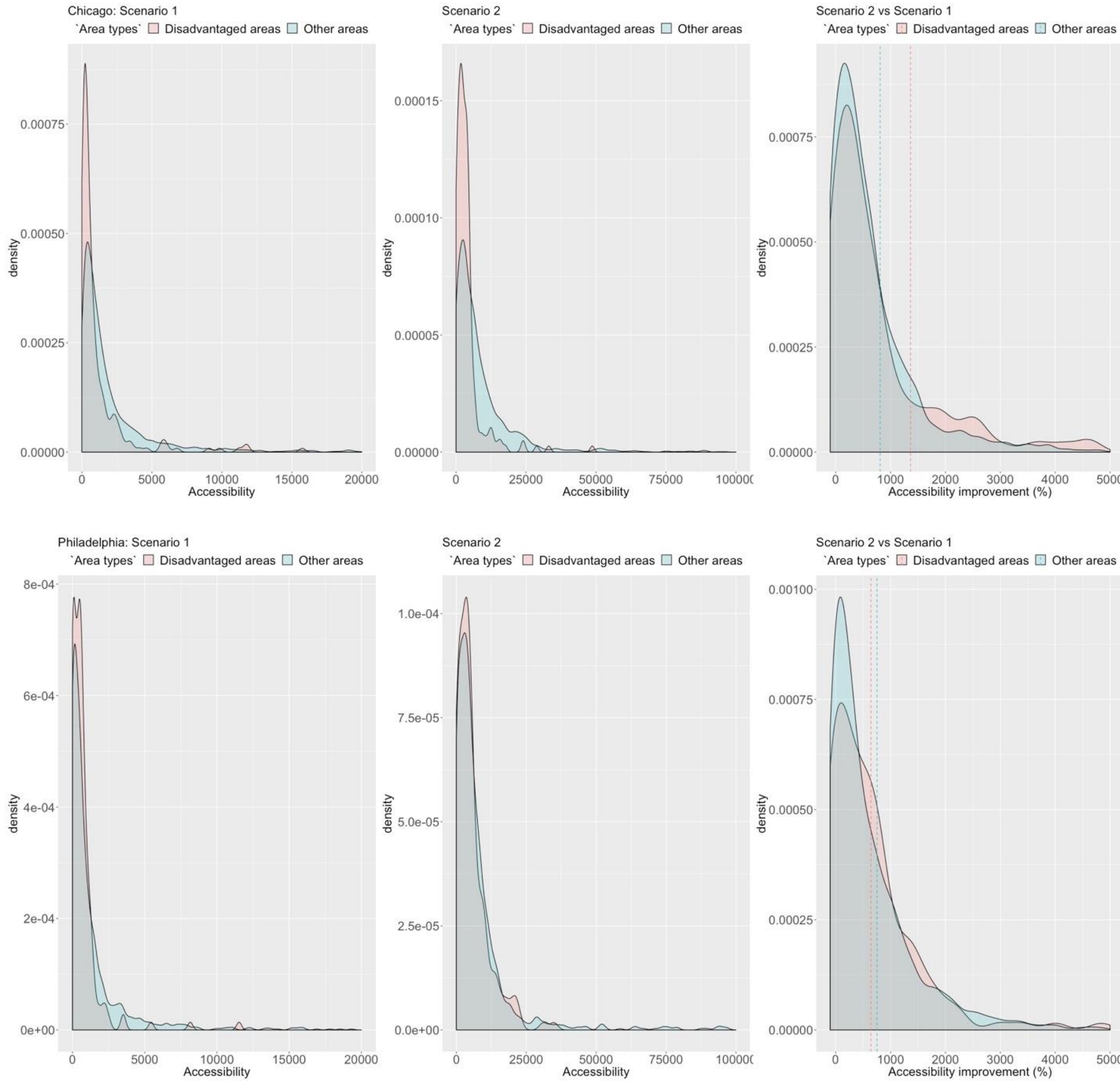

Figure 13. Histogram of accessibility (two scenarios) and improvements in Chicago and Philadelphia.

Figure 14 and Figure 15 show the absolute value of accessibilities for each scenario and accessibility improvements (scenario 1 vs scenario 2) in Chicago and Philadelphia. There are two completely different patterns that emerge between absolute value of accessibility and accessibility improvement. As might be expected, there are specific areas with low accessibility in either scenario 1 or 2, for example, the west and south of Chicago (the most left picture in Figure 14). In scenario 1 and 2, there are even some block groups with zero accessibility. As mentioned earlier, these result from limited transit service within the maximum travel time or insufficient bicycle paths. Many of the zero accessibility block groups are located in disadvantaged areas where there is not frequent transit service and the cycling environment is unsafe. However, the block groups with high levels of improvements are much more evenly distributed throughout Chicago and Philadelphia (the most right picture in Figure 14 and Figure 15), which is totally different from the spatial distribution of block groups with absolute high accessibility in scenario 1 or 2. In Philadelphia, there are large areas with negative accessibility improvements. Using Google Map, it is clear that these areas are mainly within an airport and ports along the Delaware River in Philadelphia. Figure 16 shows the distribution of block groups at different levels of accessibility improvements under the aforementioned classification framework.

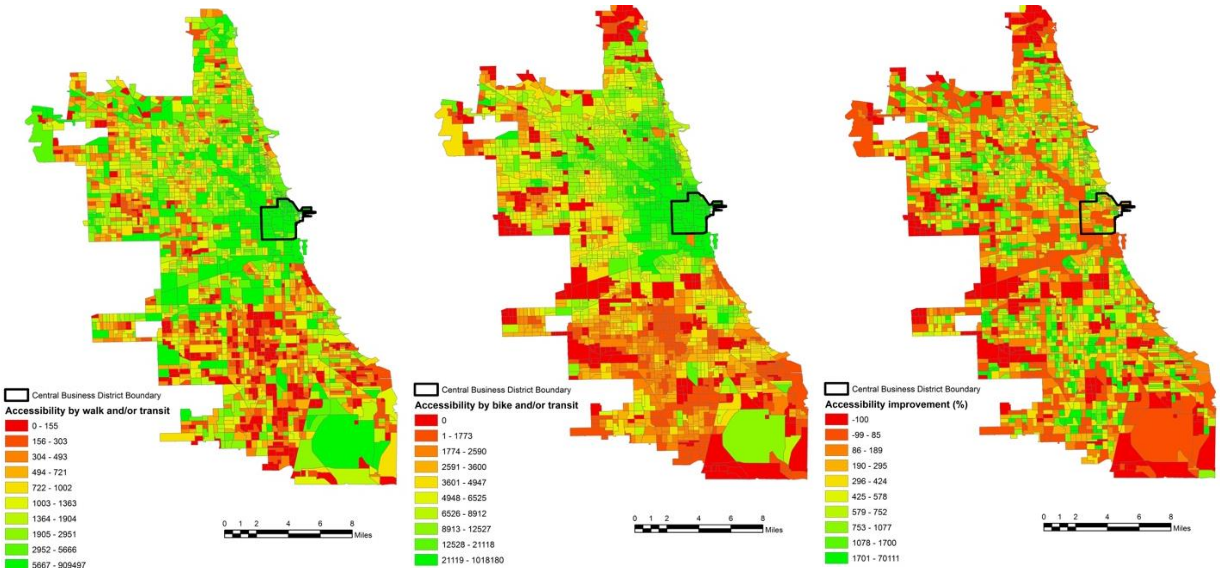

Figure 14. Spatial distribution of accessibility (two scenarios) and improvements in Chicago.

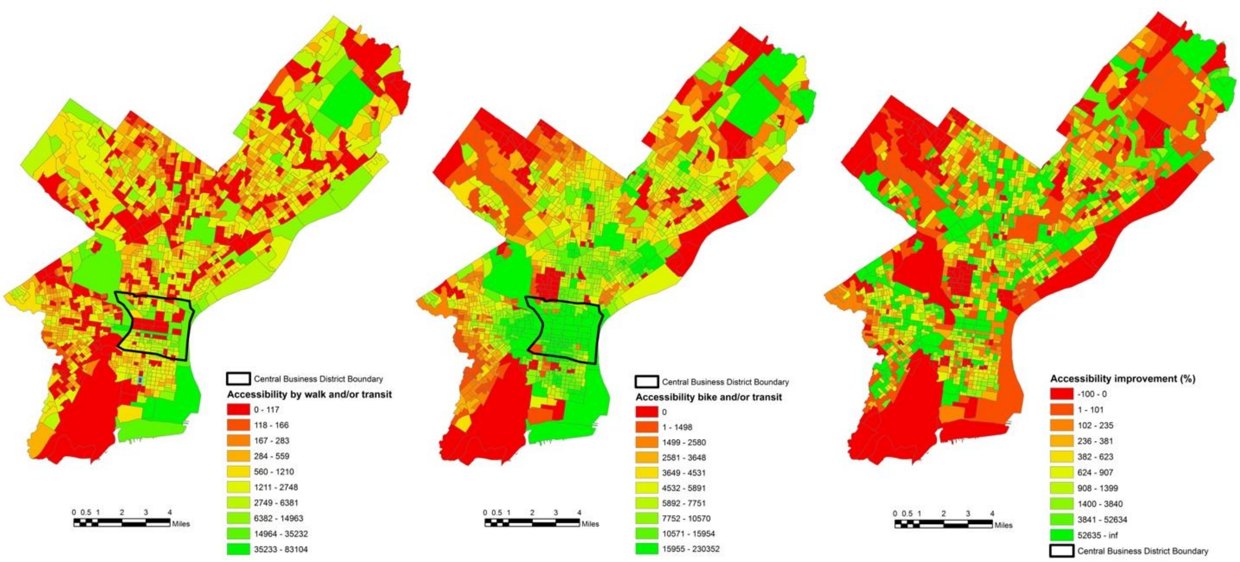

Figure 15. Spatial distribution of accessibility (two scenarios) and improvements in Philadelphia.

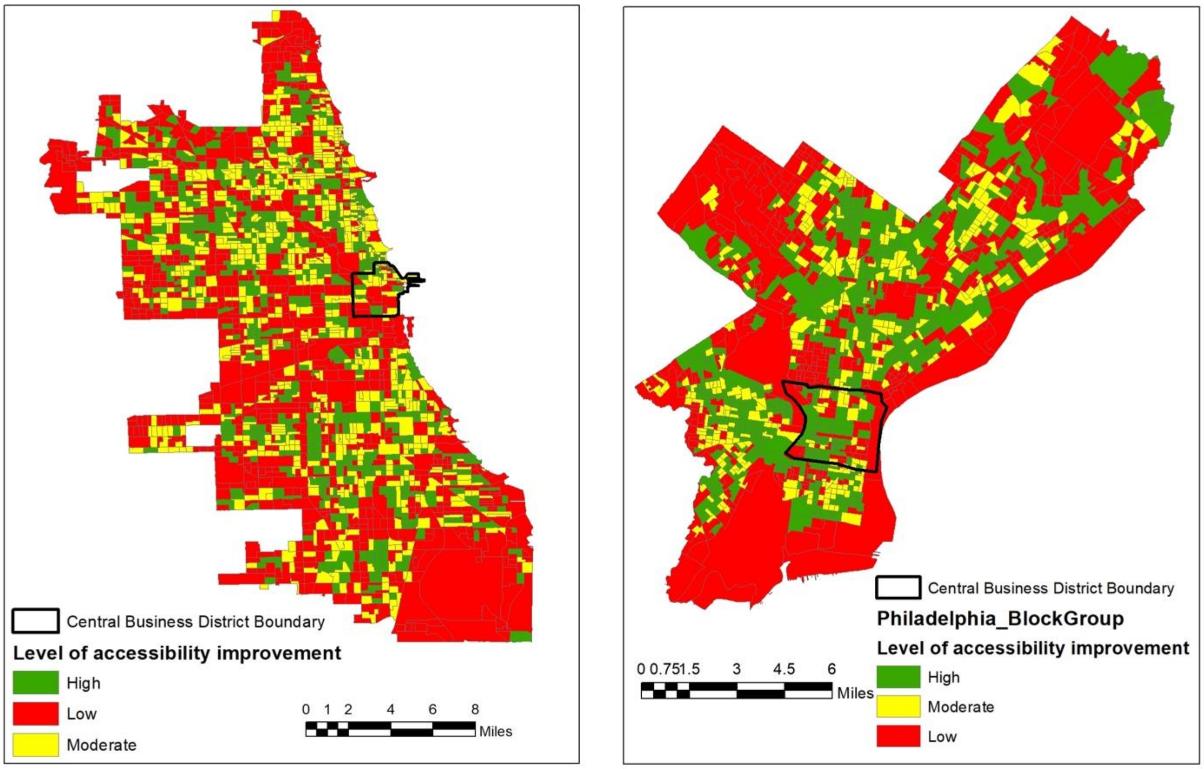

Figure 16. Distribution of block groups at different levels of accessibility improvements.

Priority Areas for Bikeshare Stations in Disadvantaged Communities

Recall from Table 2 that I had four categories of priority areas. In this study, categories A (Very high priority for bikeshare stations) and B (High priority for bikeshare stations) refer to areas in which we are mostly concerned with equitable access to bikeshare systems. In Chicago 3.9% (0.7%+3.2%) of all block groups are captured by the A and B categories; these block groups should be considered high priority areas for the expansion of bikeshare systems (Table 9). Approximately 5.6% (1.5%+4.1%) of the block groups in Philadelphia are identified as high priority areas for bikeshare stations. In both Chicago and Philadelphia, nearly one third of them (38.5% for Chicago and 37.9% for Philadelphia) are labeled with intermediate priority for bikeshare stations. Almost a quarter of block groups (23.1% for Chicago and 24.9% for

Philadelphia) are categorized as high priority areas for bikeshare and bike infrastructure. These results clearly indicate that there are sufficient numbers of areas of demand to support targeted bikeshare systems.

Table 9 Distribution of block groups in four categories in Chicago and Philadelphia.

Category	Chicago	Philadelphia
A	16 (0.7%)	20 (1.5%)
B	73 (3.2%)	55 (4.1%)
C	881 (38.5%)	507 (37.9%)
D	528 (23.1%)	332 (24.9%)
Others	791 (34.5%)	422 (31.6%)
Total number of block groups	2289	1336

Note:
A: Very high priority for bikeshare stations
B: High priority for bikeshare stations
C: Intermediate priority for bikeshare stations
D: High priority bikeshare and bike infrastructure combined need areas

Current Bikeshare Station Locations

I also compared the current bikeshare stations to those block group categories I classified. As shown in Table 10, both Chicago (0.3%) and Philadelphia (1.0%) have a small number of stations sited in disadvantaged areas that provide very high accessibility improvements. For category B, Chicago has only 3.3% of stations in this group, while Philadelphia has 2.9% of stations. Comparing percentages of current bikeshare stations located in areas identified as high priority for bikeshare systems (category A and category B), Philadelphia performs better than Chicago, but Philadelphia also has a much smaller system than Chicago. This suggests that Indego's stated intention to design a bikeshare system with equitable access across different populations has been to some degree accomplished. There is another interesting finding; in

Chicago, the proportion of bikeshare stations in category D (high priority bikeshare and bike infrastructure combined need areas) is nearly three times greater than in Philadelphia. This may be the result of differences in the spatial distribution of bicycle infrastructure and disadvantaged populations. Note that category D includes some disadvantage block groups with limited bike paths. In Chicago, there are a certain number of bikeshare stations in the south and west where a high overlap between disadvantaged population and areas with insufficient bicycle paths occurs.

Table 10 Distribution of bikeshare stations in four different categories in Chicago and Philadelphia.

Category	Chicago	Philadelphia
A	2(0.3%)	1 (1.0%)
B	19 (3.3%)	3 (2.9%)
C	253 (43.6%)	51 (48.5%)
D	68 (11.7%)	4 (3.8%)
Others	239 (41.1%)	46 (43.8%)
Total number	581	105

Note:
A: Very high priority for bikeshare stations
B: High priority for bikeshare stations
C: Intermediate priority for bikeshare stations
D: High priority bikeshare and bike infrastructure combined need areas

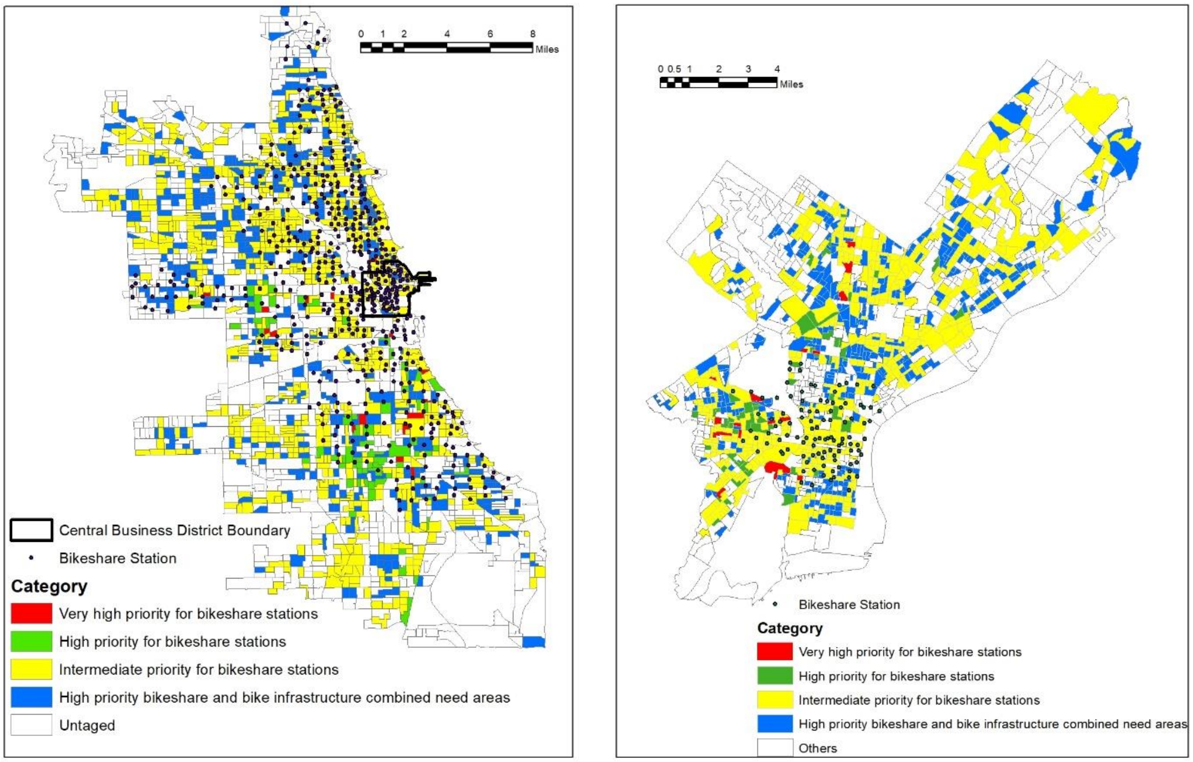

Figure 17. Map of current bikeshare stations and block group classifications in Chicago and Philadelphia.

DISCUSSION

The Current Bikeshare Station Siting

I have quantitatively demonstrated that bikeshare stations in both Philadelphia and Chicago tend to be located in areas with more affluent and white populations. This is consistent with findings from the qualitative investigation by McNeil, Dill, MacArthur, Broach, et al. (2017) and the demographic information analysis using bikeshare stations' buffer areas by Ursaki and Aultman-Hall (2016). Additionally, the overall number of bikeshare stations in every block group tends to be higher in those block groups having a higher percentage of white population (Figure 18). Having limited bikeshare stations in disadvantaged areas affects the bikeshare usage there. Taking Chicago as an example (Figure 19), most of the bikeshare stations with high numbers of annual origination or destination trips are located in areas with greater white population. Many bikeshare system programs claim to have taken equity into consideration for station siting (Howland et al., 2017; Shaheen, Martin, Cohen, Chan, & Pogodzinski, 2014), but, as with bikeshare operators, have lacked a quantitative method or index for confirming the allocation of stations is equitable (Howland et al., 2017). While guidelines for implementing bikeshare systems are available (National Association of City Transportation Officials, 2014), they tend to suggest, somewhat simplistically, locations with heavy pedestrian or visitor flow or adjacent to safe bicycle infrastructure. They also tend to provide guidance on physical bikeshare station siting types and design principles such as how to fit a bikeshare station into a street parking lot. When compared with the physical design of a station, I would argue that siting a bikeshare station at a location where residents actually benefit from it is more important. The index I developed shows that not enough bikeshare stations are placed in disadvantaged areas in Chicago and Philadelphia, despite the substantial benefits bikeshare would bring to these communities.

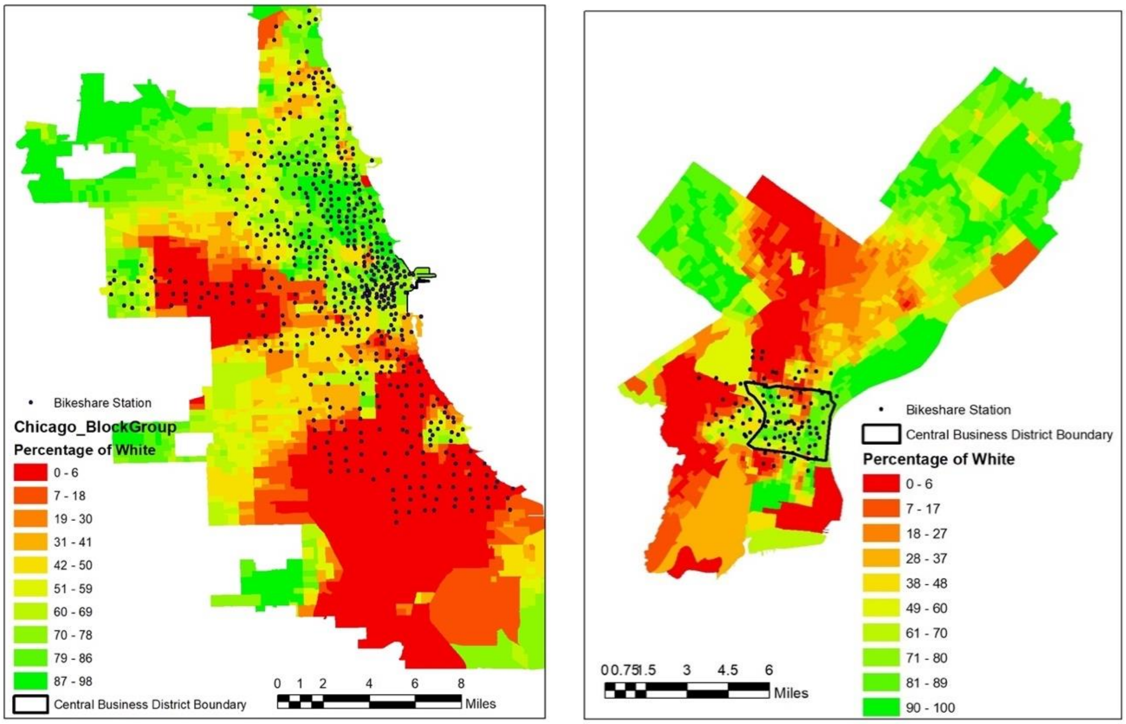

Figure 18. Distribution of bikeshare stations and white population in Chicago and Philadelphia.

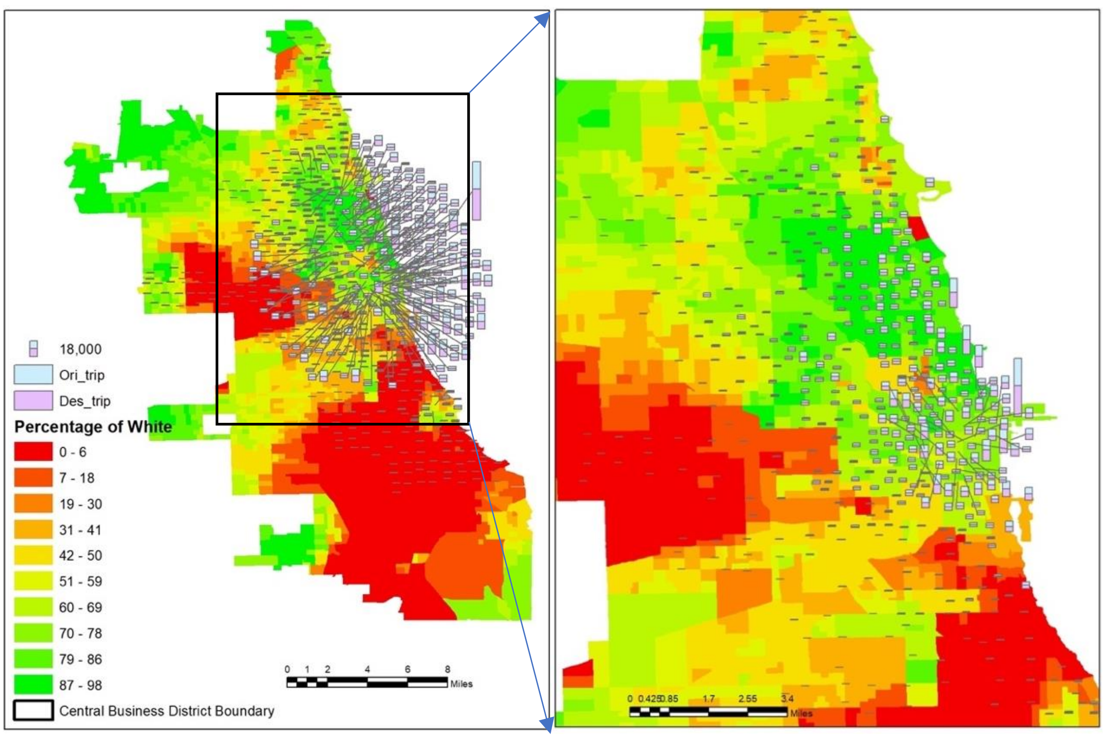

Figure 19. Number of annual origination ("ori_trip") and annual destination ("des_trip") trips for every station in Chicago.

Policy Insights for Elimination of Access Barriers and Potential Accessibility Improvement for Disadvantaged Communities (Dock-base or Dockless Systems)

The index developed in this study can help planners identify high-priority bikeshare investment areas where such investments would improve accessibility to opportunities for disadvantaged populations. The granularity of our analyses is census block group. There are two reasons to conduct spatial analyses at this level. First, on average, there is usually at least one bikeshare station in a census block group, making it easy to use the block group as a planning unit when a bikeshare system considers expanding. Secondly, the presence of bikeshare stations within walking distance is just one of many barriers residents of disadvantaged communities face. In our analysis, the average area of block groups is 263,140 and 272,869 square meters in Chicago and Philadelphia, respectively, which is approximately a 500-meter square. If a disadvantaged block group has a bikeshare station, the average walking distance for residents in this block group to get access to the station is within a reasonable 400-meter range (Cohen, 2016). In this way, our scale-appropriate index can identify the priority areas for bikeshare stations and help to eliminate access barriers for disadvantaged populations. Our index also identifies areas that need more bike paths, which could help planners in allocating funds for improving bicycle infrastructure.

Lessons from Two Case Study Cities

As mentioned in section above, the two bikeshare systems in Chicago and Philadelphia are owned by the cities and operated by two for-profit companies (Motivate and B-Cycle, respectively). Both systems have tried to include more disadvantaged areas into their service areas by offering, for example, discounted membership for low-income households. This is implemented through an agreement between bikeshare operators and local cities. Municipalities could reduce taxes on those bikeshare operation companies or develop metrics to measure bikeshare equity to incentivize companies to offer greater coverage in disadvantaged neighborhoods.

Finally, even though the two bikeshare systems I studied are similar in addressing bikeshare equity issues, there is still a difference in how they developed their operational strategies. As noted by other research (Buck, 2013; Howland et al., 2017), the extension of a large bikeshare system will increase the potential to cover greater numbers of disadvantaged areas. However, as our study implies, a smaller bikeshare system still early in its development (like Indego in Philadelphia) can also make a significant reduction in access barriers for disadvantaged communities. Chicago has a 581-station system compared to the 105-station system in Philadelphia. Both Chicago and Philadelphia have made efforts to guarantee equitable access, but the Philadelphia system is a good example of proactively attempting to eliminate access barriers for disadvantaged communities. Taking disadvantaged communities into early consideration and developing a clear metric to represent different kinds of populations are critical factors to making bikeshare systems more equitable. In the early stages of planning, Philadelphia reflected on how to implement their system. To eliminate the access barrier for disadvantaged communities, 20 out of the first 60 bikeshare stations were planned to be located in low-income communities with the remaining 40 to be located in the greater Center City and University City (Hahn, 2014). Moreover, Indego in Philadelphia reconsidered all the barriers (payment systems, membership models, and perceptions about bikeshare) for low-income members. Our research quantitatively shows that access barriers for use of bikeshare can be overcome, to some extent, by carefully considering each factor in the early stages of designing a bikeshare system.

Limitations and Future Research Directions

It is important to emphasize there are limitations to this study. For one, in our accessibility analysis I assumed two scenarios, walk-to-transit and bike-to-transit, to focus on benefits of bikeshare systems. However, in reality bicycles are not usually the primary transport mode. If more information about traffic demand and transport mode split in disadvantaged areas were available, I could have precisely estimated the number of bike trips and created a more nuanced model for accurate estimation of accessibility improvement by bikeshare systems. Second, the travel times are averaged across entire block groups, and therefore only offer an approximate travel time between every block group pair. Third, in the accessibility analysis, other important travel elements such as monetary cost of travel could be included since cost is also an essential factor of concern for disadvantaged population. Finally, dockless bikeshare systems have become increasingly prevalent. Our study does not include dockless systems because these new systems have no physical bikeshare stations and dockless bikeshare data are not directly available. The dockless systems may be more efficient to cover disadvantaged areas since a physical station is not necessary to expand their service areas. However, more studies are needed to compare the expense to dynamically relocate bikes to cover more areas (dockless) and the financial support to open new bikeshare stations (dock-based). Despite these limitations, this study contributes by providing a better understanding of how prioritized investments in bikeshare can improve essential accessibility for disadvantaged communities.

CONCLUSIONS

Bikeshare programs can play an important role in sustainable transportation systems by offering a viable mode choice for many types of last mile trips. However, recent bikeshare systems tend to target more affluent and white-dominated areas. To shed light on this problem, this paper conducts an accessibility analysis with and without bikeshare. Based on our quantitative analysis, bikeshare systems can produce substantial accessibility improvements for disadvantaged communities. Average accessibility improvements for disadvantaged communities can be greater than those experienced in other areas. Furthermore, our research presents a new index that identifies bikeshare station locations providing high potential accessibility improvement to jobs and essential services for disadvantaged communities. By comparing these potential locations with current dock-based bikeshare station siting, our research clearly demonstrates that most of the current bikeshare stations in Chicago and Philadelphia are not located in high priority areas for bikeshare stations if we consider disadvantaged populations. Through these two study cities, I learn that a bikeshare system in its early stages can proactively attempt to eliminate access barriers for disadvantaged communities with consideration of equitable accessibility.

CHAPTER 3: BIKESHARING ACTIVITIES IN DISADVANTAGED COMMUNITIES (A CASE STUDY IN CHICAGO)

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; S. Shaheen, Guzman, and Zhang 2010), and recently, dockless systems. Self-serve kiosk 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 systems (National Association of City Transportation Officials 2017, 2010–16). With the introduction and growing prevalence of dockless systems the numbers of both bikeshare systems and bikes continue to increase. New services using scooters are providing other options in many urban settings.

These 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, Washington, and Haworth 2014; Wang and Zhou

2017). Among their benefits, bikeshare systems can provide reduced traffic congestion, improved accessibility and an environmentally friendly urban transportation option (Woodcock et al. 2014). BSSs also provide benefits in terms of improving physical health, eliminating the maintenance burden of bicycle ownership, and reducing the risk of bike theft and vandalism, and bike storage requirements, (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). Among these, financial constraints are a primary issue that discourages disadvantaged populations from joining bikeshare programs (McNeil, Dill, MacArthur, and Broach 2017). Fishman, Washington, & Haworth (2012) found that the membership fee is an expense that discourages people, especially 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.

Examples can be found on official BSS websites and in the media of current BSS efforts to expand systems to cover disadvantaged areas, to mitigate the financial barriers to participation. For instance, "*Motivate*," a for-profit bikeshare company, has promoted a five-dollar annual membership program among their operated systems. In July of 2015, Divvy launched this special 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 (Motivate International 2017b; CitiBike 2018; Motivate International 2018a; Capital Bikeshare 2018). 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 a few 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 (McNeil, Dill, MacArthur, and Broach 2017; Buck 2013; Cohen 2016; Bernatchez et al. 2015). Another vein of research develops bikeshare ridership estimation models with spatiotemporal and demographic variables, including income. However, these models do not consider the disaggregate impacts related to disadvantaged communities. Information about how many trips generated in disadvantaged areas is limited. Further, there is a lack of research studying the impacts of financial barriers in disadvantaged areas at the station level. To address these gaps, this study examined the relationship between bikeshare ridership and disadvantaged communities. In doing so, I estimated an econometric model relating ridership to system demographics, and environmental variables and used the model to analyze marginal effects and elasticities of variables significantly affecting ridership. The results clarify the impacts of the financial barriers by analyzing the proportion of bikeshare trips made by annual members, and comparing ridership expenditures between users in disadvantaged and other areas. Finally, I discuss the implications of these results in fostering a more sustainable and equitable transportation system.

LITERATURE REVIEW

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 per 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., slope of a road).

In addition to these aggregate models, disaggregate 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 preceding 24 hours 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 improve 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 bikeshare ridership predictions in disadvantaged areas. 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 the financial barrier is removed. Cohen's study (2016) did not analyze trip features, e.g., trip duration and trip spending, using trip data from low-income communities. The literature review also showed that ridership prediction models do not consider overdispersion in bikeshare ridership data. In general, there are research gaps regarding the magnitude of the financial barrier for bikeshare ridership in disadvantaged communities, and the use of appropriate models to consider the nature of travel data characteristics of the BSS mode.

CASE STUDY CITY AND DATA DESCRIPTION

This research selected Chicago as a case study city considering its large-scale bikeshare system and determination to address equity issues in bikeshare. 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 their database to the public for all Divvy bikeshare trips from 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 (subscriber or day user). A day user is a rider who purchases a 24-hour pass, and a subscriber 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 a particular station can be calculated.

This research required complementary safety data in addition to all the data described in Chapter 1 and Divvy's ridership data. As indicated in multiple research papers, safety concerns are an important consideration when selecting travel modes and are particularly relevant when cycling (Griffin et al. 2008; Christie et al. 2011; Fishman et al. 2014). This study considers two types of safety issues: bicycle crashes with vehicles, and street crime (violent offenses). Chicago has an online database of crash data from 2009 to 2014 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. Furthermore, land use can affect bicycle trip generations (Barnes and Krizek 2005; Dill and Voros 2007). Thus, I collected area information of recreation places such as parks and the National Register of Historic Places.

METHODOLOGY

To accurately estimate ridership, publicly available bikeshare trip data was used, as well as demographic and spatiotemporal data for every census block group in the study area. First, I 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, I estimated an econometric model for annual ridership for each station, and conducted the marginal effect and elasticity analyses. Further, I analyzed subscription rates and actual trip charges at the station level within different areas using historical bikeshare trip data. Figure 20 illustrates the process followed to conduct the analyses.

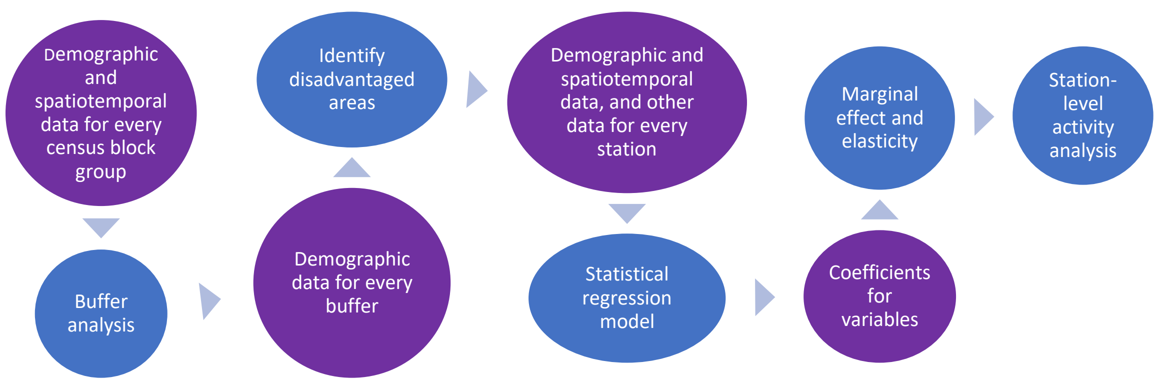

Figure 20. Analysis process.

Buffer Analysis

According to previous research, the average distance for access to a bikesharing station is 400 meters (Cohen 2016). I 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 11. There is one variable: percentage of young population, which refers to the percentage of the population aged between 20 and 35. People ages 20 to 35 are reported to be consistently overrepresented as bikeshare users (Buck et al. 2013; Daddio and Mcdonald 2012; S. A. Shaheen 2012). Thus, I considered the percentage of young population instead of average age in the later regression analysis since two block groups with the same average age may have different age compositions.

Table 11 Summary of key variables considered in the analyses.

Variable	Abbreviation	Description	Source
Dependent			
Total origin trips	O_Trip	The total number of bikeshare trips that originate from a bikeshare station	Divvy bikeshare system operator
Total destination trips	D_Trip	The total number of bikeshare trips that terminate at a bikeshare station	Divvy bikeshare system operator
Independent			
System-specific factors			
Capacities	Capacity	The 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
Households	HH_2010	Total number of households	Census 2010
White race	Pec_Whi	Percentage of white race	Census 2010
Average age	Ave_age	The average age of population	Census 2010

Percentage of young population	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 of workforce	ACS 2014
Employment rates	Emp_rate	Employed population divided by total population of work force	ACS 2014
Environmental factors (All these factors are summary for a buffer)			
Intersections	Int_points	The number of intersections in a buffer	OpenStreetMap
Walk network density	WBN_des	The total length of walkable paths divided by the area of a buffer	OpenStreetMap
Bike path density	BN_des	The total length of bike paths divided by the area of a buffer	OpenStreetMap
Transit stops	Transit	The number of transit (bus and railway) stations	Google Place API
Groceries	Grocery	The number of grocery stores	Google Place API
Schools	School	The number of schools	Google Place API
Hospitals	Hospital	The number of hospitals	Google Place API
Parks	Park_Nm	The number of parks	Chicago Data Portal
Park areas	Park_area	The total areas of parks	Chicago Data Portal
Number of historical places	Land_Nm	The number of historical places	Chicago Data Portal
Crash	Crash	The number of bicycle and pedestrian collisions with vehicles resulting in injuries	Illinois Department of Transportation (DOT)
Crime	Crime	The number of crimes such as aggravated assault, rape, arson, battery, theft, and other violent offenses.	Chicago Data Portal

Identification of Disadvantaged Communities

Different from the criteria to select disadvantaged communities in Chapter 1, one of the three criteria, the percentage of household owning less than one vehicle, is removed in this chapter. In this research, disadvantaged communities refer to a region where low-income populations and people of color live. The threshold for low-income is increased because the portion of bikeshare stations identified as disadvantaged areas would be extremely small if the threshold from Chapter 1 were used. Finally, the study identified those block groups with a median household income below $50,000 (200% of the federal poverty line for a household with four people) (U. S. Department of Health & Human Services 2016; Jiang, Ekono, and Skinner 2016). Then, I set thresholds of low, moderate and high using the mean and standard deviation of the percentage of minority populations within each buffer. Table 12 shows the threshold levels for minority populations (Turner, Hottenstein, and Shunk 1997).

Finally, the process identified whether a bikeshare station buffer is a disadvantage area or not. Thus, for example, a buffer is defined as a disadvantaged area if it satisfies: a) a median household annual income below $50,000 and b) percent of white race below 41.64% in Table 12.

Table 12 Criteria for disadvantaged communities.

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

Note: 1. "Mean" is the mean of percentage of white race;
2. "SD" stands for "Standard deviation".

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 into a model could change the variance (Agresti 2013). Alternatively, and considering the potential for over dispersion in origin-destination trip matrices, I also evaluated negative binomial regression models. This study analyzed ridership for trip origins and destinations independently.

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, considering the different attributes of continuous and binary variables, I estimated marginal effects for them separately. For continuous variables, the marginal effect for variable x_k is:

$$M_{x_k} = \frac{1}{N}\sum_{i=1}^{N}\frac{\partial E(y_i)}{\partial x_k} = \frac{1}{N}\sum_{i=1}^{N}\frac{\exp\left(\hat{\beta} x_i\right)}{\partial x_k} = \widehat{\beta_k}\bar{y} \qquad (2)$$

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:

$$M_{x_k} = \frac{1}{N}\left[\sum_{i=1}^{N}(\exp(x\beta' + \beta_b) - \exp(x\beta'))\right] \qquad (3)$$

where β' and β_b are the coefficients for continuous and binary variables, respectively (Hilbe, 2011).

To further understand the influence of a variable, I measured the elasticity of every variable. In contrast to the preceding marginal effects related to absolute changes, elasticity is related to the percentage of change of the dependent and independent variables. It is represented as:

$$E_k = M_{x_k} \times \frac{\bar{x}}{\bar{y}} \quad (4)$$

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

Station-Level Analysis

Membership and usage fees are important barriers for disadvantaged communities to access and use bikeshare systems (McNeil, Dill, MacArthur, Broach, et al. 2017; Howland et al. 2017). As mentioned, every trip record distinguishes whether the user is an annual member or a day user. This study calculated the proportion of trips by subscribers for every bikeshare station, and then associated its subscription rate with demographic information for its catchment area. In this way, I 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 13) to estimate each trip's cost with the available trip duration information. Both annual members and 24-hour pass holders (hereinafter called "day users") can enjoy unlimited 30-minute free rides. However, after the first 30 minutes of each trip, the pricing scheme differs between an annual member and a day user. For every additional 30-minute period, a day user has to pay more than an annual member does, which is set as an incentive for more annual subscribers. Estimating the trip costs, and trying to allocate a portion of the subscription or the 24-hour pass fees to each trip was challenging because Divvy does not assign a unique ID to subscribers or day users. For trips by subscribers, the gender and birth year information is not sufficient to identify individual subscribers. For these reasons, it is not possible to know which trips are taken by the same subscriber or day user, or to estimate the annual expenditures for a specific individual (subscriber or day user). Considering these limitations in the data, I assigned a bikeshare trip to the station it starts from or terminates at, and estimated the average trip time and expenditure on a single trip for subscribers or day users at the bikeshare station level (for both origin trips and destination trips). After estimating the average trip time and costs, I 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 13 Price scheme (in dollars) for Divvy in 2016.

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

RESULTS

This section shows the results of the empirical analyses in Chicago following the aforementioned methodology. Firstly, I mapped the spatial distribution of bikeshare stations identified in disadvantaged communities. Then, I estimated the statistical regression model, and conducted the marginal effect and elasticity analyses. Finally, I analyzed bikeshare trip expenditures from stations in disadvantaged communities.

Bikeshare Station Distribution

This sample data has 475 observations (based on the available ridership data), which are buffers of 475 bikeshare stations. Using the criteria identifying disadvantaged communities, I identified 99 out of 475 station buffers as disadvantaged communities. Examining the distribution of these stations, Figure 21 shows that the majority concentrate 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 Figure 21) are in the central business district.

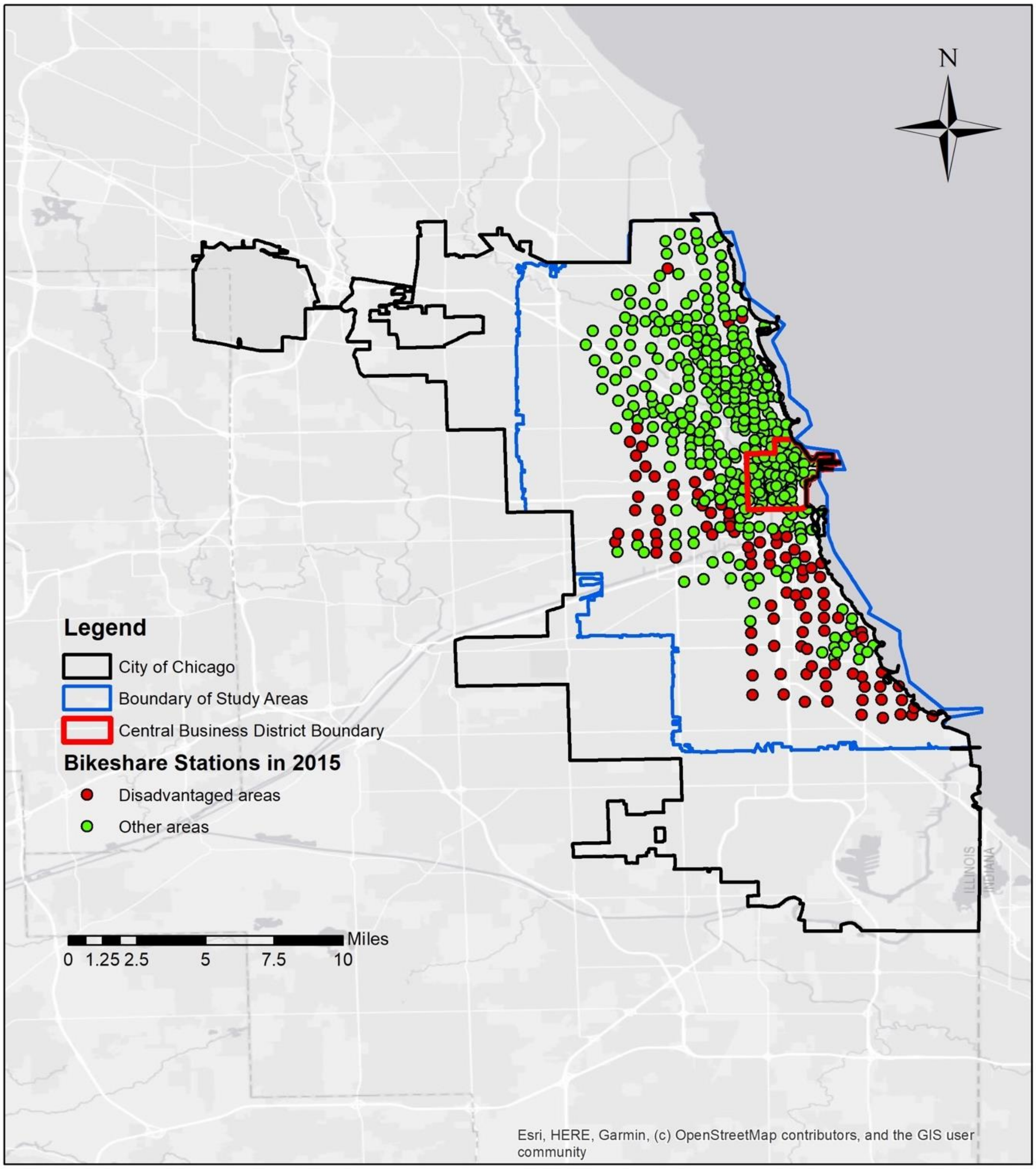

Figure 21. Distribution of bikeshare stations in Chicago.

Bikesharing Ridership Estimation

The descriptive statistics for all variables compiled for station buffers are listed in Table 14. Since the density of the bikeshare stations in Chicago's downtown area is significantly greater 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 (Figure 22) appears to be normally skewed or normally distributed. Thus, the overlap of buffer data does not affect the effectiveness of the following analyses.

Table 14 Descriptive statistics for all variables.

Variable	Min.	Median	Mean	Max.	Variance
Total origin trips	15	4889	7464	89248	77690229
Total destination trips	17	4822	7464	98590	81187422
Capacities	11	15	17.69	47	30.48
Stations within 500 meters	1	1	1.92	8	1.60
Stations within 1k meters	1	4	4.51	20	13.81
Stations within 2k meters	1	14	16.99	52	122.95
Stations within 4k meters	4	56	53.61	132	718.32
Population	301	3875	4105.4	12872	5022957
Households	104	1722	1994.3	8714	2140887
White race (%)	0.38	59.54	54.38	93.34	649.08
Average age	21.2	32.36	33.07	51.02	18.71
Percentage of young population (%)	14.82	37.75	36.91	70.09	129.5
Population aged 5-9	3	130	141	775	11161
Population aged 10-14	3	99	122	679	9884
Population aged 15-19	1	149	187	1391	28436
Population aged 20-24	13	342	433	1967	108312
Population aged 25-34	59	1008	1161	4647	722303
Population aged 35-44	29	571	578	1705	104523
Population aged 45-54	14	372	424	1506	65116
Population aged 55-64	11	282	347	1676	65971
Population aged 65-74	9	148	198	1416	35551
Population aged 75-84	3	78	107	762	11908
Population aged 85-up	0	28	44	367	2627

Median Income ($ per year)	12140	66969	66904	147407	840623667
Low-vehicle households (%)	49.75	80.02	79.73	97.66	105.76
Labor force	146	2431	2608	9267	2796727
Employment rates	46.73	92.35	89.86	98.54	54.13
Intersections	7	105	171.3	1513	40064
Walk network density (meter per 10000 square meters)	29.7	121.2	128.6	400.2	2307.23
Bike path density (meter per 10000 square meters)	0	53.22	59.27	195.97	1397.01
Transit stops	0	9	10.99	44	53.27
Groceries	0	2	2.48	15	6.80
Schools	0	5	6.41	60	59.02
Hospitals	0	1	4.36	84	122.28
Parks	0	1	1.33	5	1.09
Park areas (square meter)	0	5126.9	33723.2	406487.0	4326573869
Number of historical places	0	1	2.49	29	16.76
Crash	3	67	105.4	469	8577.58
Crime	10	309	483.5	4093	344148.8

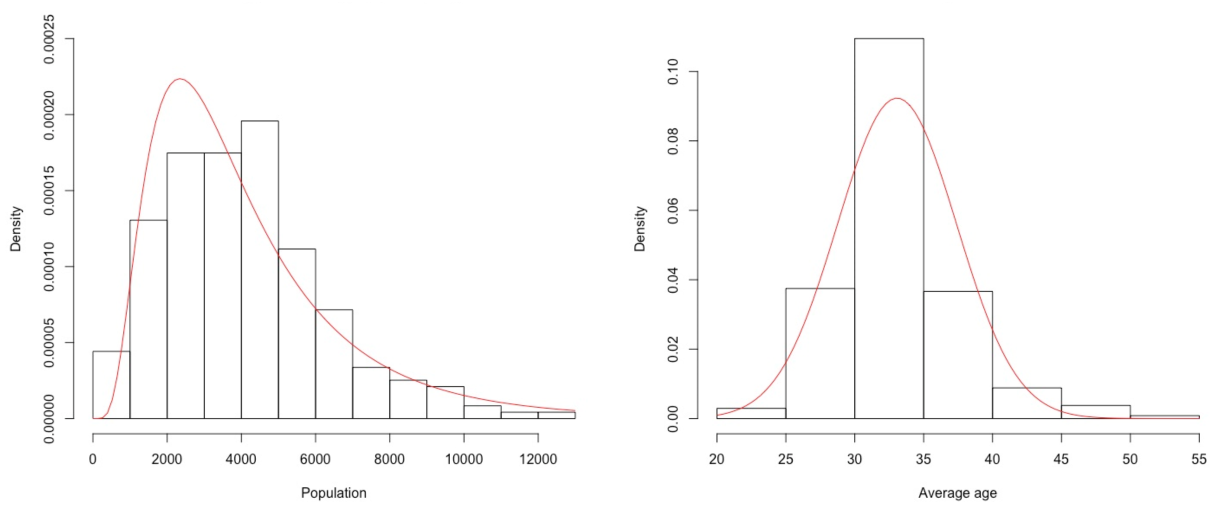

Figure 22. Frequency distribution of population and average age in buffer areas.

After compiling data for Chicago, I estimated the correlation matrix of all the numerical variables. Figure 23 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 a wealthy area.

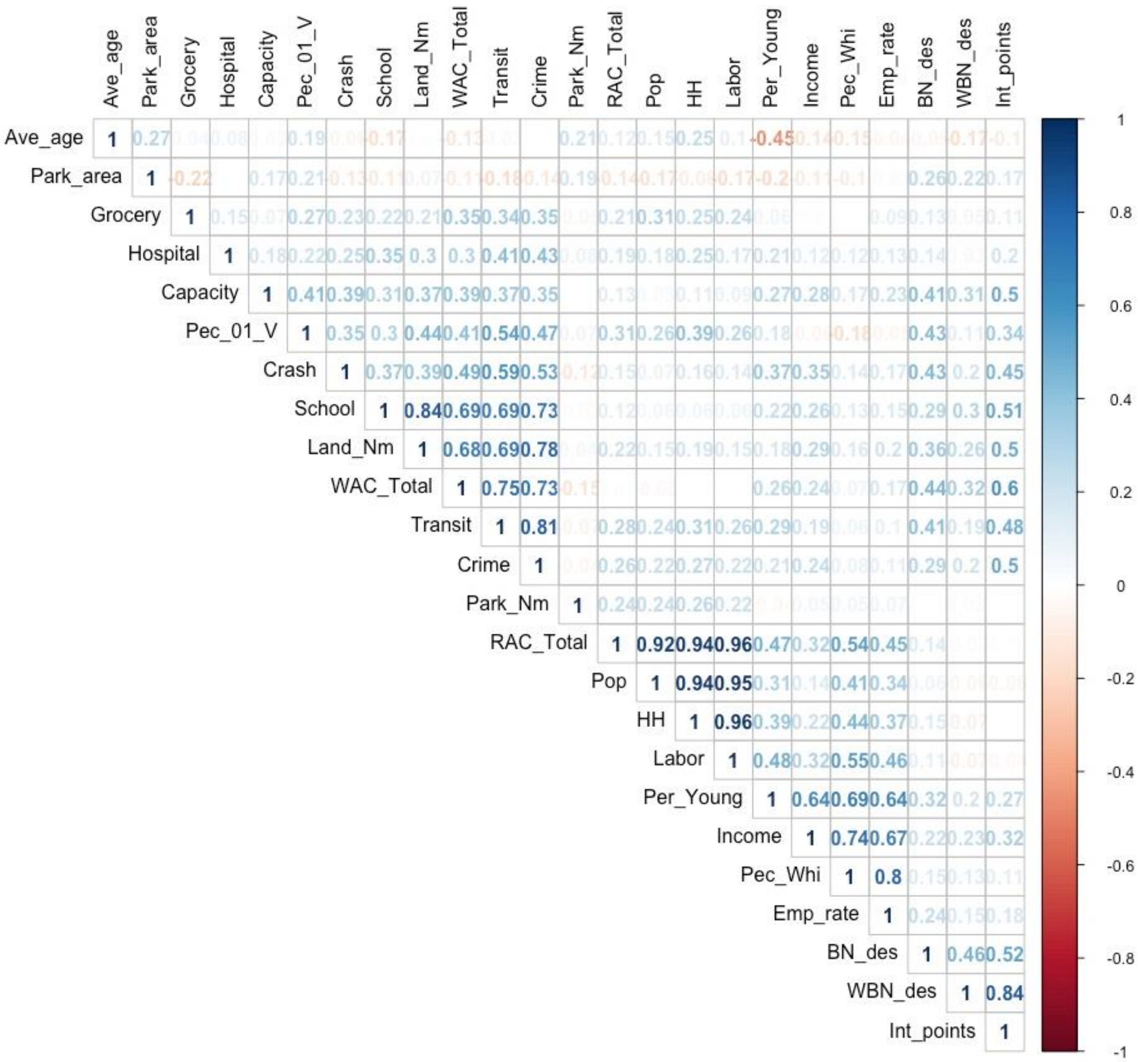

Figure 23. Correlation matrix of all numerical variables (abbreviations as shown in Table 11).

During the model estimation process, I controlled for collinearity, removed statistically insignificant variables, and compared the model’s Akaike information criterion (AIC) index to develop a better model that represents bikeshare ridership. Note that the capacity of a station may be increased or decreased because it is a dynamic decision based on observed bikeshare demand by the systems' operators. Thus, in the final regression, capacity is dropped out. There are several variables that are generally thought to be correlated with trip demand but are not included in the final model. For example, population is highly correlated with labor number and is not selected.

Since I have two dependent variables (productions and attractions) to estimate, Table 15 and Table 16 show the regression results for the two models represented. I 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 term of fitting the ridership data. Besides, Table 15 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 number, bike path density, park area, transit station number, percentage of young population, and number of bikeshare stations within 500 meters 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, I found the percentage of young population to be statistically significant in predicting bikeshare ridership. McNeil, Dill, MacArthur, and Broach (2017) found that bikeshare systems are more popular among younger populations. The negative coefficient of station area types (disadvantaged area or not) proves the influence of existing barriers to disadvantaged communities enjoying bikeshare.

Table 15 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 number	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 population	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.

The regression results for trip attractions (Table 16) also show that the NB model is better than the Poisson model considering the AIC index (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, I 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 16 Annual bikeshare ridership estimation models for trip attractions.

Variables	Poisson model Coefficient	Significance	Negative binomial model Coefficient	Significance
Constant	-1.626×10^{4}	**	-3.528×10^{-1}	
Labor number	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 population	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.

Marginal Effect and Elasticity

To gain a deeper understanding of the influence of these variables, I conducted marginal effects and elasticity analyses for the resulting NB models (Table 17 and Table 18). From the perspective of marginal effects, the change of area type from disadvantaged to other will increase annual trips by 2163 on average for productions, and 2080 for attractions. The second greatest impact is from number of bikeshare stations within 500 meters. If the number of bikeshare stations within 500 meters 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 impact. One percent increase in employment rate increases total bikeshare trips by around seven percent (6.89% and 7.23%). Among the rest of the variables, percentage of young population has the second biggest elasticity. A 1% increase in percentage of young population will cause a 1.18%/1.14% increase in 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.

Table 17 Marginal effects and elasticities of the NB model for trip productions.

Variable	Marginal effects	Elasticity (%)
Labor number	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 meters	704	0.18
Percentage of young population	265	1.18
Number of transits	165	0.24
Area type (1: disadvantaged areas; 0: other areas)	-2163	-

Table 18 Marginal effects and elasticities of the NB model for trip attractions.

Variable	Marginal effects	Elasticity (%)
Labor number	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 meters	611	0.16
Percentage of young population	257	1.14
Number of transits	178	0.26
Area type (1: disadvantaged areas; 0: other areas)	-2080	-

Subscription Rate and Trip Expenditures by Demographic Information

Figure 24 shows the subscription rates of trips at the station level. The mean proportion of trips made by subscribers is lower in disadvantaged communities than in other areas. To further verify this finding, I conducted a t-test to identify if the difference of the mean proportions between disadvantaged areas and other areas is statistically significant. The p-value of the t-test is 0.025, which is less than the significant level (alpha = 0.05). I concluded that the proportion of trips by annual members in disadvantaged areas is significantly less than that of other areas. Previous research has also proved 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 aforementioned D4E program in Chicago has helped more people of color become bikeshare members (Greenfield 2018). Since I have no access to the demographic information of Divvy's subscribers, 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.

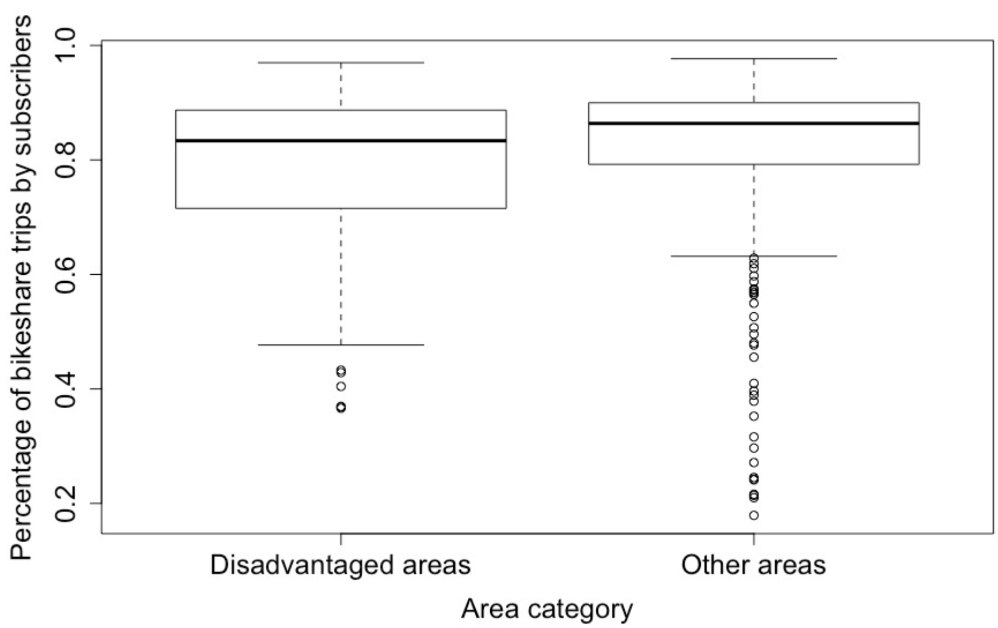

Figure 24. Boxplot of the proportion of trips made by subscribers.

Additionally, I analyzed the average trip time and trip costs for each station to understand bikeshare activities in disadvantaged and other areas. Table 19 and Table 20 show descriptive statistics (e.g., mean and median) for average trip time and trip cost per station. Since there are trips originated from and terminated at one station, I analyzed the average trip time and trip cost for origin trips and destination trips, respectively. As mentioned in the previous section, because of lack of data, I 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, I distinguished trips produced or attracted at a station and separated trips by subscribers and day users.

Table 19 shows the differences between subscribers and day users, with the former making shorter trips, possibly because of the differences in the use fee scheme (Table 13). However, the average trip time for day users is at least twice that of subscribers. Comparing trip time for subscribers in disadvantaged and other areas, residents in disadvantaged areas are likely to make a longer (time) trips, consequently, they tend to spend more on bikeshare trips than users in other areas.

Table 19 Statistics for average trip time (in minutes) per station.

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

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

Table 20 shows that the average expenditure for subscribers is less than one dollar in all areas. Based on the price scheme in Table 13 and the data in Table 20, most subscribers ride for less than 30 minutes. Additionally, subscribers in disadvantaged communities spend approximately twice as much per trip as subscribers 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 median value. The maximum of average trip expenditure for subscribers is 0.99 dollars in disadvantaged communities for trip productions, which is almost three times that (0.34 dollars) of other areas. 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. Accessibility to schools, hospitals, jobs, and other locations may explain the longer distances that users from these communities experience. McNeil, Dill, MacArthur, and Broach (2017)'s survey study shows that using bikeshare can save money on transportation overall, and could potentially reduce spending on health care because of frequent exercise from bikeshare use. However, accessibility to these and other critical locations is an equity issue experienced in many cities. Another potential reason to explain the higher average trip costs is a lack of a thorough understanding of the price scheme. Residents from disadvantaged communities tend to be low-frequency users, who may not reflect enough time to understand the fare structure in Table 13. There could be other reasons that explain the longer trips, though there is a lack of information about the exact trip purpose. For instance, the results from the NB model and the expenditures hint that subscribers in disadvantaged communities might use bikeshare to commute to work or for other work-related purposes. In general, understanding this behavior requires additional information and research.

Table 20 Statistics for average trip expenditures (in dollars) per station.

Trip type	Station type	User type	Min.	1st quantile	Median	Mean	3rd quantile	Max.
Trip productions	Disadvantaged	Subscriber[1]	0.00	0.04	0.08	0.14	0.18	0.99
		Day user[2]	0.08	0.66	1.10	1.46	1.98	5.55
	Others	Subscriber	0.01	0.03	0.04	0.05	0.06	0.34
		Day user	0.00	0.72	0.93	1.04	1.25	4.44
Trip attractions	Disadvantaged	Subscriber	0.00	0.04	0.09	0.18	0.15	1.17
		Day user	0.17	0.72	1.38	1.59	2.10	6.32
	Others	Subscriber	0.01	0.03	0.04	0.05	0.07	0.58
		Day user	0.18	0.69	0.94	1.03	1.29	3.66

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

When comparing the expenditures of non-subscribers, casual users in disadvantaged communities still spend more on bikeshare trips, but the difference is not significant. One reason for this may be that the proportion of trips by day users is relatively small (20% on average), which makes casual trip length easily affected by random factors (e.g., weather). On the other hand, the trip purposes of casual users (very likely to be tourists) vary more than those of subscribers. Diverse trip purposes result in a wide range of bikeshare trip lengths.

DISCUSSION

In the regression model for total bikeshare trips, I mentioned that employment rate has the greatest elasticity. To further analyze the employment influence on bikeshare ridership, this study compared 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 supposed to live in the buffer 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 workers are from the LEHD database, as described in the section above.

Overall, bikeshare demands are greater in an area with either more job opportunities or employed labor force. However, Figure 25 to Figure 28 show that most disadvantaged areas have a deficit in job opportunities (i.e., more workers live in the area than work in the area) regardless of the kind of jobs. Thus, users in disadvantaged areas may have to reach job locations further away from their residential areas, as compared to residents of other areas.

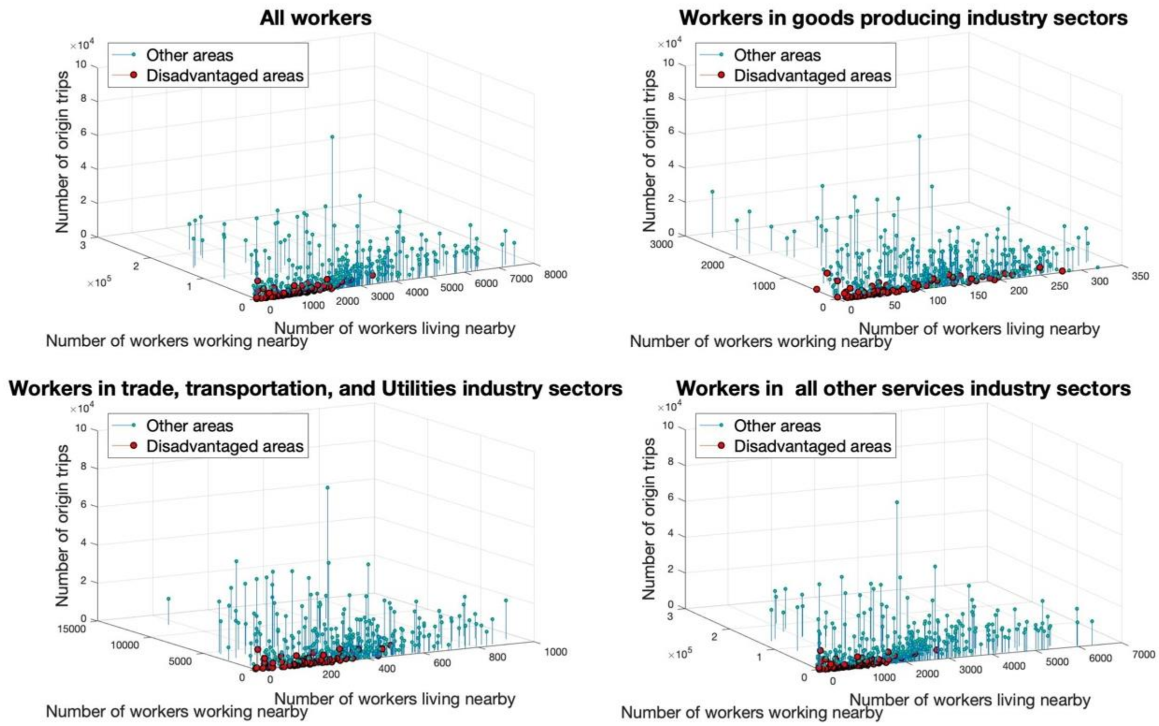

Figure 25. Number of trip productions against job data by sectors.

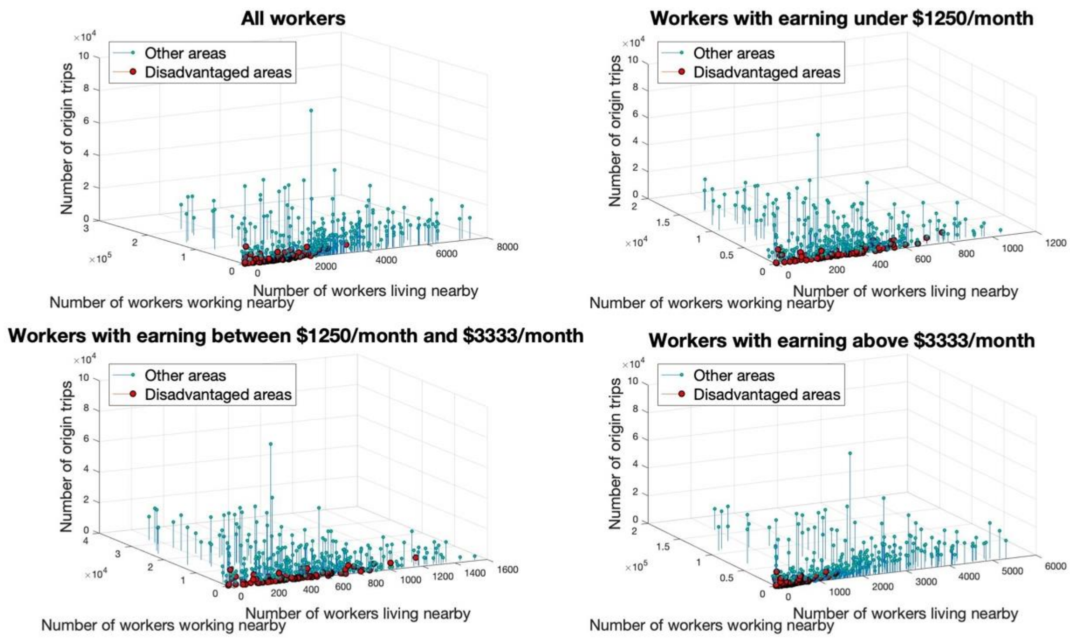

Figure 26. Number of trip productions against job data by monthly income.

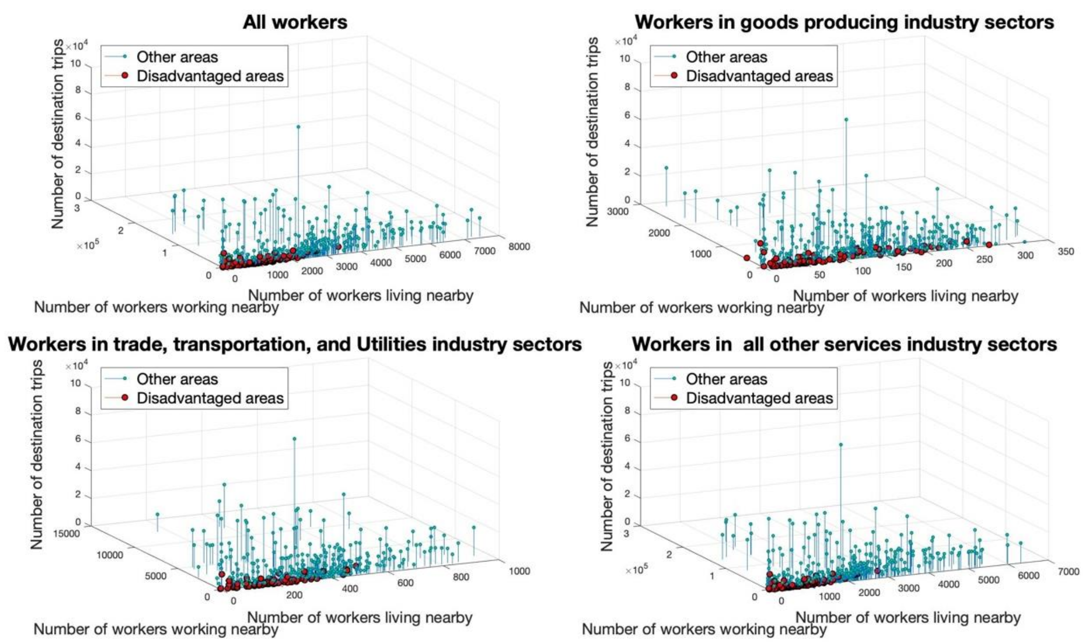

Figure 27. Number of trip attractions against job data by sectors.

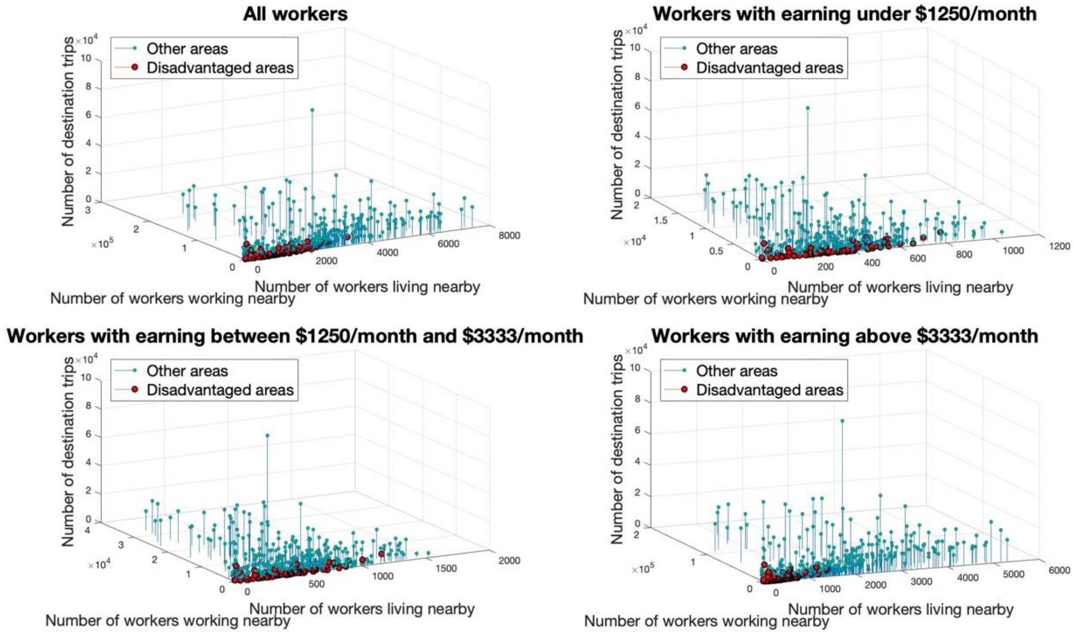

Figure 28. Number of trip attractions against job data by monthly income.

For stations in disadvantaged areas, I focused on the relationship between 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), Figure 29 shows the relation between workers living nearby and trip productions (or attractions). 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.

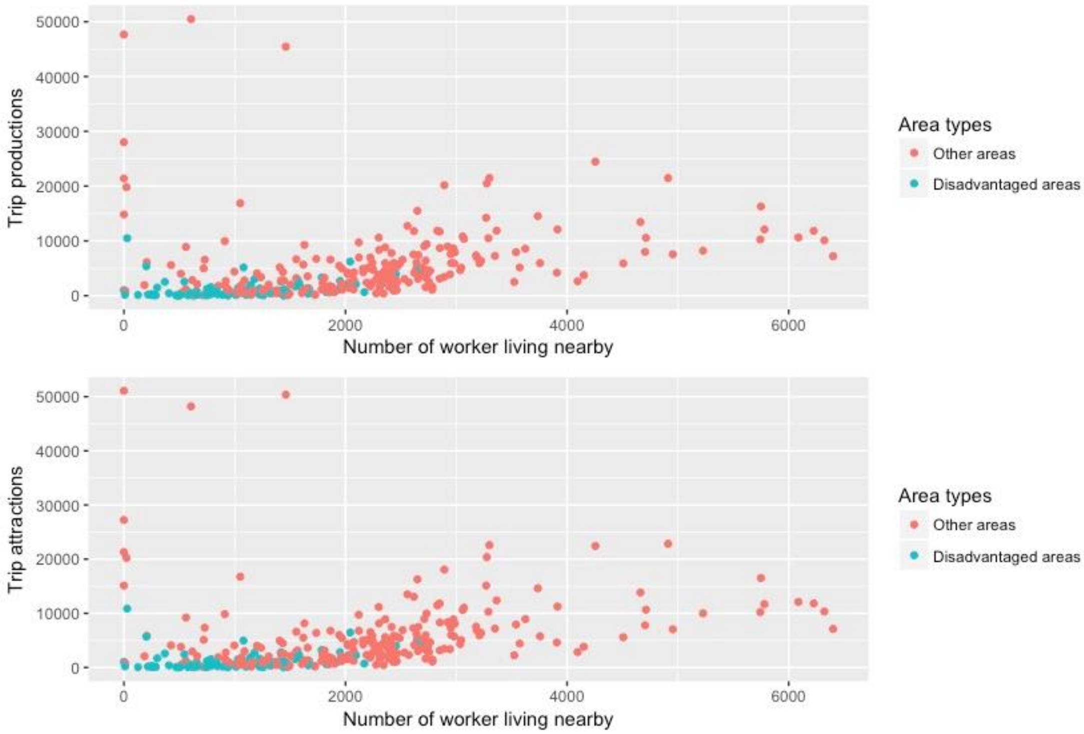

Figure 29. Number of trip productions or attractions against number of workers.

Examining employment data by industry sector reveals that there are fewer workers living in disadvantaged areas no matter what kind of jobs. However, the gap is smaller for workers in food producing-related industries. Considering job data by earnings (Figure 26 and Figure 28), areas (disadvantaged or other) with more better-paid workers are more likely to generate a higher bikeshare demand. However, residents near the buffer areas of a disadvantaged bikeshare station are less likely to have high-paying jobs. Overall, the number of workers living in a disadvantaged area will positively influence the bikeshare demand there. Considering the previous marginal effect and elasticity analyses, this explains why employment rate is so important in determining bikeshare demand, especially in disadvantaged areas given the limited job opportunities there.

CONCLUSIONS

The work estimates bikeshare trip demand based on a number of key system and socio-economic variables. The estimated NB model provides insight into the impact of socio-economic variables, especially for individuals in disadvantaged communities, that affect their trip productions and attractions. Further, the marginal effect of bikeshare location is the greatest, which means that if a bikeshare station is located in a disadvantaged community, the number of annual trips at that station are noticeably lower relative to stations in affluent and white communities. As shown by our regression model, employment rate has a significant marginal effect, and the greatest elasticity to improve ridership. More importantly, three main findings emerge from the analysis of the Divvy bikeshare trip data. First, most bikeshare users tend to make trips of less than 30 minutes, regardless of whether the trip is located in a disadvantaged or other area. The second result is that the rate of trips made by subscribers is smaller in disadvantaged areas than in other areas, which may result from multiple barriers that discourage low-income individuals from securing memberships. The last, but most important conclusion, is that residents in disadvantaged areas make much longer trips than residents in other areas, if they are already subscribers.

Our research provides quantitative confirmation of the existence of equity problems in the bikeshare industry. Clearly not enough bikeshare stations or services are provided in disadvantaged areas. Solving the equity problems in bikeshare systems should be a cooperative goal of for-profit companies and local governments. For-profit companies will tend to cover wealthier and highly-educated populations to generate more revenue. Local governments should offer incentives to companies that provide services in disadvantaged communities. For example, local municipalities could reduce taxes for those bikeshare companies that site more stations in low-income communities, or offer more affordable membership fees (e.g., $5 annual fee in Chicago). Consistent with the findings from other research, this work shows that there are financial barriers to disadvantaged communities accessing and using bikeshare systems. However, after joining as annual members, disadvantaged populations tend to rely more on bikeshare and enjoy real benefits, such as saving money on transport.

Inspired by this research, I would like to offer three suggestions for future policies designed to develop municipal bikeshare systems. First, when a city wants to have a socially inclusive bikeshare system, it needs to cooperate with the private-sector operator(s) to design a metric by which to measure whether the system has included more diverse groups or populations. Second, low membership fees, like the “D4E” program, are a practical and effective way to encourage more people from disadvantaged communities to participate. As more and more cities are introducing their own systems, I strongly recommend the use of early-stage promotions of reduced membership fees for low-income and other traditionally disadvantaged populations. These promotions, and the bikeshare systems generally, will be more successful if a robust community is engaged. Community outreach is more efficient than online advertisement for disadvantaged populations given varied access to smartphones or other technical devices. Based on Divvy’s price framework, subscribers will have 30-minute or shorter trips for free. The historical data show that the maximum trip time for subscribers in disadvantaged communities is very close to 30 minutes, which demonstrates that those populations try to make the most of this subscription benefit without any marginal cost. Another reason for longer trip times in disadvantaged areas is that users there may have limited other reliable modes for travel. A study in Lyon (France) shows that the majority of bikeshare members are not dependent on public transport originally. On the contrary, they mostly have multiple mode choices in their everyday travel (Raux, Zoubir, and Geyik 2017). This insight may lead to another suggestion of extending the time limit for free rides for subscribers from disadvantaged communities. In these disadvantaged areas, transit services are not frequent enough to cover the potential demand (Giuliano 2005; Ricciardi, Xia, and Currie 2015). The low reliability of transit service necessitates that disadvantaged populations spend more time waiting and scheduling. However, the availability of bikeshare systems and longer free rides may make it possible for more direct trips to destinations, or connections to micro transit, or areas with more frequent transit services. This potential benefit needs further deep study to be verified.

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. If that information were available, this study could accurately measure average trip costs by distributing the membership fee or daily fee across the number of trips. Moreover, more detailed analyses could identify additional impacts for disadvantaged communities. The demographic information of users is also unclear. More detailed demographic information would be valuable, as the analyses assume that users are likely to live near the trip start station and share characteristics with the residents in the associated buffer. 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 lives more convenient.

CHAPTER 4: AN ENTROPY-BASED MODEL FOR BIKESHARE TRIP DISTRIBUTION WITH EQUITY INSIGHTS

INTRODUCTION

Bikeshare has become more and more prevalent around the world. The total number of bikeshare trips keeps increasing year after year (NACTO 2018). Many cities have joined in the trend to introduce their own bikeshare systems. Currently, there are two main types of bikeshare systems in the US. The dock-based system currently dominates, which requires a user to pick up and return a bike to a physical station. Compared to the fixed location bike service, the newer dockless bikeshare system has shown the potential to replace the dock-based one. More and more cities are open to this new type of system and have released a certain number of permits to selected bikeshare operators, including JUMP Bikes, LimeBike, and ofo, among many others.

As the public is attracted to this new travel mode, it has attracted more and more research attention as well. Several researchers have conducted surveys of bikeshare users and their trip purposes (Buck et al. 2013; McNeil, Dill, MacArthur, and Broach 2017). These studies have addressed equity issues in bikeshare and have shown that the majority of current bikeshare users are white, high-income, and well-educated. There exists a bikeshare service gap for traditionally disadvantaged populations and traditional disadvantaged communities. In addition to these survey-based studies, researchers have developed models for estimating ridership for bikeshare trips (Froehlich, Neumann, and Oliver 2009; Rixey 2013; Froehlich, Neumann, and Oliver 2009). Research on destination choices for bikeshare is another area which has an important practical application (Faghih-Imani and Eluru 2015).

However, there is limited information about trip distance and trip time distribution for bikeshare trips, especially for disadvantaged areas. How long bikeshare users spend on trips and the differences in spending among various users have not been deeply analyzed. This kind of information is important for both bikeshare operators and local governments. With an accurate picture of trip time distribution, a bikeshare planner can estimate destination choices with more confidence. Users' behaviors in trip spending, especially for disadvantaged areas, can help operators to design more suitable policies for disadvantaged users to reduce some of the barriers they face. This chapter will introduce a destination competing model to estimate destination choices and analyze spatial patterns of parameters in this model. This research uncovers that accessibility improvements especially job opportunities, are an important incentive for more bikeshare trips in disadvantaged areas. Annual members from disadvantaged areas are more likely to travel longer distance to other areas in order to reach more services. However, these disadvantaged population are more sensitive to extra change after a free ride and that marginal cost for a bikeshare trip will eventually restrict their flexibility in using bikeshare services.

LITERATURE REVIEW

Destination choice models are a subject of frequent debate among researchers and practitioners. There are a plenty of studies analyzing destination choices for personal vehicle and transit. The fast development of bikeshare leaves a vast research gap for people to better understand how this share economic makes biking trips more attractive for people. Among many equity researches in bikeshare, destination choice has not emerged as a hot topic for bikeshare users in disadvantaged areas.

The most well-known destination choice model is a traditional gravity model (Wilson 2013). The gravity model comes with many different forms, to name a few, doubly constrained distribution model, self-deterrent distribution model with quadratic costs, and distribution model based on competing destinations (de Grange, Fernández, and de Cea 2010). The doubly constrained distribution model is the traditional form of gravity model established by Wilson (Wilson 2013). This traditional form is developed based on the idea of minimization of entropy in transportation systems. More complicated than the traditional gravity model is the competing destination model, which includes the attractiveness and accessibilities of destinations (de Grange, Fernández, and de Cea 2010). A study also proves the competing destination model performs better than the traditional gravity model in a state-to-state migration study (Hu and Pooler 2002). In their model, they estimated distance decay parameters for every origination and analyzed the spatiotemporal pattern of distance decay estimates.

Destination choice research directly related to bikeshare is limited. After examining the paucity of research, there are two main approaches based either on statistical methods (see, for example, (Faghih-Imani and Eluru 2015, Kumar et al. 2016)) or on network model from computer science fields (Hu et al. 2017, Maystre and Grossglauser 2017). An example of the statistical model to estimation destination choice is a research based on Chicago Divvy bikeshare system. Other than improving on conventional model, they applied a multinomial logit model to estimate destination choice with bicycle infrastructure variables, land-use and built environmental characteristics, and trip attributes (Faghih-Imani and Eluru 2015). In their regression model, the trip attribute does not cover trip price that is a crucial barrier for low-income populations. For research based on models from computer science fields, many studies touch the edge of destination choice when dealing with bikeshare rebalance or bikeshare station ridership estimation. For example, many bikeshare rebalance studies analyze destination choices for bikeshare system (Maystre and Grossglauser 2017, Hu et al. 2017). A researcher group applied the idea of "PageRanking", which comes from computer science to measure the importance of a website based on its relationship with other websites (Bryan and Leise 2006). They estimated the activeness of every station based on a station's circumstances and its relationship with surrounding stations. This PageRanking algorithm is a novel idea to measure station activeness from an aggregate view.

All of those models mentioned earlier have not focused on low-income or disadvantaged populations. There is limited information about how these populations make their bikeshare trips and how they choose their destinations. These questions are imperative for bikeshare strategists and developers who are attempting to eliminate barriers for low-income and disadvantaged communities.

CASE STUDY CITY AND DATA DESCRIPTION

This research selected Chicago as a case study city as well. This section presents bikeshare trip data applied in the calibration of the competing destination model and demographic data for spatiotemporal analysis. The Divvy bikeshare in Chicago releases their database for all bikeshare trips. 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 24-hour pass user) from July 2013 to June 2018. Since trip records cover trip duration information, the price for every bikeshare trip can be calculated according to their pricing structure. However, the historical data does not include the trip distance information. To fill this missing information, I applied Google distance application programming interface (API) to calculated distance and estimated trip time by bike between every OD pair. Exploring this database, I can also calculate the real origin-destination matrix for the Divvy bikeshare system. This data will serve as true data to calibrate our competing destination model. I compiled demographic data from multiple resources including Census 2010 and American Community Survey (ACS) data. The demographic data in this study refer to race and income, which are used to classified if bikeshare station is located in disadvantaged area or not.

METHODOLOGY

The concept of Entropy in urban transport modelling was introduced by Wilson (2013). Based on the entropy-maximum theory, a classical gravity modal was developed to estimate trip distributions. Until now, several enhanced gravity models have been developed (de Grange, Fernández, and de Cea 2010). This paper now presents a consolidated distribution model to model bikeshare trip distribution, which brings together the important features of both destination station and bikeshare trips. After stating the construction process of the entropy-based competing-destination model, an equivalent logit modal will be introduced to calibration the model.

Entropy-Based Competing-Destination Model

First, considering the most important characteristics of entropy models described in literature review chapter, a multi-objective problem is developed:

$$\max\{T_{ij}\}\ F_1 = \sum_{ij} T_{ij}(ln\, T_{ij} - 1) \tag{5}$$

$$\min\{T_{ij}\}\ F_2 = \sum_{ij} T_{ij} C_{ij} \tag{6}$$

$$\max\{T_{ij}\}\ F_3 = \sum_{ij} T_{ij}\, ln\, S_{ij} \tag{7}$$

s.t

$$\sum_{j} T_{ij} = O_i \quad \forall i \quad (\mu_i) \tag{8}$$

$$\sum_{i} T_{ij} = D_j \quad \forall j \quad (\gamma_j) \tag{9}$$

In Equation (5), T_{ij} is the total number of trips between origin i and j. The Equation (5) is a simplified version of maximizing entropy function using Stirling's short approximation ($\ln x! = x \ln x - x$). In Equation (6), C_{ij} is the travel distance or travel time between origin i and destination j. In Equation (7), S_{ij} is an index to measure the attractiveness of travelling between origin i and destination j, which takes the form of:

$$S_{ij} = \sum_{k=1}^{w} \Delta Opp_k \times Weight_k \tag{10}$$

where ΔOpp_k is the difference of opportunity k between origin i and destination j, $Weight_k$ is the weight for Opportunity k since some opportunities (e.g., jobs) may be more important than others. A previous research (Niemeier and Qian 2018) has proved that bikeshare systems can bring significant accessibility improvement for disadvantaged communities. Thus, I want to maximize accessibility improvement by all bikeshare trips.

The three objective functions can be merged into one substitute optimization problem as follows:

$$\max F_4 = \sum_{ij} T_{ij}(ln\, T_{ij} - 1) - \beta \left(\sum_{ij} T_{ij}\, C_{ij} \right) + \rho \sum_{ij} T_{ij}\, ln\, S_{ij} \tag{11}$$

In order to obtain the set of T_{ij} which maximizes the objective function in Equation (11) subject to constraints (8) and (9), the Lagrange $\mathcal{L}$ has to be maximized.

$$\begin{aligned} \mathcal{L} = & \sum_{ij} T_{ij}(ln\, T_{ij} - 1) - \beta \left(\sum_{ij} T_{ij}\, C_{ij} \right) + \rho \sum_{ij} T_{ij}\, ln\, S_{ij} \\ & + \sum_{i} \mu_i (O_i - \sum_{j} T_{ij}) + \sum_{j} \gamma_j (D_j - \sum_{i} T_{ij}) \end{aligned} \tag{12}$$

By solving this Lagrange function (12) with respect to T_{ij}, we will obtain the following functional form:

$$T_{ij} = A_i O_i B_j D_j (S_{ij})^{\rho} e^{-\beta c_{ij}} \tag{13}$$

$$A_i = \frac{1}{\sum_j B_j D_j (S_{ij})^{\rho} e^{-\beta c_{ij}}} \tag{14}$$

$$B_j = \frac{1}{\sum_i A_i O_i (S_{ij})^{\rho} e^{-\beta c_{ij}}} \tag{15}$$

In Equation (13), ρ is a parameter to measure influence of attractiveness of each OD pair. It has been stated that the value of ρ is determined by empirical research (Hu and Pooler 2002; de Grange, Fernández, and de Cea 2010). The sign of ρ is determined by two forces: competition forces and agglomeration forces. Competition forces measure how people want to travel to areas with more accessibilities and agglomeration forces reflect the willingness to travel within a specific area, such as an area with more job opportunities. A positive value of ρ means that competition forces is dominant while the agglomeration force will be principal if the sign of ρ is negative or close to zero. β is the travel decay parameter, which measures the willingness of people travel between two locations.

Parameter Estimation

Parameter estimation for destination choice model has been a frequently debated subject among researchers and practitioners. In a research by de Grange, Fernández, and de Cea (2010), Poisson model and logit model are proved to be identical to solve the parameter estimation problem for a entropy-based destination choice model. In the following context, the identical relation of Poisson model and logit model is proved again regarding parameter calibration for the Equation (13).

Poisson distribution

The probability function for Poisson distribution is

$$P\left(\frac{N_{ij}}{T_{ij}}\right) = \frac{e^{-T_{ij}} \cdot (T_{ij})^{N_{ij}}}{(N_{ij})!} \tag{16}$$

where N_{ij} is the estimated number of trips between origin i and destination j and T_{ij} is the observed number of trips between origin i and destination j.

Equation (13) was substituted in Equation (16):

$$P\left(\frac{N_{ij}}{T_{ij}}\right) = \frac{e^{-A_i O_i B_j D_j (S_{ij})^{\rho} e^{-\beta C_{ij}}} \cdot (A_i O_i B_j D_j (S_{ij})^{\rho} e^{-\beta C_{ij}})^{N_{ij}}}{(N_{ij})!} \tag{17}$$

The values of parameter ρ and β in Equation (17) can be solved by maximizing the following log-likelihood function:

$$\begin{aligned} \max\ \ln L = \sum_i \sum_j [&-A_i O_i B_j D_j (S_{ij})^{\rho} e^{-\beta C_{ij}} \\ &+ N_{ij}(\ln A_i + \ln B_j + \rho \ln S_{ij} - \beta C_{ij})] \end{aligned} \tag{18}$$

Given that $\sum_{ij} T_{ij} = \sum_{ij} N_{ij} = T$ is a constant, Equation (18) is equivalent to

$$\max\ \ln L = \sum_i \sum_j [N_{ij}(\ln A_i + \ln B_j + \rho \ln S_{ij} - \beta C_{ij})] \tag{19}$$

Logit model

Based on Equation (13), a logit probability function is defined:

$$P = \frac{T_{ij}}{\sum_{ij} T_{ij}} = \frac{A_i O_i B_j D_j (S_{ij})^{\rho} e^{-\beta C_{ij}}}{\sum_{ij} -A_i O_i B_j D_j (S_{ij})^{\rho} e^{-\beta C_{ij}}} = \frac{e^{\mu_i + \gamma_j + \rho \ln S_{ij} - \beta C_{ij}}}{\sum_{ij} e^{\,\mu_i + \gamma_j + \rho \ln S_{ij} - \beta C_{ij}}} \tag{20}$$

Similar to the process to simplify Equation (18), the log likelihood function for solving parameters in Equation (19) takes the form:

$$\max\ ln\, L = \sum_i \sum_j [N_{ij}(ln\, A_i + ln\, B_j + \rho\, ln\, S_{ij} - \beta C_{ij})] \tag{21}$$

Observing Equations (19) and (21), I conclude that Poisson and logit model are identical to estimate parameters in the entropy-based competing-destination model in this study. Considering the trip data for every O-D pair is a non-negative variable, a Poisson model is finally adapted to calibration the parameters in Equation (13).

RESULTS

In this chapter, I select the Divvy bikeshare system in Chicago as an example to examine a competing destination model. Since the profiles for annual members and day pass users are different, I analyzed them separately. In this way, we can observe the differences in travel behavior of bikeshare trips. Besides splitting trips between subscribers and day pass users, I also divide OD pairs into four categories based on area types of origination stations and destination stations as shown in Figure 30. By comparing calibration results using trip data from different OD types, we can know how people from disadvantaged areas utilize bikeshare and what the features of their bikeshare trips are.

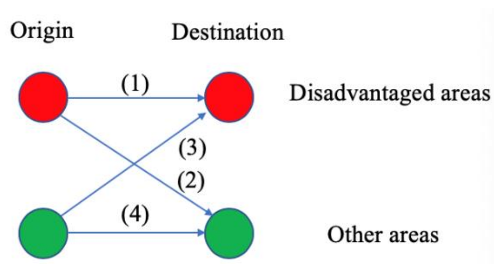

Figure 30. OD type classification.

Model Calibration Results Using Distance as Travel Decay

Calibration results for our destination competing model is shown in Table 21. First, for the value of ρ for annual members, accessibility difference is obviously more important for people from disadvantaged communities since ρ is bigger for OD type 1 than other OD types. For OD type 2 and 3, they include trips generated from disadvantaged areas or terminated there. The ρ for OD type 2 or 3 is not less than that of OD type 4, which prove that users from disadvantaged areas are attracted to area with accessibility improvements. Thus, accessibility improvement (e.g., jobs, grocery stores) plays an important role to attract disadvantaged population to choose bikeshare as a transport mode. Research has shown that bikeshare systems can bring significant accessibility improvement especially for disadvantaged areas where current bikeshare systems have not provide enough services (Niemeier and Qian 2018). Thus, there exist a gap between potential bikeshare demand and bikeshare service supply in disadvantaged areas. Current development strategies of bikeshare systems should be shifted from targeting particular cyclist groups to fill the demand for bikeshare services in unrepresentative areas in traditional urban planning.

Secondly, I compare the β of different OD types for subscribers. For users cycle within disadvantaged areas, they tend to make short trips, which is indicated by the smaller value of β. This may result from the fact that the range of distances between stations both within disadvantaged areas are smaller compared with trips between disadvantaged areas and other areas or both within other areas. If we compare the distance decay parameter for OD type 2, 3 and 4, the ranges of trip distance are similar among these OD pairs. However, users from disadvantaged area still tend to make short trips. There are couple of reasons behind this phenomenon. Recall that the distance information is from Google API. In reality, bikeshare users may travel for a longer distance than the estimated one. Even though I know nothing about the true distance information, this calibration results could still provide some suggestions for bikeshare planning. For example, bikeshare operators may shorten the distance between stations in disadvantaged areas, which may result in more trips there.

All the findings from subscribers cannot be totally applied to day pass users. The differences of ρ value for different OD types is more significant for day pass users. For OD type 4, ρ is even negative (-0.04). One reason may be that day pass users, who tend to be tourists, are more likely to travel within the Chicago downtown area where there are many shopping malls, historical sites, museums, and other attractions. Different from subscribers, the preferences of trip distance are similar across trips within different OD types, which should be caused by the profile of day pass users.

To test the prediction capacity of our model, R^2 and Log-L (log-likelihood) are utilized. It is reasonable that the prediction error increase as the size of OD matrix become greater, as well as the Log-L. Additionally, the prediction error for day pass users are smaller compared with that for subscribers. The reason may be that total number of trips by day pass users is much smaller than that of annual members, which make the model produce better performance.

Table 21. Calibration results using trip distance for annual members and day pass users.

User type	O-D type	ρ	β	R^2	Log-L
Annual members	1	0.12	-0.83	0.60	-18083.83
	2	0.07	-0.76	0.60	-53533.27
	3	0.10	-0.76	0.62	-50132.30
	4	0.07	-0.59	0.46	-1134310.18
Day pass users	1	0.12	-0.47	0.62	-5138.53
	2	0.01	-0.47	0.86	-15291.10
	3	-0.02	-0.45	0.82	-15623.75
	4	-0.04	-0.41	0.84	-269644.92

Note: 1. Disadvantaged areas to disadvantaged areas; 2. Disadvantaged areas to other areas; 3. Other areas to disadvantaged areas; 4. Other areas to other areas.

As stated by many researchers, trip distance is an important factor to affect destination choices (Faghih-Imani and Eluru 2015; de Grange, Fernández, and de Cea 2010). This paper summarized the histograms of trip distance for different OD pair categories. Similarly, annual members and day pass users are treated separately. Within annual members or day pass users, four different OD categories are considered, which is same with the model calibrations. Figure 31 displays histograms of modeled and observed trips in different trip length for subscribers.

From the aspect of trip length distribution, the model proposed in this paper generated a perfect prediction no matter for the peaks and tails of the trip length distribution. Additionally, the most frequent trip length is within one to three kilometers no matter where a bikeshare trip starts or ends. However, for bikeshare trips within disadvantaged areas, the proportion of long-distance trips (e.g. longer than six kilometers) is smaller than within other areas. The tail of histogram of distance for bikeshare trips from or ended in other areas is heavier than that of bikeshare trips both from and ended in disadvantaged areas. This means that users from disadvantaged areas will make longer trips if their destinations are located in other areas, where these may exist more job opportunities, and better grocery store, among many others.

The trends of histograms in Figure 32 for day pass users are not same with that for annual members, even though most of the trips fall into the time range of one to three minutes. When predicting trips for day pass users, the CD model doesn't behavior as perfect as for annual members. The reason is that annual members tend to make bikeshare trips regularly for a particular purpose once they prefer bikeshare to other transport modes. On the contrary, a large proportion of day pass users are travelers (Buck et al. 2013). It is more difficult to predict destination choices of day pass users since there are so many uncertainties in their travel behaviors. If comparing histogram of trip length distribution in same OD category for annual members and day pass users, the tail of the distribution for day pass users is heavier than that for annual members. Particularly, for bikeshare trips of day pass users from or ended in other areas, there a considerable amount of bikeshare trips within nine to ten kilometers.

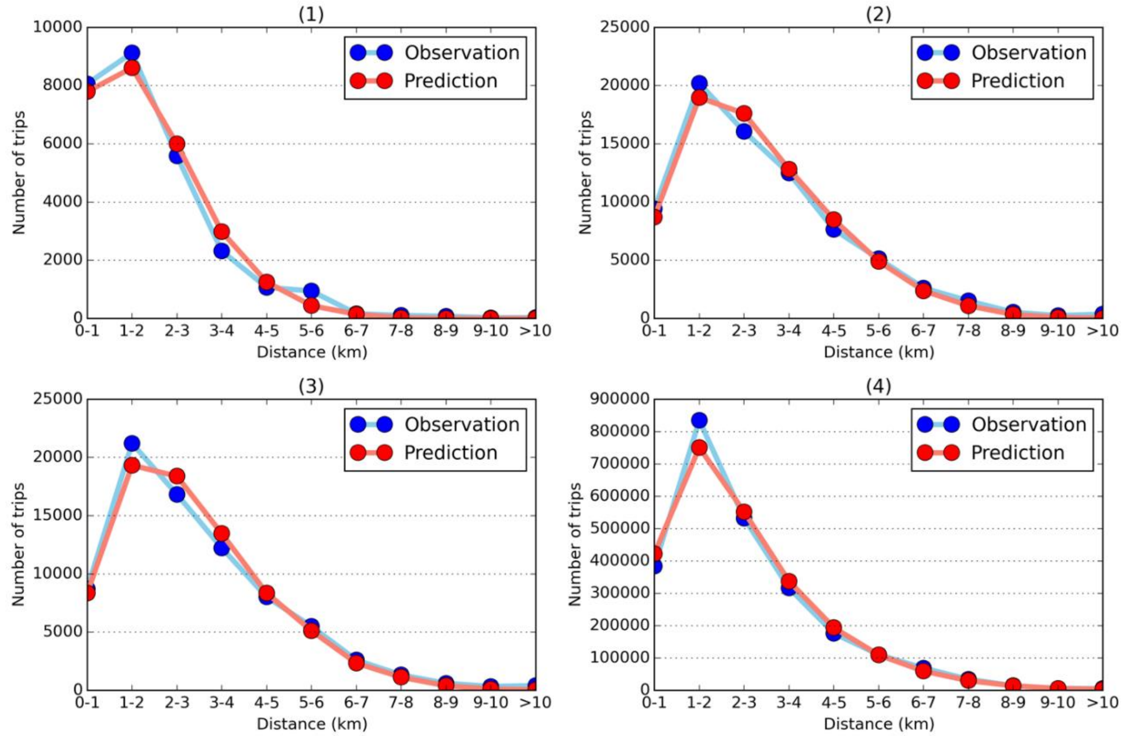

Figure 31. Histogram of modeled and observed trips for annual members (OD types: 1. Disadvantaged areas to disadvantaged areas; 2. Disadvantaged areas to other areas; 3. Other areas to disadvantaged areas; 4. Other areas to other areas.)

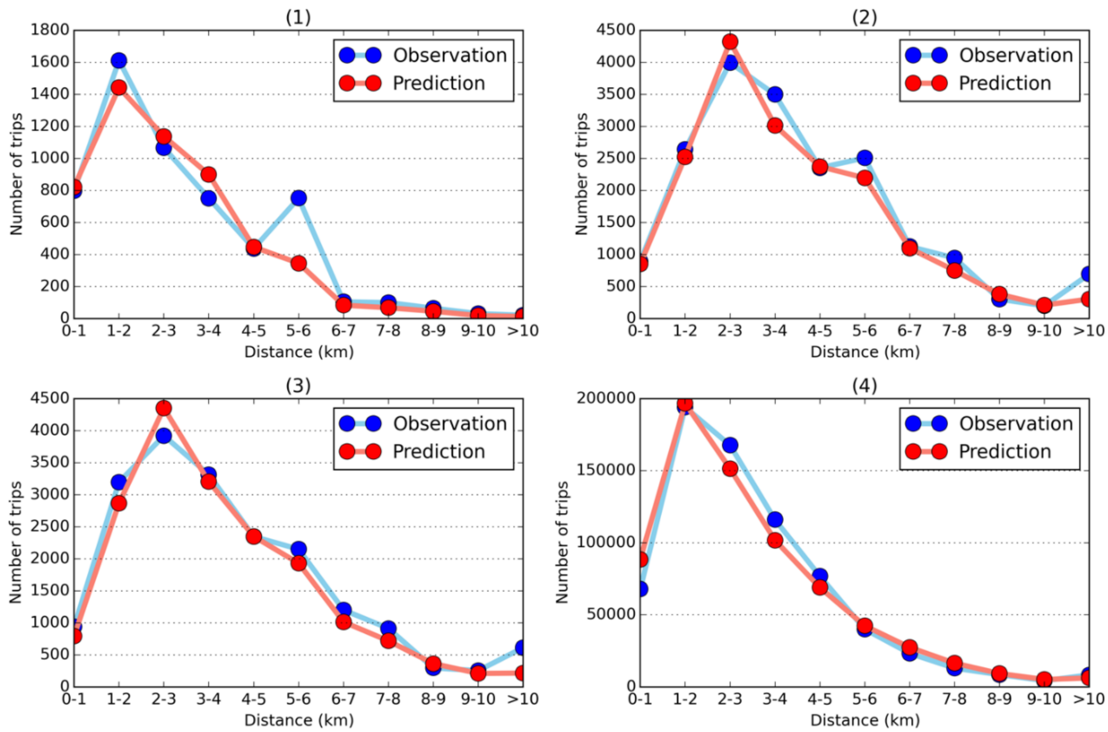

Figure 32. Histogram of modeled and observed trips for day pass users (OD types: 1. Disadvantaged areas to disadvantaged areas; 2. Disadvantaged areas to other areas; 3. Other areas to disadvantaged areas; 4. Other areas to other areas.)

Model Calibration Results Using Travel Time as Travel Decay

After using trip distance distribution to estimate travel decay, I applied trip time (Google API estimated trip time) as travel decay to calibration this model. It is important to note that there two types of travel time in this paper. One is the travel time by Google API and another one is the actual average trip time between originations and destinations. Since our model is developed to provide suggestions on future bikeshare planning, it is reasonable to use the Google API estimated trip time. Thus, our model can be applied to other areas where bikeshare systems have not been implemented.

Table 22 shows the calibration results using Google API trip time. Since the trip distance used before is also estimated by Google API, the correlation between trip distance and trip time by Google API is extremely high. Thus, most of the findings are same with those from previous model calibration using trip distance.

Table 22. Calibration results using Google API trip time for annual members and day pass users.

User type	O-D type	ρ	β	R^2	Log-L
Annual members	1	0.13	-0.24	0.61	-17753.98
	2	0.07	-0.22	0.62	-52308.30
	3	0.10	-0.22	0.64	-48628.92
	4	0.10	-0.16	0.45	-1116741.07
Day pass users	1	0.15	-0.15	0.66	-4905.44
	2	0.01	-0.15	0.86	-14757.02
	3	-0.01	-0.14	0.83	-15025.35
	4	0.00	-0.13	0.86	-255195.43

Similarly, this paper presented the histograms for trip time distribution. For subscribers, most of the trips are less than 14 minutes, no matter for what kind of OD types. However, the most frequent trip time for day pass users is longer than that of annual members. Especially for OD type 2, more trips are between 12 to 18 minutes. Recall that the most frequent trip distance for both annual members and day pass users are almost the same in Figure 31 and Figure 32. However, this difference becomes significant from the perspective of trip time. This indicates that day pass users tend to spend more time on same distance trip than annual members, which is reasonable since tourists do not have a strict time plan on most cases.

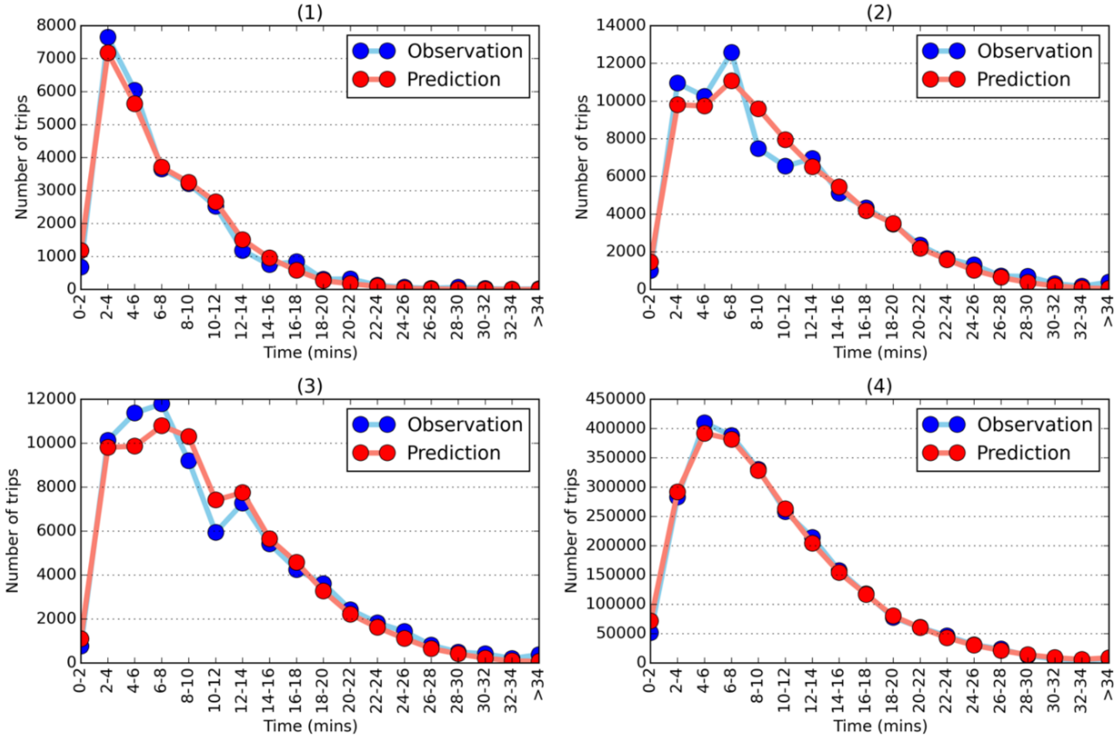

Figure 33. Histogram of modeled and observed trips for annual members (OD type: 1. Disadvantaged areas to disadvantaged areas; 2. Disadvantaged areas to other areas; 3. Other areas to disadvantaged areas; 4. Other areas to other areas.

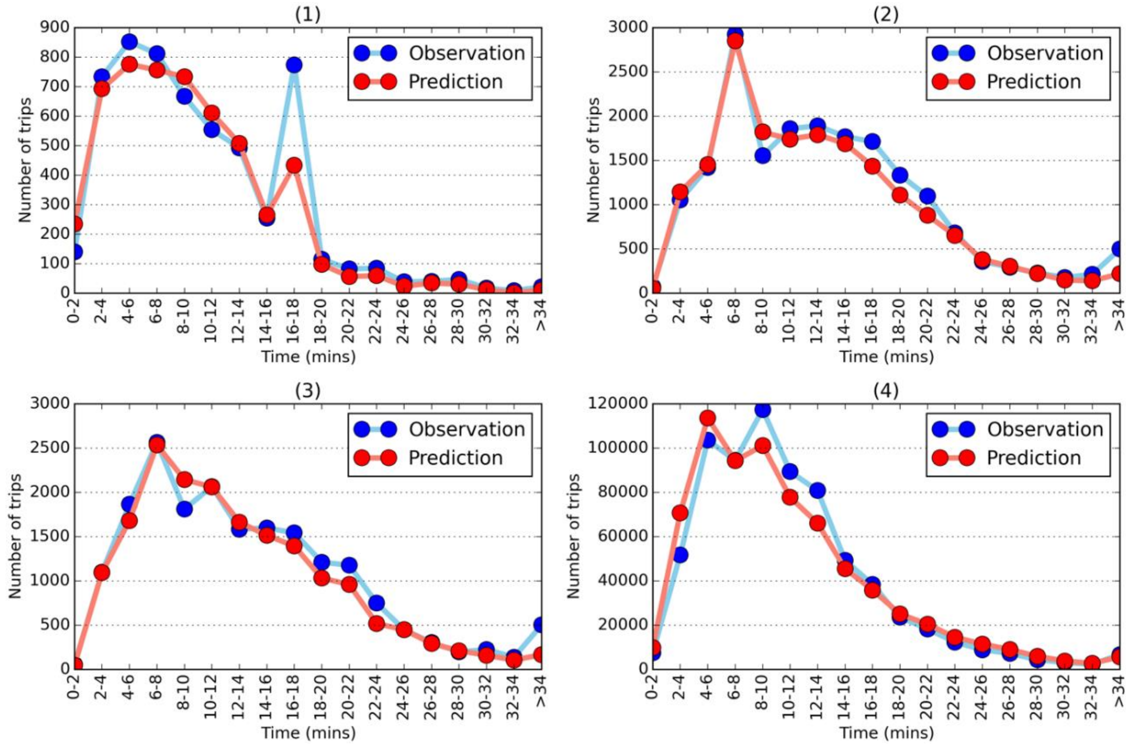

Figure 34. Histogram of modeled and observed trips for day pass users (OD type: 1. Disadvantaged areas to disadvantaged areas; 2. Disadvantaged areas to other areas; 3. Other areas to disadvantaged areas; 4. Other areas to other areas.

DISCUSSION

Real Trip Time and Google API Trip Time

In the Figure 41 in Appendix, I plotted the histograms of trip time for both annual members and day pass users under different ranges of estimated trip time. In Figure 35, for example, this row of panels only shows the histograms of bikeshare trips within 2 minutes estimated by Google API. Blue bins are for annual members, while green bins are for day pass users. More histograms of trip time within other ranges are in Appendix.

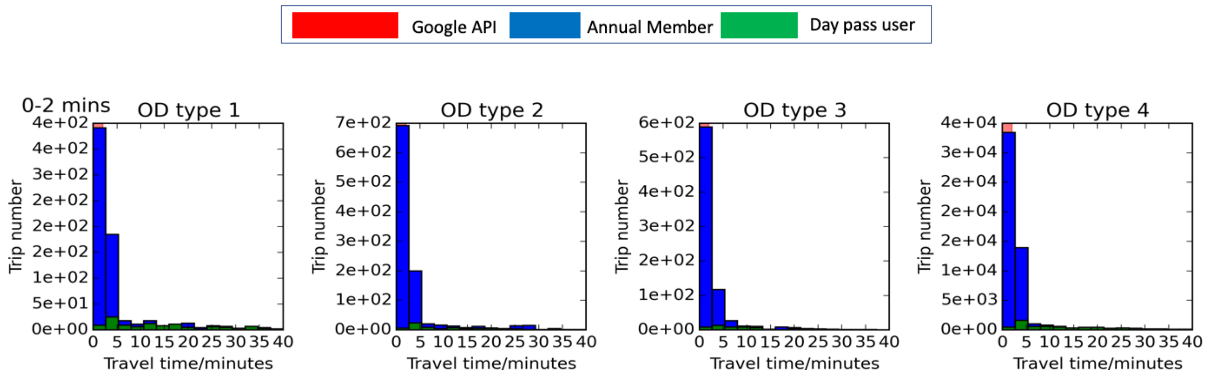

Figure 35. An example of trip time histograms for different OD types.

As we can see, subscribers stick to the shortest path more than day pass users. The reason may be that subscribers are more familiar with current bike network and they have specific trip purposes. On the contrary, day pass users are more likely to cycle around and do not have a strong time limit. There are also a proportion of users make a bikeshare trip with time shorter than Google estimates. This phenomenon may happen because their cycling speed is greater than that used by Google, or they take advantage of some shortcuts to save trip time. The real travel time by most subscribers also reveal that Google API provides a great estimation of travel time for bikeshare trips made by subscribers. Google may predict the most reliable route by bike with huge amount of historical trip data collected by Google Map. It is also possible that bikeshare users use Google Map to navigate. However, people from disadvantaged communities are less likely to own a smartphone to use advanced navigation tools. Thus, disadvantaged population could make longer trips.

Figure 36 shows the mean value and standard deviation of travel time from historical trip data. On average, subscribers tend to spend less time than day pass user as stated in preview paragraph. As trip distance become greater and greater, the differences of mean travel time for subscribers between different OD type become significant. OD trips within disadvantaged areas tend to have a higher mean travel time compared with other types of OD pairs. The reasons may be the missing of advantaged navigation tools or detour caused by insufficient bike paths in disadvantaged areas.

In general, the standard deviation (SD) of travel time increases with the rise of trip distance. There is significantly increase of travel time variance after estimated travel time is over 30 minutes. It may result from various trip purposes. A long-distance trip may fit for more trip purpose choices, which will cause the huge uncertainty in travel time. If we compare the SD of travel time for different OD types, SDs of OD type 1, 2, or 3 are greater than that of OD type 4 on most cases. This may result from the fact that there is a deficit for bicycle path network in disadvantaged areas. Users there could often detour to reach their destinations. Other reasons, e.g., unfamiliar with price scheme, may explain the longer trips as well. Note that the SD of travel time within longer trip distance range is extremely small in OD type 1, 2, and 3 because there are limited trip records. In some cases, there is only one trip record and SD is zero.

When we observe travel time of day pass user, the travel time is more unstable and difficult to predict. Unlike subscribers, the SD of day pass users for travel time within short distance trips is significantly greater than other trips. Day pass users may take recreation trips around and return their bikes to the origination.

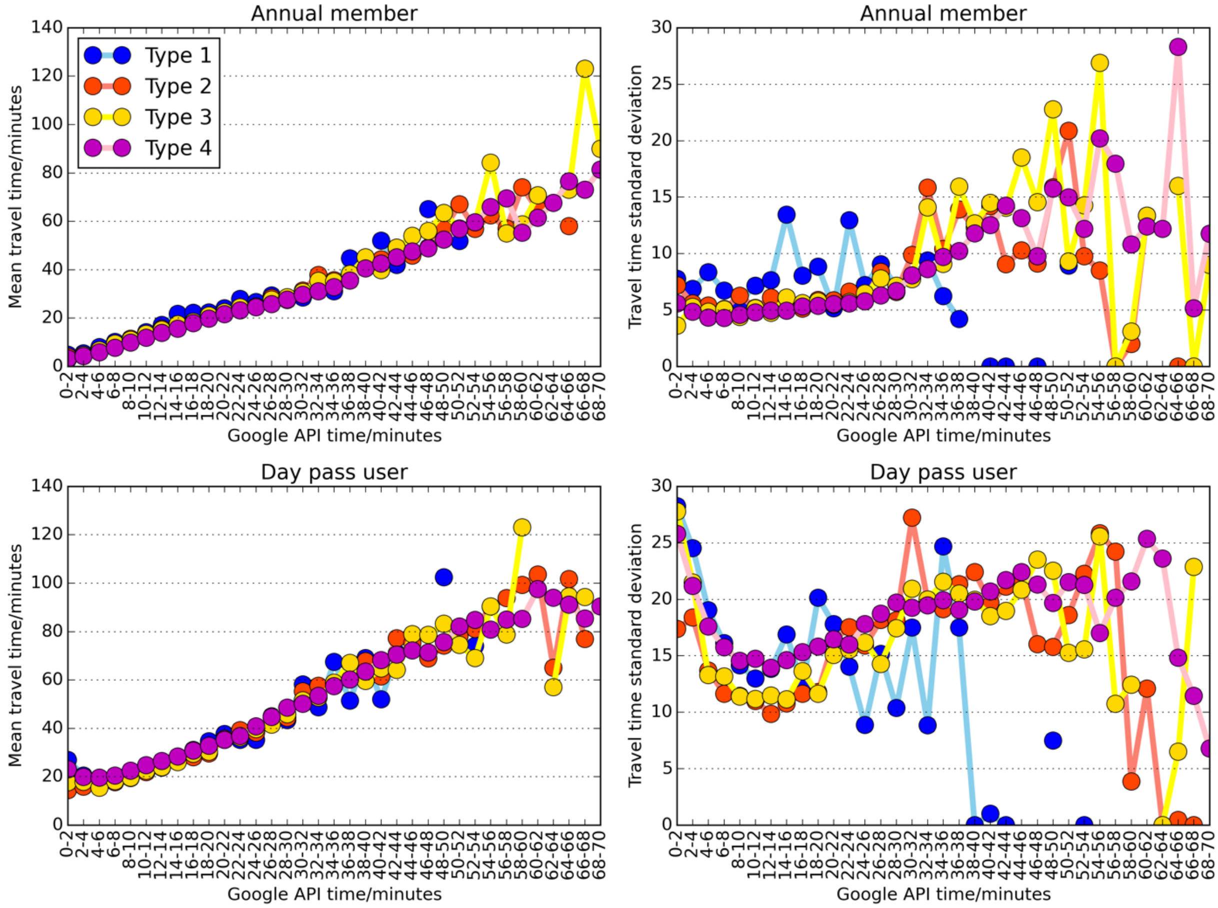

Figure 36. Mean and standard deviation of bikeshare trip time against Google API travel time.

Figure 36 shows the absolute value of real mean travel time. Now, I want to how the relative trip time variance changes with trip length. In Figure 37, the trend of relative trip time SD is totally opposite to that of absolute trip time SD in Figure 36. It is interesting to notice that relative SD for trip time in OD type 1 decrease much faster than that of other OD types. Thus, users from disadvantaged areas are more sensitive to the change of estimated trip time. As a trip becomes longer and longer, disadvantaged population will tend to keep trip time more consistent to avoid extra trip time, which may lead to extra trip charge. In Divvy bikeshare, trip price will increase every 30 minutes, no matter for subscribers or day pass users. Thus, we can see that an obvious difference of relative SD of trip time between 0-30 minutes' trips and 30+ minutes' trips.

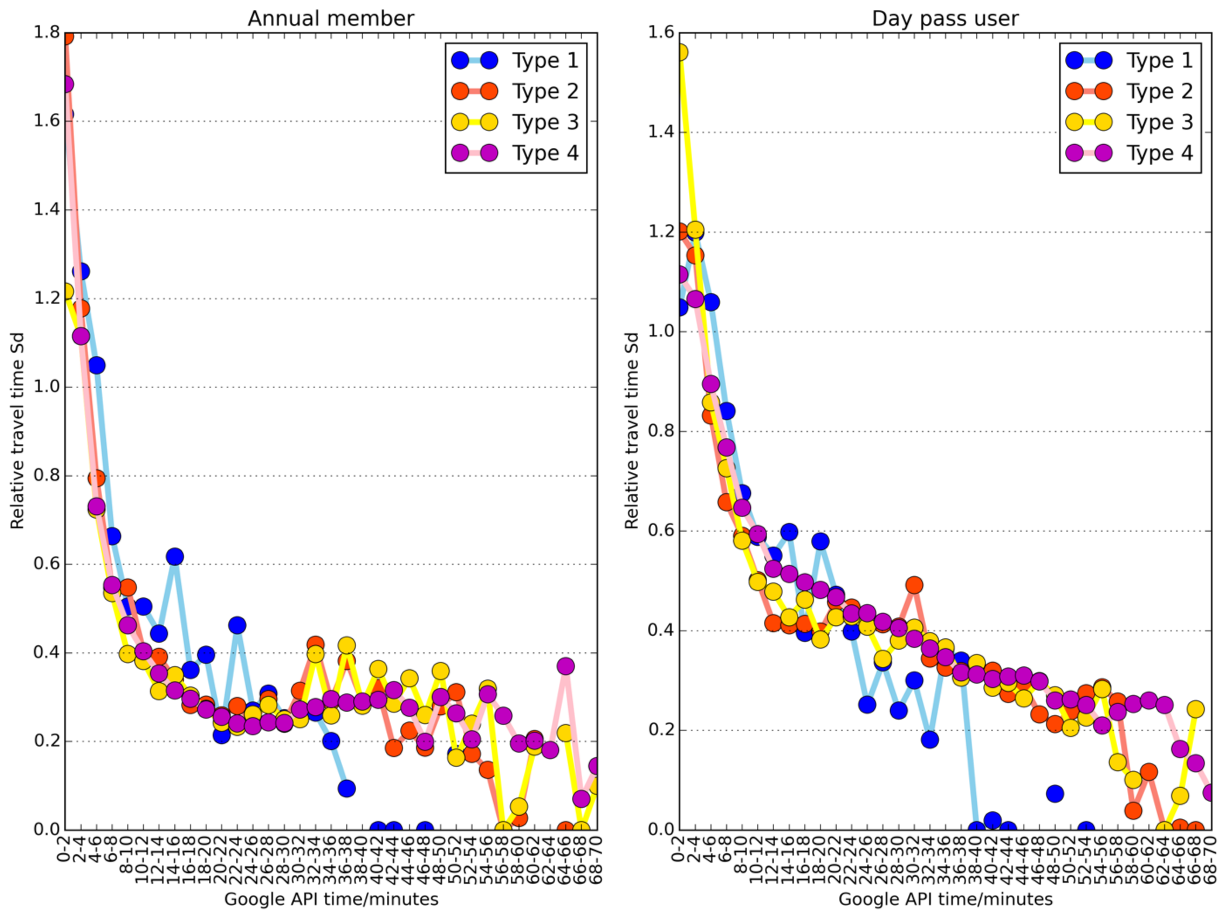

Figure 37. Relative standard deviation (SD) of bikeshare trip time against Google API travel time.

Trip Spending Difference

Trip price is positively corelated with trip time as shown in Table 23. However, since the relation is not perfect linear, there is a need to uncover the travel behaviors from the perspective of trip price. As presented in Figure 38, subscribers tend to make a trip within 30 minutes if a trip is estimated to take no more than 30 minutes. This is reasonable since subscribers want to make the most of their membership benefit (30-minute free ride). Once a trip will take longer than 30 minutes, the trip price will increase dramatically, and the standard deviation rises at the same time. There are still slight differences for trips by subscribers within different OD types. Users from disadvantaged areas are more likely to spend more than trips originated from and terminated at other areas within the same time range. Besides, the variance for trip price of OD type 1, 2, and 3 are also greater than that of type 4, especially for trip estimated to be longer than 30 minutes. There may be the same reasons to explain for the greater variance of trip price as mentioned in Section above.

Table 23. Pricing structure (in dollars) for Divvy in 2016 and 2017.

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

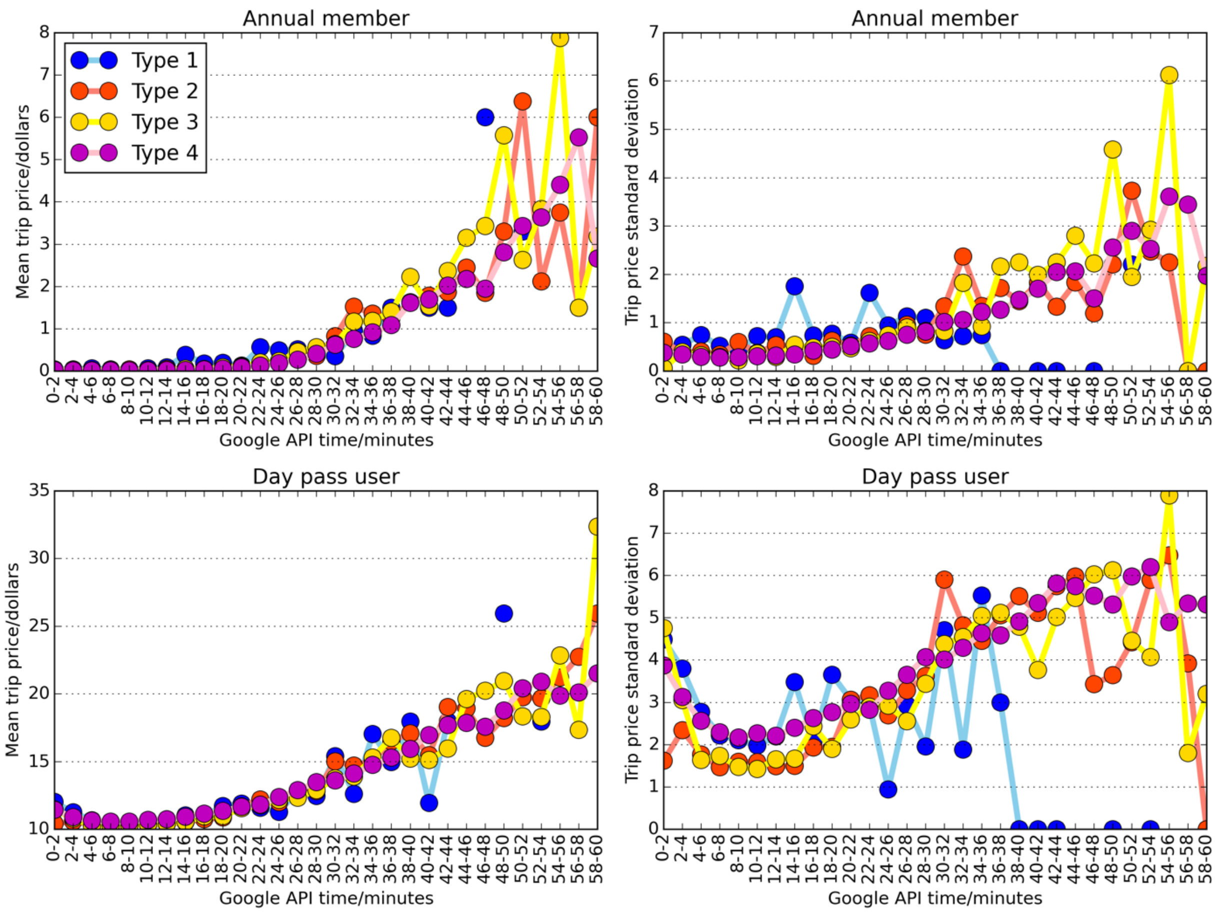

Figure 38. Mean and standard deviation of bikeshare trip price against Google API travel time.

Willing to Pay for Travel Time Variance

There are already findings regarding the behaviors of bikeshare trip in disadvantaged areas in Sections above. It is also interesting to notice how people are willing to pay for the trip time variance. This trip time variance in this study can result from signal controls at intersections, the possibility of detour, and other activity interruption during trips (e.g., shopping). The trip time variance will eventually lead to an extra charge for a bikeshare trip. In some case, a trip time variance is big which mean that a user may make other activities during a bikeshare trip. Thus, travel time variance measures how people are willing to integrate other activities into their bikeshare trips. For example, a person may do a short-time shopping during a ride since there is no bikeshare station to return bikes.

In Figure 39, the x coordination is relative trip time standard deviation, which is calculated by dividing travel time variance by average travel time for estimated travel time (Google API time) within a specific range. For example, I first grouped all bikeshare trips with estimated travel time between 0 and 2 minutes. Then, I calculated the average real travel time and corresponding travel time standard deviation. The relative trip time standard deviation is calculated by dividing the travel time standard deviation by the average travel time. Last, I calculated the average extra payment (actual spending minus estimated cost based on Google API travel time) users paid for their bikeshare trips. This relative trip time standard deviation and the average extra trip cost will be x coordination and y coordination correspondingly of a point in Figure 39. The general trend for relation between relative trip time variance and willing to extra-pay seem to follow this figure on the right. At first, with a specific range, people are willing to pay more price for extend their trip time beyond the estimated trip time. However, after a particular value of relative trip time SD, the willing to pay for more trip time decline. This phenomenon is more obvious in trips of OD type 1. Thus, users from disadvantaged areas spend less on the same level of relative trip time variance than users from other areas.

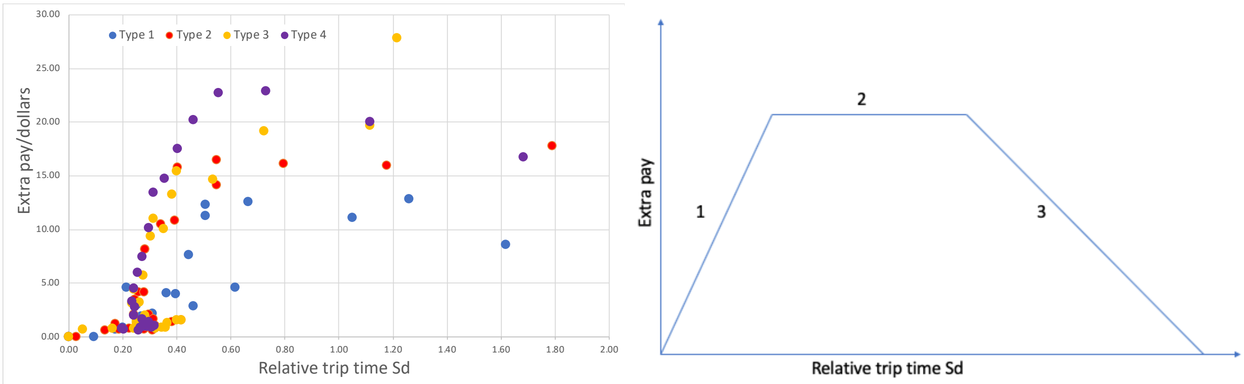

Figure 39. Price difference against relative trip time standard deviation (SD).

Trip Distribution between Origins and Destinations

To deeply understand what drive people from disadvantaged areas to other areas, I plotted these OD trip for subscribers against employment rate of originations and destinations. It is clear that station in disadvantaged areas have obviously deficit in employment rate then other areas. Since job commute is the main purpose for bikeshare trips, a low employment rate in disadvantaged areas lead significant less trips there. If we only look at OD types 1, 2 and 3, the number of OD trip increase obviously with the rise of employment rate. Job commute has been reported in several survey studies to be the main purpose for bikeshare trips (Buck et al. 2013; McNeil, Dill, MacArthur, and Broach 2017). More in-depth examination is needed of that how bikeshare systems can help increase employment rate.

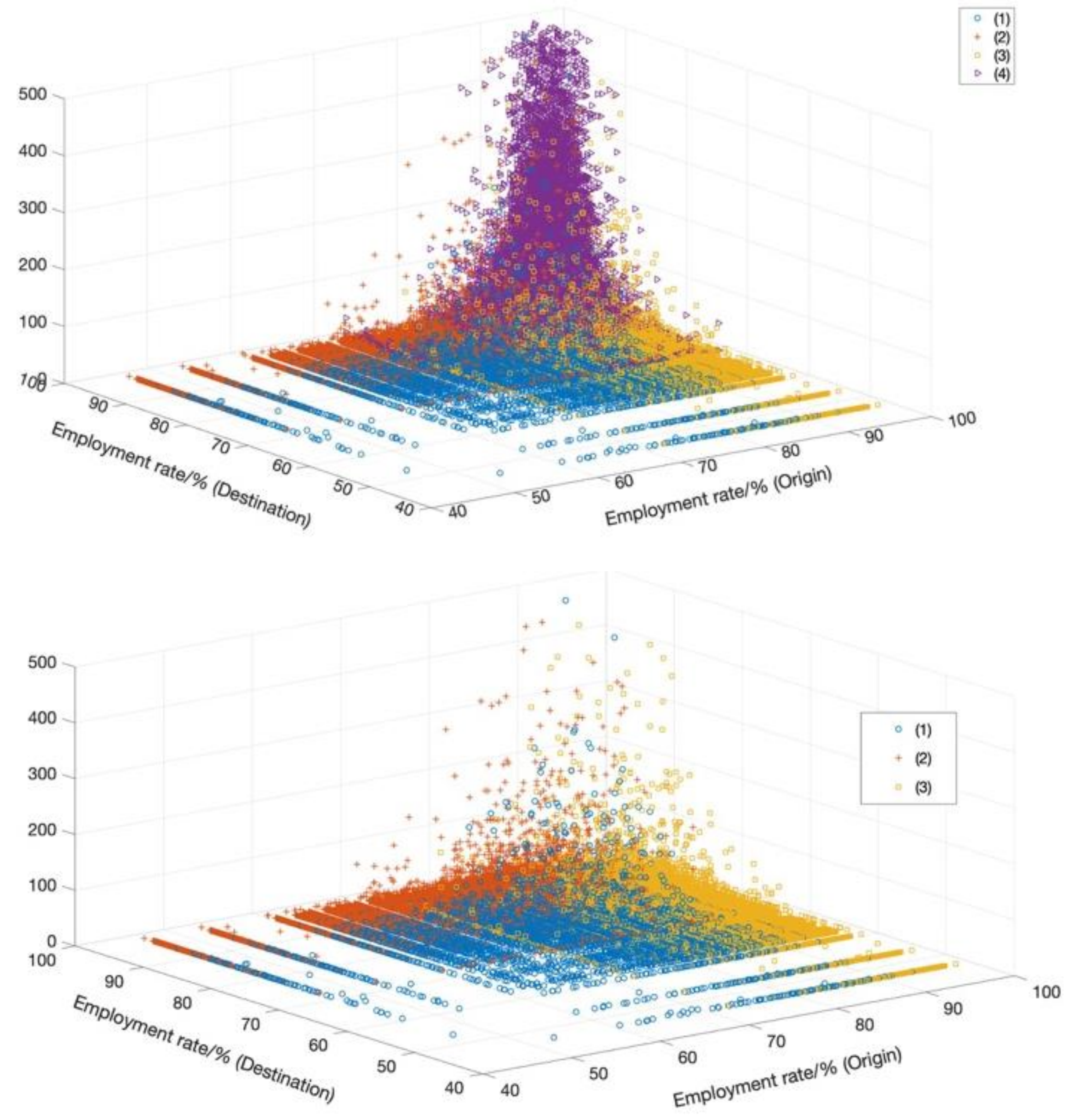

Figure 40. OD trips (annual members) against employment rate in originations and destinations (top: all four OD types; bottom: only three OD types).

CONCLUSIONS

This study develops a destination competing model to estimate bikeshare trip distributions. Before calibrating this model, I classified OD into four types based on originations/destinations in disadvantaged areas or not, which can capture the different travel patterns of bikeshare trip flow among different areas. According to the calibration results, accessibility differences between originations and destinations play an important role in attracting disadvantaged population to use bikeshare. It is also interesting to note that disadvantaged users tend to make a longer trip to other areas to improve accessibility, e.g., better food choices in more grocery stores and more job opportunities. By mapping the employment rate against OD trips, I notice that trip number increases significantly with the rise of the employment rate, which indicates that job commute is one of the important trip purposes for using bikeshare, no matter for disadvantaged areas or other areas. The greater ridership in higher employment rate areas may also result from more non-work trips, owning to more discretionary income. Besides, this destination choice model is calibrated for both annual members and day pass users, separately. In this way, I found that day pass users are less sensitive to the travel time even though they pay more than subscribers for extra trip time (over 30 minutes). Overall, this model provides a good estimation of distributions for bikeshare trip time and trip distance. This provides a suggestion for local governments on how to locate bikeshare stations to cover bikeshare trip demand within most frequent trip distant/time range.

In our study, Google API provides a good estimation of average historical bikeshare trip time, especially for annual members. Users from disadvantaged areas tend to finish a trip with longer time than estimated time, especially for trips estimated within 30 minutes. The variance of their bikeshare trip time is also greater than that of trips within other areas. This phenomenon is more obvious when trip estimated time is within the free ride time range (30 minutes). If a trip is predicted to be longer than 30 minutes, the variance of trip time drops significantly for trips within disadvantaged areas. This means that disadvantaged populations are more sensitive to the extra fees.

Annual members from disadvantaged areas seem to pay a little more than other users for trips within similar distance. Their trip price variance is likewise greater. However, once the trip time is over 30 minutes, disadvantaged populations will try to spend less, and their trip time tend to be consistent. It is important to notice bikeshare users' willing-to-pay (WTP) for trip time variance since users from disadvantaged areas are more sensitive to the variance of trip time. The strong sensitive to extra change will seriously influence their flexibility in using bikeshare. Additionally, there are not enough bikeshare stations located in their living areas. If we could increase the time limit for free ride, it could promote more trip bikeshare demand in these disadvantaged areas. They could make a long trip to reach far destination or cycle slowly to keep safe on road with no extra charge.

Trip purposes of bikeshare trips are not available and I could do more dedicated analysis for trip time/distance distributions of different trip purposes if I could get access to that data. If the route for every trip is available, I could know how long a bikeshare user really spend on cycling and what reason causes more time than estimated. Combining route information with local road network can also answer this question that to what extend the extra trip time is caused by insufficient bicycle infrastructure or unfamiliar with road network. Overall, this study provides some remarkable equity insights on travel behaviors on bikeshare for disadvantaged populations.

<u>CHAPTER 5: FUTURE RESEARCH PLAN</u>

This research has applied spatial analysis, statistical regression, and model calibration to explore travel behaviors of disadvantaged users using bikeshare services, and provide planning suggestions for developing a socially inclusive bikeshare system. However, as stated in previous chapters, there are a certain number of limitations in this study because of data availability, constrain of research time, and emerging advanced bikeshare system (e.g., dockless and electric bike). In the future, I will continue to collect more bikeshare data, especially related to dockless bikeshare and trip level bikeshare purposes, and other micro-mobility activity data (e.g., shared scooter). More detailed data for both trips and users' information can make most of quantitative methodologies to uncover the travel behaviors of disadvantaged users when using micro-mobility services. More importantly, I am interested in studying how these micro-mobility services are connected with public transit systems, and to what extent these services can improve health status for disadvantaged communities. These research ideas can help public better understand micro-mobility services, which will finally promote these sustainable transport systems. This research will assist city planners and municipalities to understand how to better design socially inclusive micro-mobility services to supplement current public transit systems.

CHAPTER 6: SUMMARY AND CONCLUSIONS

Bikeshare programs can play an important role in sustainable transportation systems by offering a viable mode choice for many types of last mile trips. However, recent bikeshare systems tend to target more affluent and white-dominated areas. This quantitative analysis demonstrates bikeshare systems can produce substantial accessibility improvements for disadvantaged communities. Furthermore, our research presents a new index that identifies bikeshare station locations providing high potential accessibility improvement to jobs and essential services for disadvantaged communities. By comparing these potential locations with current dock-based bikeshare station siting, our research clearly demonstrates that most of the current bikeshare stations in Chicago and Philadelphia are not located in high priority areas for bikeshare stations if we consider disadvantaged populations. Through these two study cities, we learn that a bikeshare system in its early stages can proactively attempt to eliminate access barriers for disadvantaged communities with consideration of equitable accessibility.

The work also estimates bikeshare trip demand based on a number of key system and socio-economic variables. More importantly, the estimated regression model provides evidence about the impact of socio-economic variables, especially for individuals in disadvantaged communities that affect their trip productions and attractions. Furthermore, the marginal effect of bikeshare location is the greatest, which means that if a bikeshare station is located in a disadvantaged community, the number of annual trips at that station is noticeably lower relative to stations in affluent and white communities. By analyzing the historical bikeshare trips, I notice that residents in disadvantaged areas make much longer trips than in other areas if they already are subscribers. After joining as annual members, disadvantaged populations can enjoy real benefits by bikeshare, such as saving money on transport. Inspired by those findings from historical bikeshare trip data, I think of two suggestions on future policy for developing bikeshare: low membership fees and longer extended free-ride time.

Finally, this study develops a destination competing model to estimate bikeshare trip distributions. According to the calibration results, accessibility differences between origins and destinations play an important role for attracting disadvantaged population to use bikeshare. It is also interesting to note that disadvantaged users tend to make a longer trip to other areas to improve accessibility. By mapping the employment rate against OD trips, I notice that trip number increase significantly with the rise of employment rate. It indicates that job commute is an important trip purpose for using bikeshare no matter for disadvantaged areas or other areas. Our destination choice model is calibrated for both annual members and day pass users, separately. In this way, I found that day pass users are less sensitive to the travel time since their time schedules are flexible. Overall, our model provides a good estimation of distributions for bikeshare trip time and trip distance. This can provide a suggestion for local governments on how to locate bikeshare stations to cover bikeshare trip demand within most frequent trip distant/time range.

In conclusion, this dissertation work fills some important research gaps in bikeshare equity study. Through a novel and thorough quantitative research, this work provides practical suggestions to both local municipalities and bikeshare industry managers who are concerned with providing a socially inclusive bikeshare service.

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APPENDIX

Table 24 Data for candidate cities (part 1)

No.	State	City	Urbanized land area 2010 (square miles)	Population	Nonwhite percentage (%)	Median household annual income	State bike friendly ranking (2015)	City Bike Friendly Ranking	No. of bikeshare stations	Percentage of households with no vehicles/%	Vehicles per household
1		Washington DC	1322	649,111	59.8	$67,572	-	Silver	373	37.9	0.9
2	Washington	Seattle	1010	652,405	29.4	$70,172	1	Gold	66	34.91	1.4
3	Minnesota	Saint Paul	52	294,873	39.9	$49,469	2	Bronze	146	14	1.5
4	Minnesota	Minneapolis	1022	400,070	29.8	$50,563	2	Gold	65	18.1	1.3
5	Massachusetts	Boston	1873	645,966	47.1	$53,583	4	Silver	140	35.8	0.9
6	Utah	Salt Lake City	278	191,180	24.9	$50,827	5	Silver	25	12.8	1.5
7	Oregon	Portland	524	609,456	23.9	$55,571	6	Platinum	Will develop	15	1.5
8	Colorado	Boulder	32	101,500	12	$57,428	7	Platinum	39	9	1.6
9	Colorado	Fort Collins	109	152,061	10.37	$56,464	7	Platinum	Will develop	5.4	1.9
10	Colorado	Denver	668	649,495	30	$51,089	7	Silver	87	11.7	1.5
11	California	Sacramento	471	479,686	55	$48,034	8	Silver	Will develop	11.1	1.6
12	California	San Diego	732.4	1,355,896	57.1	$63,456	8	-	100	7.6	1.7
13	California	San Francisco	524	837,442	51.5	$77,485	8	Gold	84	30.4	1.1
14	Wisconsin	Madison	151	243,344	21.1	$49,546	9	Gold	36	13.1	1.4
15	Wisconsin	Milwaukee	545	599,164	63.1	$35,186	9	Bronze	35	19.2	1.3
16	Maryland	Baltimore	717	622,104	68.37	$42,266	10	Bronze	Will develop	30.6	1.1
17	New York	New York City	3450	8,406,000	67.3	$54,700	11	-	332	38.6	0.8

18	Pennsylvania	Pittsburgh	905	305,841	34	$42,004	12	Bronze	14	25.2	1.1
19	Pennsylvania	Philadelphia	1981	1,553,000	54.5	$36,836	12	Silver	60	33.1	1
20	Illinois	Chicago	2,443	2,719,000	68.3	$47,099	14	Silver	476	27.3	1.1
21	Michigan	Detroit	1337	688,701	91.1	$24,820	18	-	42	25.2	1.1
22	Arizona	Phoenix	1147	1,513,000	28.93	$46,601	19	Bronze	41	9.1	1.6
23	Arizona	Tucson	353	526,116	52.8	$35,720	19	Gold	Will develop	12.7	1.5
24	Idaho	Boise	133	214,237	11.12	$47,847	21	Silver	27	6.4	1.7
25	Florida	Miami	1239	417,650	27.4	$31,070	24	Bronze	75	21.5	1.2
26	Georgia	Atlanta	2645	447,841	61.6	$46,485	25	-	Will develop	16.9	1.3
27	Rhode Island	Providence	545	177,994	45.47	$36,378	26	-		19.6	1.3
28	Texas	Houston	1660	2,196,000	50.7	$45,353	30	Bronze	29	10	1.5
29	Texas	Austin	523	885,400	34.64	$56,351	30	Silver	50	6.9	1.6
30	Texas	Fort Worth	1779.1	792,727	40.31	$52,430	30	-	43	6.5	1.7
31	Missouri	Kansas City	678	467,007	39.32	$45,551	34	Bronze	27	11.2	1.5
32	South Carolina	Spartanburg	190	37,647	52.89	$32,499	44	Bronze	5	-	-
33	Alabama	Birmingham	530	212,113	77.7	$31,152	50	-	40	15.1	1.4
34	Montana	Missoula	45.2	66,788	6.43	$44,232	46	Gold	Rent bike shop	7	1.7

Note: 1. All data were collected from September to December 2015;

2. "-" indicates that no information was available;

3. City area and population data are from the website links: https://www.census.gov/dataviz/visualizations/026/508.php, https://en.wikipedia.org/wiki/List_of_United_States_cities_by_population_density, and https://en.wikipedia.org/wiki/List_of_United_States_urban_areas;

4. Race percentage data are from Wikipedia;

5. Median household income data are from the website link: http://www.city-data.com/;

6. Bicycle friendly data are from the official website of the League of American Bicyclists;

7. Vehicle ownership data are from the website link: http://www.governing.com/gov-data/car-ownership-numbers-of-vehicles-by-city-map.html;

8. The population of Chicago in this table is 2,719,000, which is different from the population (2,869,555) calculated later. The reason is that we included some areas (e.g., Evanston in the north of Chicago) where has been covered by the Chicago bikeshare system (Divvy);

9. The population of Philadelphia is 1,553,000 in this table, which is slightly greater than 1,551,773 calculated by 2010 Census data later;

10. The size of some bikeshare systems increased during our research period. The number of the bikeshare stations in Chicago had increased from 476 to 581. The bikeshare system (Indego) in Philadelphia had 105 bikeshare stations when the report was done in September 2017.

Table 25 Data for candidate cities (part 2)

No.	State	City	Public Transit		Protected bike path	Average monthly temperature (°F)				Average annual precipitation		Average annual snowfall (inch)
			Bus transit/Bike racks available	Metro or railway/Bike racks available		Jan.	April	July	Oct.	inch	days	
1	DC	Washington DC	Metrobus/Yes	Washington Metro/Yes	Yes	34.9	56.1	79.2	58.8	39.35	113	17.1
2	Washington	Seattle	King County/Yes	Seattle Center Monorail and link light rail/No	Yes	40.9	50.2	65.3	52.7	37.07	155	11.4
3	Minnesota	Saint Paul	Metro Transit/Yes	Metro/-	-	13.1	46.6	73.2	48.7	29.41	115	49.9
4	Minnesota	Minneapolis	Metro Transit/Yes	Metro/-	Yes	13.1	46.6	73.2	48.7	29.41	115	49.9
5	Massachusetts	Boston	MBTA Bus/Yes	MBTA/Yes (some available)	Yes	29.3	48.3	73.9	54.1	42.53	127	42.8
6	Utah	Salt Lake City	Utah Transit Authority/Yes	Trax light rail/-	Yes	29.2	50	77	52.5	16.5	91	58.7
7	Oregon	Portland	TriMet/Yes	Max light railway/Yes	Yes	39.9	51.2	68.1	54.3	37.07	153	6.5
8	Colorado	Boulder	RTD/Yes	No/-	Yes	34.6	49.5	72.5	51.8	20.66	89	89
9	Colorado	Fort Collins	Transfort/Yes	No/-	Yes	31.1	41.5	66.5	50.1	16.05	81	57
10	Colorado	Denver	RTD/Yes	Light Rail/Yes	Yes	29.2	47.6	73.4	51	15.81	89	60.3
11	California	Sacramento	Sacramento Regional Transit District (RT)/Yes	Light Rail/Yes	Yes	46.3	58.9	75.4	64.4	17.93	58	-
12	California	San Diego	San Diego Metropolitan Transit System/Yes	Trolley car/Yes	-	57.8	62.6	70.9	67.6	10.77	41	-

13	California	San Francisco	Golden Gate Transit/Yes	Light Rail and Bay Area Rapid Transit/Yes	Yes	49.4	56.2	62.8	61	20.11	63	-
14	Wisconsin	Madison	Madison Metro/Yes	No/-	Yes (only one)	17.3	45.9	71.6	49.3	32.95	120	43.8
15	Wisconsin	Milwaukee	Milwaukee County Transit System/Yes	No/-	Yes (only one)	20.7	45.2	72	51.4	34.81	125	47
16	Maryland	Baltimore	Maryland Transit/Yes	Light Rail and Baltimore Metro Subway/-	Planning	32.3	53.2	76.5	55.4	41.94	115	21.5
17	New York	New York City	MTA Subway/Yes	Train or light rail/Yes (only off rush hour)	-	23.6		82		46.42	122	26.7
18	Pennsylvania	Pittsburgh	PAT Transit/Yes	Light Rail/-	Yes	27.5	49.9	72.6	52.5	37.85	152	43.6
19	Pennsylvania	Philadelphia	SEPTA/Yes	Regional Rail and PATCO Speedline/Yes	Yes	32.3	53.1	77.6	57.2	42.05	117	20.8
20	Illinois	Chicago	CTA/Yes	light Rail / Yes	Yes	22	47.8	73.3	52.1	36.27	125	38
21	Michigan	Detroit	Detroit Department of Transportation/ Yes	Ann Arbor-Detroit Regional Rail/-	Yes	24.5	48.1	73.5	51.9	32.89	135	41.3
22	Arizona	Phoenix	Valley Metro/Yes	Light Rail/Yes	Yes	54.2	70.2	92.8	74.6	8.29	36	-
23	Arizona	Tucson	Sun Tran/Yes	StreetCar/Yes	Yes	51.7	66	86.5	70.5	12.17	53	1.2
24	Idaho	Boise	Valley Regional Transit/Yes	No/-	Planning	30.2	50.6	74.7	52.8	12.19	89	20.6
25	Florida	Miami	Metrobus/Yes	Metrorail/Yes		68.1	75.7	83.7	78.8	58.53	131	-
26	Georgia	Atlanta	MARTA Bus/Yes	MARTA Train/Yes	Yes	42.7	61.6	80	62.8	50.2	115	2.1
27	Rhode Island	Providence	Rhode Island Public Transit Authority/Yes	No/-	-	28.7	48.6	73.3	53	46.45	124	36
28	Texas	Houston	METRO Bus/Yes	Metrorail/Yes	Yes	51.8	68.5	83.6	70.4	47.84	105	0.4

29	Texas	Austin	Capital Metropolitan Transportation/Yes	Metrorail/Yes	Yes	50.2	68.3	84.2	70.6	33.65	85	0.9
30	Texas	Fort Worth	The T/Yes	DART Rail/Yes	-	44.1	65	85	67.2	34.73	79	2.6
31	Missouri	Kansas City	KCATA/ Yes	No/-	Planning	26.9	54.4	78.5	56.8	37.98	104	19.9
32	South Carolina	Spartanburg	SPARTA/Yes	No/-	-	42	60.4	79.2	61.1	48.45	101	1.6
33	Alabama	Birmingham	MAX/ Yes	No/-	Yes	42.6	61.3	80.2	62.9	53.99	117	1.5
34	Montana	Missoula	Mountain line/Yes	No/-	Yes	20.2	44.1	67.8	44.8	14	102	36.9

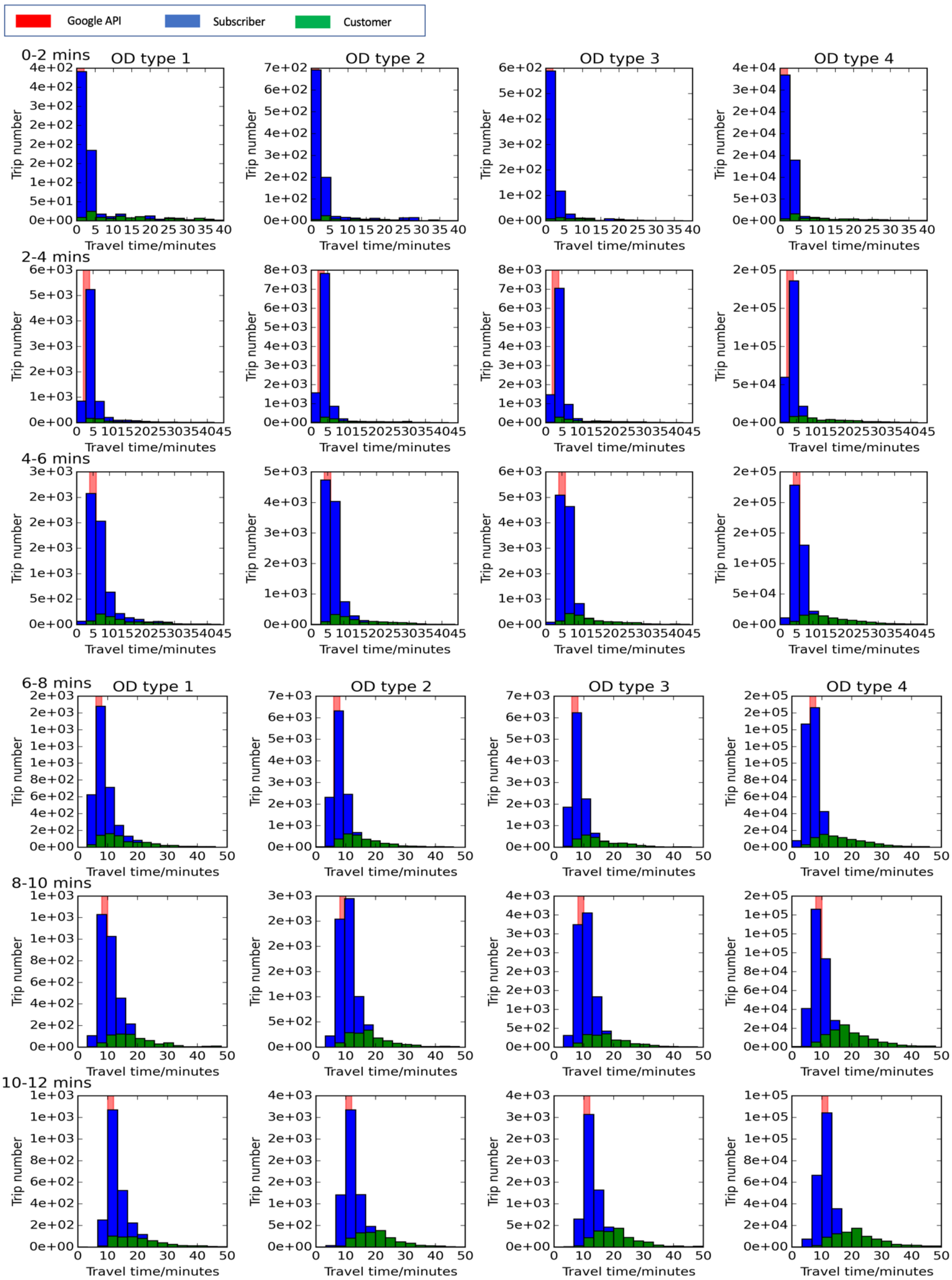
Note: 1. All data were collected from September to December 2015;

2. "-" indicates that no information was available;

3. Protected bike path data are from the website link: https://docs.google.com/spreadsheets/d/11H0gArHxo6kMop1I18yMcq7ArbNrwaGBLmIXgqI1Gjk/edit;

4. Climate and weather date are from the website links: http://www.usclimatedata.com/, https://www.infoplease.com/science-health/weather/climate-100-selected-us-cities, and https://batchgeo.com/map/us-cities-rainy-days-per-year;

5. Public transit data are from the website links: https://en.wikipedia.org/wiki/List_of_bus_transit_systems_in_the_United_States, https://en.wikipedia.org/wiki/List_of_United_States_rapid_transit_systems_by_ridership, https://en.wikipedia.org/wiki/List_of_United_States_light_rail_systems_by_ridership.


Google API
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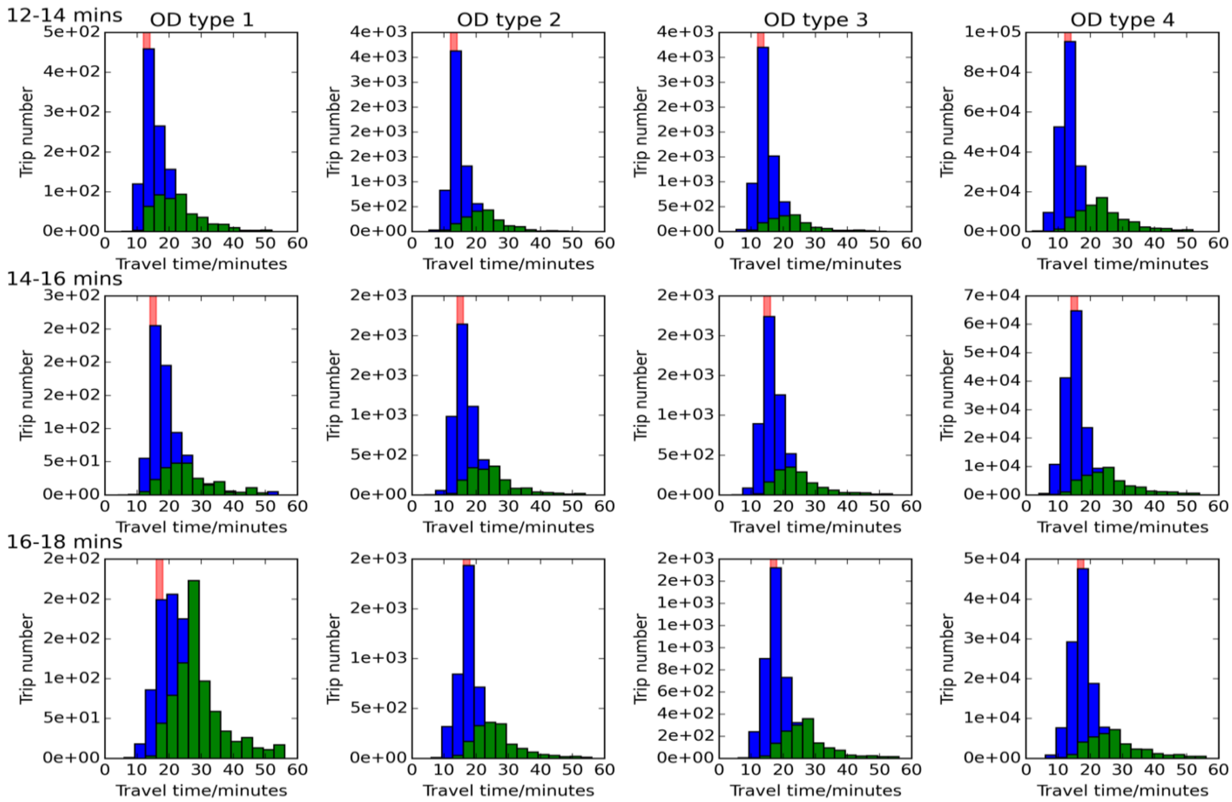
Travel time/minutes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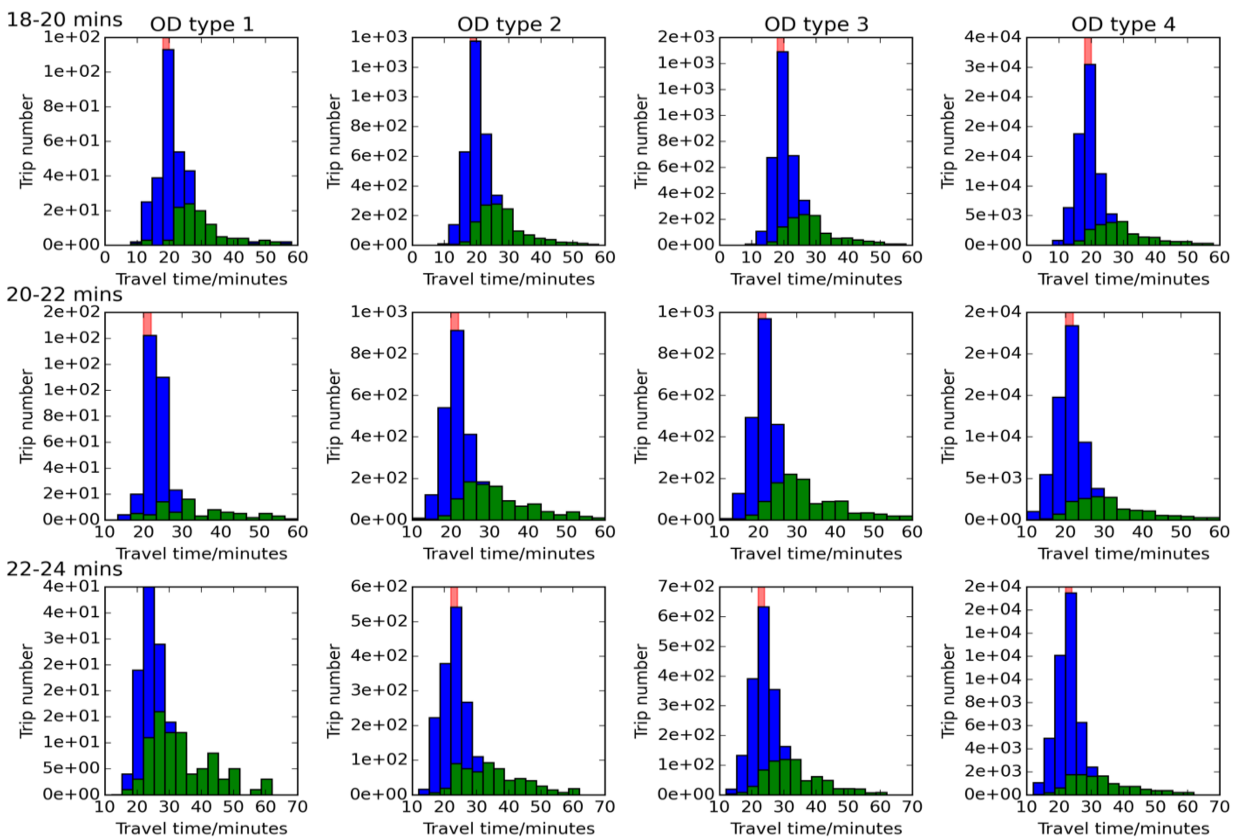
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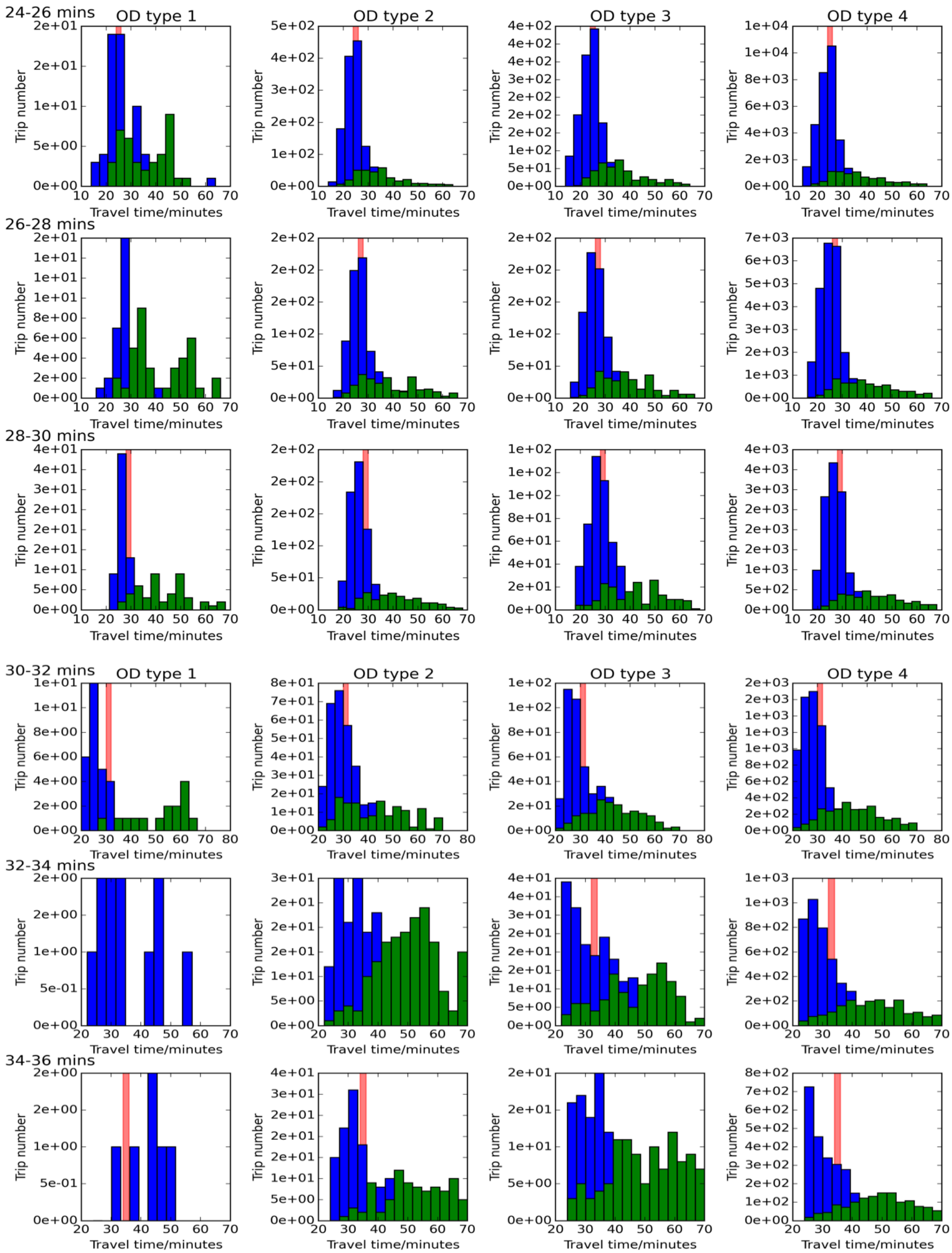

Figure 41. Histogram of bikeshare trip time under different OD types.