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# Public Transit and Micro-mobility: Identifying the Impacts of Bikeshare on Public Transit Ridership in the City of Chicago

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# PUBLIC TRANSIT AND MICRO-MOBILITY: IDENTIFYING THE IMPACTS OF BIKESHARE ON PUBLIC TRANSIT RIDERSHIP IN THE CITY OF CHICAGO

by

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**ABSTRACT**

PUBLIC TRANSIT AND MICRO-MOBILITY: IDENTIFYING THE IMPACTS OF BIKESHARE ON PUBLIC TRANSIT RIDERSHIP IN THE CITY OF CHICAGO

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The variation of transit and bike share access amongst the communities in Chicago, in terms of their social, ethnic and economic segregation was investigated. The findings identify the area suitable for implementation of micro mobility as a first and last mile option. Based on transit connectivity and population mix, the communities are ranked into five groups: 1) Central: excellent transit and bike share access serving the micro mobility purpose; 2) North Side : good transit access which can be improved further amongst young age groups to improve transit ridership; 3) Far North Side : disproportionate transit and bike share distribution with excellent connectivity of transit and bike share in east and poor moving west; 4) North West , West and Near west and South west Side : has majority of hispanic population, black and low income population with a poor access to transit and bike share; 5) South Side, Far South West Side and Far South East side: high population of low income, senior , disability and black with very poor access to bus and bike share; Extensive improvement in transit service , bike share access and cost subsidy is needed. Severe imbalance exists in access to transit and bike share amongst the 77 communities in the city of Chicago.

Bike share’s contribution towards increase or decrease in transit ridership was also investigated. A 25.9% increase in average bus stop level ridership and a 10.7% increase in average rail station level ridership was found to be associated with introducing bike share.

To

all my mentors, family members and friends

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| | |
|---|---|
| ADA | Americans with Disabilities Act |
| ACS | American Community Survey |
| APTA | American Public Transportation Association |
| ATE | Average Treatment Effect |
| ATT | Average Treatment Effect on the Treated |
| BSS | Bike Share System |
| CaBi | Capital Bike share |
| CBG | Census block group |
| CTA | Chicago Transit Agency |
| C-T | Cycle Transit Integration |
| EPA | Environmental Protection Agency |
| GIS | Geographic Information System |
| glm | Generalized Linear Model |
| IIA | Irrelevant Alternatives Assumption |
| MARS | Multivariate adaptive regression splining |
| NB | Negative Binomial |
| NCD | National Council on Disability |
| NHGIS | National Historical Geographic Information System |
| NHTS | National Household Travel Survey |
| NYCT | New York City Transit Authority |
| OLS | Ordinary Least Square |
| PSM | Propensity Score Method |
| S-GWR | Semi-Parametric Geographically weighted regression model |
| SLD | Smart Location Database |
| UCLA | University of California, Los Angeles |
| VIF | Variance Inflation Factor |
| ZINB | Zero Inflated Negative Binomial Model |

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# CHAPTER 1

# INTRODUCTION

# 1. Background

The importance of public transportation has attracted considerable attention in recent years as today's society progressively demands mobility. This also led to an upsurge in the popularity of bike share systems. Bike share is increasingly becoming popular around the world as a flexible, healthy, cheap and sustainable mobility solution.  These adaptable characteristics of bike share has also enabled it to secure its position as mode to bridge the first and last mile gap between transit station and our destination. This has emerged many researches associated with success determinants or optimization of bike share service or distribution. Other researches also assess the effects of bike share on different transit modes. Many of these researches has identified that large cities like Northeast Seattle, Chicago, and Los Angeles, have extensive transit networks that stretch over hundreds of miles whereas some other areas lack access to transit. Strong transit systems are often located in regions with high population density such as downtowns in larger cities and a reliable combination of transit and bike share system is what makes those areas public transportation dependent [1]. Past studies have also found that disadvantages communities often have poor access to transit and bike share. A nationwide survey of 35 Bike Share Systems (BSS) found that more than three quarters (1,556 or 2,063 or 75.4 percent) of bike sharing stations in Unites Stated are situated in communities with relatively stable economic conditions whereas as only 245 (or 11.9 percent) stations were located in communities with serious economic adversity [2]. Hence while integration of bike share and transit becomes increasingly popular, this integration is unsuccessful in meeting the needs of the less privileged population.

According to the ACS, 18% of commuters in Cook County, Illinois use public transportation as a mode of mobility. The national average is 4.9% [3], [4]. While being well-known for its escalating influence in the global economy, the Chicago region is also recognized for its patterns of racial

and economic seclusion. Chicago is also the home to 2.7million residents and ranks in the top quarter as economically segregated city [5]. A study by 2014 University of Illinois at Chicago Voorhees Center found that in forty year duration between 1970 to 2010, out of 77 of Chicago community areas, 9 has undergone a process of redevelopment while the communities concentrated with poverty stricken population has increased from 29 to 45 [6]. As the economic segregation continues towards becoming more severe, the city has seen an exponential rise in the popularity in its bike share use contributing six million trips, totaling more than 13 million miles by Divvy riders, taken since its launch in 2013 [7]. While Chicago transit , accumulated a total of 468.44 million annual ridership bus and rail combined in the year 2018 alone [8]. Divvy stations operated in close proximity to transit station in many locations while divvy has also undergone several expansions to its station locations with its escalating bike trips.

These facts reveal question on whether Chicago has an even distribution of transit and bike share stations in all 77 of its communities. This leaves an area for this research to explore the accessibility of transit as well as bike share service in all communities in Chicago. The 77 Chicago communities can be evaluating the suitability of implementation of the micro mobility as a first and last mile options while others may still have some room for improvements.

## 1.1. Research Motivation

Chicago not only has one of well-integrated transit system in the United States but is also the home to one of the most successful bike share system in the nation. Since its birth in 2013 Divvy has continued to witness exponential increase in trips as well has instantiated multiple expansions of its locations. Subsequently, the city is also known for its economic and racial segregation. This makes room to investigate whether the economic and racial segregated region are getting adequate access to transit or bike share. This will also

highlight whether the expansions of Divvy are being made in regions where there is lower density of service or where there is highest ridership. Past researchers have identified that low income areas and areas populated by ethnic minorities generally have low ridership. The current transit and bike share state and the preexistent economic and racial segregation sets a stage to take an insight into ***"whether this trend is due to personal choice or access to transit or bike share?*** "This also opens doors to ***"identify the trend of transit and bike share use amongst different population group and compare it to their accessibility to transit and bike share."***

## 1.2. Organization

This thesis has been organized into five chapters. Chapter 1 contains introduction, background, research motivation, overall organization of the research and literature review. Chapter 2 focusses on the preliminary analysis of the results. This chapter put emphases on the preliminary analysis associated with the overall trend in transit and bike ridership over years and compares with factors like change in population growth over years; Makes an initial analysis of the distribution of transit (bus/rail) and bike share service in the city of Chicago and finally analyses the percent of population in each neighborhood of different population group identified to influence transit or bike share ridership. Chapter 3 performs a statistical analysis to identify the factors affecting transit ridership in presence and in absence of bike share; The statistical analysis results are then compared with the distribution of those factors in each community in Chicago and finally with the accessibility to bus , rail or bike share service ; Based on the findings of the interpretation of results, this chapter classifies the 9 Chicago Community sides into 5 groups based on their access to transit or bike share. Chapter 4 extracts the factors that significantly affects transit ridership to find the influence of the contributing factor towards increasing or decreasing ridership of transit stations

with bike share; This chapter introduced the method of propensity analysis , matching technique and method to find the contributory effect; The chapter then estimates the increase in transit ridership associated with bike share .Lastly the trends of the monthly variation of influence by contributing factors for rail service was analyzed. Finally chapter 5 draws an overall conclusion on the current condition of transit and bike share in each of the ranked community groups and suggested possible improvements for each ranks to reach its goal to implement bike share as a first and last mile option; Makes possible recommendations to transit agency based on the findings of the results and makes future recommendation for future research in this area.

# 2. Literature Review

With the rise in popularity of micro mobility vehicles around the world many research has addressed the issue of the impact of placement of these micro mobility vehicles in the existing built in environment [9], the effect of micro mobility vehicles on transit ridership and their effect on everyday human activities. Cervero analyzed the different dimensions of built-in environments such as design, density and diversity and identified that intensities and mixtures of land use significantly influence decisions to drive-alone, share a ride, or patronize transit [10]. In a different study by Ewing and Cervero, it was found that mode choices depend on both the built environment and socioeconomics but  is more reliant on socioeconomic conditions [11]. Study also found that distance to metro rail station, transportation infrastructure; land use mix and socioeconomic activities significantly effect first and last like travel behavior.

“Transit Dependency” people are referred to by people who reside in household with no private vehicle available. However, the eligibility of being “ transit dependent” is reliant on not only

owning personal vehicle but also on elderly (over age 65) population, population under the age of 18 and population under poverty or median income level [12]. Social exclusion can be the consequence of inequalities in public transit systems around the world as a result of the variations in service, accessibility, and affordability of public transit. Such social disparities often occurs amongst low-income riders, minorities, disabled people [13]. Public transportation accessibilities for people with disabilities is foremost for the in lowering poverty and can enable the contribution of people with disabilities in economic, social and political processes. Although there has been many development in transportation systems in advancement of the ease of use to the urban public transportation system, the current situation still fails to meet the requirements of people with disabilities [14]. Barriers to safely navigate in public transit has been encountered frequently by the transit users with physical disability or age-related limitations. Very often the failure in providing accommodation for passengers with physical limitations are due to the gaps that are preexistent in the infrastructure despite of the promising improvements to the accessibility in public transit [15], [16].

## 2.1. Factors affecting transit and bike share

### 2.1.1. Income and Ethnicity

A survey based study on 56 united states bikes hare systems show that the major factor that affects equity in bike share system are cost , access and outreach to a bike share system aside from staff availability and funding [17]. The study analyzed the equity policies and metrics, the degree to which equity considerations affect a variety of system practices, what the existing barriers to utilizing bikeshare are for target populations, and what challenges the bikeshare system entity faces

in addressing those barriers. Another study performed on the Philadelphia's bike share system (Indego) showed that bike share trips generated by docking stations located in lower income are mainly for work commute purpose. The study also reinstated the past findings that lower income area produce lower number of trips in comparison with other while other variables such as transit access and stations proximity to bike lanes have been controlled. However, the study only reflects the situation and population around the docking station location. The study does not reflect the behavior of the users with respect to bike share as a mode choice in other part of the city. The study also does not reflect whether the trend in bike share pattern is a result of incentives provided by the City of Philadelphia to the low income population [18] .

Low-income, Black, and Hispanic communities have a propensity to encounter smaller share of mobility/accessibility, higher level of health issues and greater number of pedestrian- and bicycle-related fatalities. Nevertheless, research shows that alternative transportation and active living plans and programs—including bike share primarily aided medium and high income neighborhoods [19], [20]. Although the acceptance of non-motorized modes has increased, the possibility of traditionally under privileged populations are again being sidelined or have inadequate access to benefits of existing and future emerging bicycle- and pedestrian-oriented facilities and plans. These concerns led to a growing number of studies and advocacy efforts aimed at identifying and removing barriers to bike share in traditionally unattended regions [21]. Inaccessibility to stations is also found to a major cause of low bike share usage amongst low income population. A research performing a nationwide of Bike share facility showed that more than three quarters (1,556 or 2,063 or 75.4 percent) of bike sharing stations across the US were stationed amongst communities with higher or medium income range whereas only 245 (or 11.9 percent) stations were located in communities with higher economic hardship [2], [21]. This

emphasizes the importance of further study into how transit and bike share services are distributed amongst different population of ethnic minority and low-income group. In majority of the cities, the poor are likely to live in cities with more public transportation and are less centralized when the suburb-central city gap in public transit is reduced [22].

(National Council on Disability) NCD (2015) provided some updates recently on some chosen cities around United States, providing information on the nature of barriers or negligence public transportation users with disability face. Barriers of technical discrepancy such as inoperable lifts and ramps on fixed route transit bus are not only the case rather false claims of inoperable lifts or ramps to avoid boarding a person with a disability have also been identified. Other barriers identified includes failure to stop for public transportation user with disability, unpleasant attitudes of drivers, steep slope for ramp use, failure to clear wheelchair securement zones for people with disabilities, inadequate timing for stop announcement, and failure to provide route identification etc. Issues associated with fixed route rail transit has also been identified which includes failure to provide level-entry boarding at new or altered stations, absence of an accessible substitute when level-entry boarding is unfeasible, unreachable stations and cars, difficulties with reservations, and failure to provide dual-mode communication in the station or on the track [23]. These barriers require attention by providing improved policy to make public transportation more accessible to population with special disability needs. Also, spatial availability of public transportation where disabled population is concentrated is also essential in order to increase their mobility. A recent study on barriers faced by disabled public transportation users have found significant barriers for people with disabilities using public transportation and complementary paratransit services. The study suggested that the barriers to these transit systems are physical and attitudinal in nature, and as a result, and has suggested physical improvements to the current conditions [24] (Table 1).

Table 1: Summary of past study on transit and bike share use amongst low income, ethnic minority and population with disability.

| Study | Issues | Method | Data | Contribution |
|---|---|---|---|---|
| **Low income and Disabled** | | | | |
| Howland, McNeil, Broach, Rankins, MacArthur and Dill (2017) [17] | Equity policies and metrics, the degree to which equity considerations affect a variety of system practices, what the existing barriers to utilizing bikeshare are for target populations, and what challenges the bikeshare system entity faces in addressing those barriers | Survey | Results of representatives from 56 U.S. bikeshare systems | Bikeshare systems reported cost, access, and outreach as the largest barriers to equity, in addition to overall funding and staff levels. |
| Caspi and Noland ( 2019) [18] | Do lower income group generate bike trips? | Multivariate regression models | Travel patterns: 1-year data for Philadelphia's Indego Bikes share (April 2017-March 2018) | Bike share trips taken from docking stations in lower income areas are for mainly work commute trips. Lower income areas generate lesser trips while controlling for other factors such as transit access and stations proximity to bike lanes. |
| Miller and Savage(2017) [25] | Demand response to transit fare increase affect low income? | Pooled Regression | Data from four fare increases on mass-transit rail in Chicago | Lower income riders may have a tighter budget constraint but fewer alternatives |
| Qian and Jaller (2019) [26] | Station level analysis of bike share activity in disadvantaged population | Negative Binomial regression | Bikeshare station capacity, population, employment rate, bike path density, park area, and number of stations within 500 meters, Area with disadvantaged population | Rate of trips made by subscribers is smaller in disadvantaged areas than other (multiple barriers that discourage low-income individuals to have a membership). Residents in disadvantaged areas: longer bikeshare trips than in other if they already are subscribers. Since after joining as annual members, disadvantaged populations can enjoy real benefits by bikeshare, such as saving money on transport. |
| Bezyak, , Sabella, and Gattis,( 2017). [24] | Barriers to public transportation use for population with disability | Online survey and Pearson's chi-square analyses | Questions on public transportation and paratransit use. Other factors: Gender, Disability status, Employment status, City size | Barriers to these transit systems are physical and attitudinal in nature, and as a result, modifications to the physical environment and educational opportunities to reduce negative attitudes toward individuals with disabilities are recommended. |

### 2.1.2. Effect of variable age group

A study by UCLA on life cycle shows that transit use is high among individuals in their early 20s, declines as individuals progress into their 30s, and stabilizes until 65, or near retirement. The propensity to make a trip has been found to be declining amongst older Canadians while aging Americans are more likely to take a ride with friends or family when they ceased driving. About 1.3 percent of all trips taken by people over age 65 are made using public transit. Public transit use is lower than that of younger people[27]. Older adults with limited or no exposure to driving have been found to be reluctant towards transit use and should be encouraged more prior to cessation to driving [28].

A study conducted by APTA in 2013 on individuals between ages 22–34 found that more than half of those who traveled by bus considered it to be an affordable option for them. They have also highlighted many other personal and societal benefits for using public transportation such as digital socializing while traveling, connecting with their communities, working on route, and reducing the environmental footprint [29].Other studies have found a statistically significant relationship between transit use and residential locations. It is presumed that people with physical disability, financial constraints and inability to drive are more likely to live close to regions which are transit oriented. It has been found that low-income households without automobiles tend to be more likely to reside in transit rich neighborhoods where they can get around more easily using public transit. So, when considering the decision making process of the youth, they consider cost to be an important part of their choice [22] and 30% of youth ages 16–25 live in households below the poverty line, and almost half live in households below 200% of the poverty line . This trend is not only common amongst youth under poverty level but also is reflected in the travel attitudes amongst highly educated youth. Younger generation under the age of 30 as well as adults report that their "ideal" neighborhood type is in an urban area—either downtown areas with a mix of land

use or urban residential neighborhoods [30]. The travel choices of millennials have also been found to be not only influenced by economic factors such as income employment etc. but also as a result of  a shift in values and preferences which may be a reason for their preference of transit [31].

A growing acceptability of Bike share has been found amongst millennials in various research. A recent study on New York city bike share showed that intersection density is positively related to younger millennials' bike share trip production while the factor was not significant for older age groups [32]. This trend in of greater significance of bike share in areas with more intersection density supports the fact that youth who are more likely to live in an urban region are also more likely to use bike share. A recent study in Melbourne Australia showed that younger generation in the age bracket of 18–34 who had access to docking station within the proximity of 250 m of their workplace were statistically significant predictors of bike share membership. The study also found that youths with high incomes has a greater odds of bike membership [33]. This shows that younger generations who have a steady financial condition uses bike share for their commuting purposes. The past study along the years have shown that younger generation prefer urbanized living and are inclined towards public transportation. Also, due to the recent trend in growing bike share facility, transit and bike share has been dwelling side by side. It is now necessary to investigate how youths are responding to bike share and transit to answer the following questions: Are younger generation a more significant user of transit or bike share? Does coexistence of transit and bike share have an effect of the younger generations' use of public transportation? (Table 2).

Table 2:Summary of past study on transit and bike share use amongst different age group.

| Study | Issues | Method | Data | Contribution |
|---|---|---|---|---|
| **Age** | | | | |
| Driscoll, Lehmann, Steven Polzin, and Godfrey [1] | The Effect of Demographic change on Transit | Estimate the number of theoretical transit trips that should occur under any given age distribution, (NHTS trip rates and transit usages by age) | NHTS, APTA, ACS | Lower share of the population in the young age cohorts have a higher propensity for transit use. Population growth is occurring in counties with lower levels of transit service and use. |
| Grisé, and El-Geneidy [34] | Assessment of Generation Difference in public transit use | Surveys. | Personal and household travel characteristics, including length of trip, mode used, and trip purpose | Older generations used public transit more than younger generations did at the same age. Public transit can provide an alternative to the automobile by safely maintaining the independent mobility of seniors; providing greater sense of dignity and aiding older adults in the challenges faced with the cessation of driving |
| APTA (2013) [29] | Identifying mobility needs of young adults | Interviews, Quantitative online Survey | | Transit is an affordable option for young age group, and they use it for Personal and societal (digital socializing, connecting with their communities) |
| Blumberg, Taylor, Michael, Ralph, Wander, Brumbagh,.(2012) [31] | Identify travel behavior of teens and adults | Statistical Models | Travel behavior teens (ages 15–26) and middle-aged adults (ages 27–61) | Economic Factors: employment status, household income, and the like—strongly influence the travel behavior of both adults and youth |
| Kailai, Gulsah and Yu.( 2018) [32]. | The focus is cohort differences among Millennials, Gen Xers and Baby Boomers. | Zero-inflated negative binominal models | NYC's Citi Bike data (trip productions at bike-share stations); Weather and built environment | Intersection density is positively related to younger Millennials' bike share trip production. However, this factor is not statistically significant for other age groups. |
| Watson, Haworth, Washington. and Fishman, (2015) [33] | Factors influencing bike share membership | Online survey and Logistic regression | Working and residential population in proximity to bikeshare (bike share membership) | Respondents aged 18 - 34 and having docking station within 250m of their workplace were statistically significant predictors of bike share membership. High income group increased the odds of membership. |

## 2.2. Emergence and Success of Bike share

With the emergence of bike sharing systems and the growth of bike sharing ridership in different parts of the world, a fair count of study has been conducted to evaluate feasibility of bike sharing systems. A study on Capital Bikeshare, Denver B-Cycle, and Nice Ride MN showed that proximity to a greater number of other bikes sharing stations demonstrates a strong positive correlation with bike ridership. Controlling for other factors such as demographic and built environment it was found that comprehensive network of stations is a critical factor supporting ridership [35]. Expanding the number of bike stations and bicycles does not have significant contribution towards improving system performance rather the greater influence in as a result of better bike infrastructure. Resulting the new trend of Bike share , funding and advertising is available but there still exists a gap in service availability due to absence of equity considerations [36].An online survey based analysis signifying 23 bike share system form considering four countries performed estimated that 44.13% of trips were made by women, 8.81% by children, 10.40% by older adults, 18.13% by ethnic minorities, and 12.67% by persons of low income. The study revealed that ease to bike share access is the top motivator from user side to use a bike share facility and on the supplier side the maximal priority if given to increasing the bike sharing users and increasing the number of trips. A gap has been identified regarding accessibility of bike share facility for low income population groups. Although several programs are undertaken to make bike share accessible to low income groups, many of the programs are performed in conjunction with low income housing and by providing free income membership. However, most of the programs are not specifically targeting minority community or specific group [37]. Gap in existence of equity in bike share service has been found in many past researches and which also coincides with the gap in equity in public transit use. While considering transit as a first and last mile option it is

necessary to consider the impact of bike share on the ridership of transit in low income, senior population and amongst different ethnic minority.

A study performed on Chicago Divvy found that neighborhood racial and ethnic diversity, proportion of condominium units, job accessibility to public transit and the average daily diversity of Divvy trips, are all strongly and positively correlated with total annual station trips. On the other hand, percentage unemployed, average distance to Divvy stations and percent of residential foreclosures are negatively correlated. The study highlighted that the use of bike share system amongst low income group and ethnic minority group is very scarce indicating that these minority group face substantial barrier to using bike share facility and hence warrants a need for expansion on the available equity program in order to facilitate increase ridership in transportation disadvantaged communities. Finally the study reinstated that accessibility of bike share service is a significant contributor to the increasing ridership of bike share facility [21].

Several researches have investigated factors like neighborhood design or characteristics of the built, accessibility or spatio-temporal relationships, distribution of bike share stations, accessibility to transit stops and jobs; others analyzed socioeconomic or demographic variables linking to population structure and economic performance. It has been found that young-adult individuals are more likely to use bike sharing than other age groups. Past research suggested that investigation on the bike-sharing behavior of the older Z generation (18-22 age group) individuals may support a better interpretation of bicycle use patterns and anticipations of future adult individuals [38].Other studies suggested that the efficiency of the bike share system is not contingent upon the size of the city where the bike share is located, rather it is dependent upon the distribution of the bike share rentals. It was also suggested that efficiency of bike share service was also dependent on the trip purpose (proximity to night club if for recreational purpose) and city expansion. For

instance, the most significant variables shaping the trend of bike share tends to be population, distance to city center, leisure associated enterprises, and transport-related infrastructure [39]. Another study performed on Chicago divvy bike share found ridership of both members and 24h users are positively related to number of employed residents nearby and capacity of the station and is negatively related to the distance to central business area and the proportion of low-income population in proximity. Number of employment has been found to be significantly affecting the trip purpose for the case of bike share [40]. This generates the question that if bike share trip generation is related to the number of working-class groups then which income level those working-class group belong to? Is the Divvy bike share in Chicago supporting the transit use hence serving as a first or last mile option? Finally, are the new expansions to Divvy stations being made in disadvantaged areas or is it otherwise? (Table 3)

Table 3:Summary of past study on Bike share: Factors affecting bike share use, Issues and socio-economic behavior.

| Study | Issues | Method | Data | Contribution |
|---|---|---|---|---|
| **Factors affecting Bike share use** | | | | |
| Rixey [35] | Station level analysis of factors affecting bike share | Regression Analysis: Bivariate correlations | Bike sharing station rental data: (Population, Jobs, Income, Non-White Population, Low-Vehicle Households | Proximity to a greater number of other bike sharing stations exhibits a strong positive correlation; Access to a comprehensive network of stations is a critical factor supporting ridership. |
| Chardon, Caruso and Thomas. (2017) [36] | Factors affecting bike share success | Iterative Mixed Model Comparison | Estimated the number of daily trips from publicly available data for 75 Bike Share Services. Trips per day per bike. | Increasing the number of bike stations and bicycles does not increase system performance. Bike infrastructure affects system performance. lack of equity considerations in system distribution |
| Smith and Hasan (2019) [21] | Social, spatial and temporal pattern of bike share. | Multivariate adaptive regression splining (MARS) | Neighborhood design; access, socio demographic variables and bike share network specific factor | Neighborhood racial and ethnic diversity, housing unit, job access -strongly and positively correlated with total annual station trips; Percentage unemployed, average distance to Divvy stations and percent of residential foreclosures are negatively correlated. |
| Yang, Zhang, Zhong, ,Zhang and Ling (2020) [40] | Spatial variation of bike share trip production and attraction | Semi-Parametric Geographically weighted regression model (S-GWR) | Divvy ridership, Trips starting station, end station, start and end time, membership information | Ridership of members and 24h users are positively related to number of employed residents; capacity of the station -negatively related to the distance to central business area and percent of low-income worker nearby. |
| Eren and Uz (2019) [38] | Factors affecting bike sharing demand | Survey | Weather, built environment, land use, public transportation, station level, socio-demographic effects, temporal factors, safety | But young-adult individuals are more likely to use bike sharing than other age groups. |

## 2.3. Micro-mobility – First and Last mile Goals

Recently Bike share continues to get more attention as first and last mile trips are getting more importance while establishing seamless connection between public transportation. However, first and last mile transportation solutions and their use are often reliant on sociodemographic and built in environment. The first/last mile problem that can be defined as the challenges caused by the built and social environment [1]. That is whether there is access to public transit or bike share to establish the first and last mile option amongst all communities.

### 2.3.1. Bus and Bike Share

A study performed on New York analyzed the effect of Citi bike share on the Daily unlinked bus trips (NYCT). Bike ridership data daily total ridership, bike membership data, Bike share trip history, and number of docks per station was considered to find the effect of bike share by implementing Difference in Difference model. The study found that there was a 2.42% reduction in daily unlinked bus trips in Manhattan and Brooklyn as a result of adding bike share [41]. Survey performed on Minneapolis and Washington D.C. showed variations in modal shift as a result of integration between bike share and bus. In Minneapolis, the shift towards using rail is more relevant to urbanized area whereas modal shift for bus is more scattered. Increased age, male, living in lower density areas and longer commute distance was identified to be characteristic associated with moving towards the direction of public transport [42]. A further study comparing Montreal, Washington D.C, St. Paul and Minneapolis showed variations of effect of shifts in travel choice.

The survey results revealed that Montreal and Washington D.C. displayed significant reduction in the bus usage which is 47% of Montreal and 39% of Washington D.C. respondents mentioned

shifting away from using bus as a mode choice. However, about 6% of Montréal and 5% of Washington D.C respondents admitted using bus more as a result of bike. However, in comparison with the percent of respondents shifting away from bus use is small. In comparison to the previous two cities Toronto demonstrated a lower percentage of respondents shifting away from bus use (21%). However, 2% of the respondents stated that bike share has increased their bus use and is a relatively small percentage with respect to 21%. Similar shifting away trend has also been found in Minneapolis, however the difference between the percent choosing bus as a result of bike share and percent shifting away from bike share is relatively small [43].

The research on New York Citi bike share and Bus compares the change in bus usage as a result of bike share by comparing the data before and after addition of bike share. The comparison does not represent the effect of adding bike share in the same time period, that is the change in percent bus usage as a result of adding bike share at the same time. The study from did not control for all the sociodemographic and built in factors which could affect the bus ridership, such as fare, population economic activity etc. The study suggested future research to contribute by analyzing the effect of equity while considering change in transit usage as a result of bike share (Table 4).

Table 4:Findings from past study: Effect of bike share on Bus ridership.

| Study | Issues | Method | Data | Contribution |
|---|---|---|---|---|
| **Bike share complement or substitute-Bus** | | | | |
| Campbell and Brakewood [41] | Impact of bike share ridership on city bus | Difference in Difference regression model (Ordinary Least Square Regression model) | Daily unlinked bus trips (NYCT); Bike ridership data daily total ridership and membership data; trip history, Citi bike station feed data with total number of docks per station. | 2.42%reduction in daily unlinked bus trips in Manhattan and Brooklyn |
| Martin and Shaheen (2014) [42] | Transit modal shift dynamics as a result of bike share. | Survey data from two us cities. ordinal regression model | Sociodemographic associated with modal shift through cross tabulations and regression | Washington D.C.: those shifting towards bus and rail transit is more dispersed. Minneapolis: the shift towards rail extends to urban core, while modal shift for bus is more dispersed. Attribute associated with shifting towards public transport: increased age, male, living in lower density areas and longer commute distance |
| Shaheen ,Martin and Cohen (2013) [43] | Public bike sharing modal shift behavior | Survey | Member survey: modal shift pattern and demographics | Montreal and Washington D.C.: most notable shifts away from bus usage. In Montreal and Washington D.C., 47% and 39% reported using the bus less, respectively. In contrast, 6% and 5% of respondents reported increasing their bus usage in those cities, respectively. In Toronto, the shift away from bus was smaller at 21% of respondents, but it still contrasts starkly with the 2% that reported increasing bus usage as a result of bike sharing. Notably, in the Twin Cities, more respondents also shift away from bus than towards it, but the difference between those increasing and decreasing is only 3%. |

### 2.3.2. Rail and Bike Share

Several studies have been performed to analyze the effect of bike share system on rail ridership. Bike sharing system has been found to be increasing Rail ridership in Washington D.C. It was found that 10% increase in CaBi trips would generate a 2.8% increase in transit ridership and indicative of serving as a first and last mile option by providing connections between rail station and trips origin and destinations. Good accessibility to bike station is concluded to be the prime factor for the increase of the rail ridership as majority of the bike share station with highest ridership are in close proximity to rail station [44].Another survey of regional train service customers in the Greater Toronto and Hamilton Ontario, Canada found safety concerns, reliability of bicycle security, and restrictions on the hours bikes are allowed on train were found to be the primary concerns expressed by survey respondents and that affects their decision making. Some other minor factors considered included appearance and comfort for respondents who do not choose train as their mode choice. Results obtain highlight existence of gender gap amongst transit users and 67% of the bike share users who uses rail transit are male. The factors analyzed by the study are gender, annual income, age, accessibility and the results indicated a greater need of attention towards equity in integration of transit and bike share [45] (Table 5).

Table 5:Findings from past study: Effect of bike share on rail ridership.

| Study | Issues | Method | Data | Contribution |
|---|---|---|---|---|
| **Bike share complement or substitute-Rail** | | | | |
| Barber and Starrett (2018) [46] | How bike share affects rail transit? | Panel regression/ Station level | Bike share ridership data from the Divvy bike share system was collected within a 400 meter (0.25 miles) | The number of bike share stations in a buffer and the number of years they have been around also has increasingly positive effects. |
| Ma, Liu & Erdoğan (2015) [44] | How Capital Bike share affect Washington D.C. metro? | Ordinary least square regression models/ Station level | Transit ridership (dependent variable); bike ridership (independent variable). Built environment, and sociodemographic | CaBi stations with the highest ridership are located close to Metrorail stations, and some have good accessibility to multiple stations. A 10% increase in CaBi trips would generate a 2.8% increase in transit ridership. |
| Griffin and Sener. (2016) [47] | Evaluates local intermodal plan goals using trip data and associated infrastructure such as transit stops and bike share station locations in Austin, Texas, and Chicago, Illinois. | Survey- Mixed methods approach | Bike share use data with proximity to rail transit are analyzed; Trip data, transit stops and bike stations | Bike sharing use data from both cities suggest a weak relationship with existing rail stations that could be strengthened through collaborative, intermodal planning. |
| Shaheen, Martin and Cohen (2013) [43] | Public transit modal shift behavior | Survey | Members of major bike sharing organization-travel behavior and modal shift, member perception about bike sharing | As with the modal shift away from bus, the results from Montreal, Toronto, and Washington D.C. suggest that bike sharing induced 50%, 44%, and 48% of respondents to reduce their use of urban rail, respectively |

# CHAPTER 2

# DESCRIPTIVE ANALYSIS

Many recent studies considering bike share systems are emphasizing on the  gap in equity in micro mobility [17], [18], [21] which is also preexistent in public transportation services. Social and demographic characteristics , economic pattern of the population and population with auto ownership have been found to have a significant effect on the level of bike share Chicago [21].

Although Chicago plays an influential role in the global economy, the city is also known for its widespread racial and economic segregation. The city of Chicago is home to 2.7million residents and is also known to be the largest city despite of losing 1 million people since 1950 [48].The escalating income equality has intensified the long lasting issue of residential , economic and racial segregation [5]. The North Shore of the City has been primarily dominated by the White homeowners while the south side of the suburbs and surrounding area has been dominated by declining population and lack of economic investments. The city's urban redevelopment and housing policies has caused majority of the African American to be located in south and west sides of the city [49]–[51]. According to the 2000 Census, over 600,000 Chicago residents, approximately 23 percent of the City's total population, reported having a disability [52]. Several past research on public transportation reported that users experience technical, operational ,and attitudinal barriers associated with the use of public  transportation [23] [24]. This demands an insight into the distribution and effect of population with disability to assess their level of usage and accessibility to public transportation.

As micro mobility becomes a popular option to solve the first and last mile issue, it becomes increasingly important to identify how these social and demographic factors are affecting the transit ridership in areas with bike share facility in comparison to an area which does not have bike share facility. Consequentially, this will also raise the question that to what extent do these factors affect ridership of transit stations who are facilitated with bike share as a first and last mile option.

## 1. Annual Ridership trend versus Population Change

The Figure 1 below show and overall declining trend in bus ridership for the city of Chicago. Between the year 2007 and 2013, a percentage decline of 10.7% of bus ridership was found. The decline trend continued sharply after the emergence of Divvy in 2013 and hence between the year 2013 to 2018 there was a further decline in bus ridership of about 12.2 %. Consequently, the rail ridership demonstrated a rise in trend between the year 2007 and 2013 with an overall increase in annual ridership of 20.38 %. On the other hand, Divvy had been increasing in popularity amongst its users since its birth in 2013. Divvy ridership shows an overall growth with some slowdowns between 2015 and 2016 and a steady decline between 2017 and 2018 as shown in the extrapolated graph inserted in the main graph. Overall, annual Divvy ridership had three phases of increase between the period of 2013 and 2018.

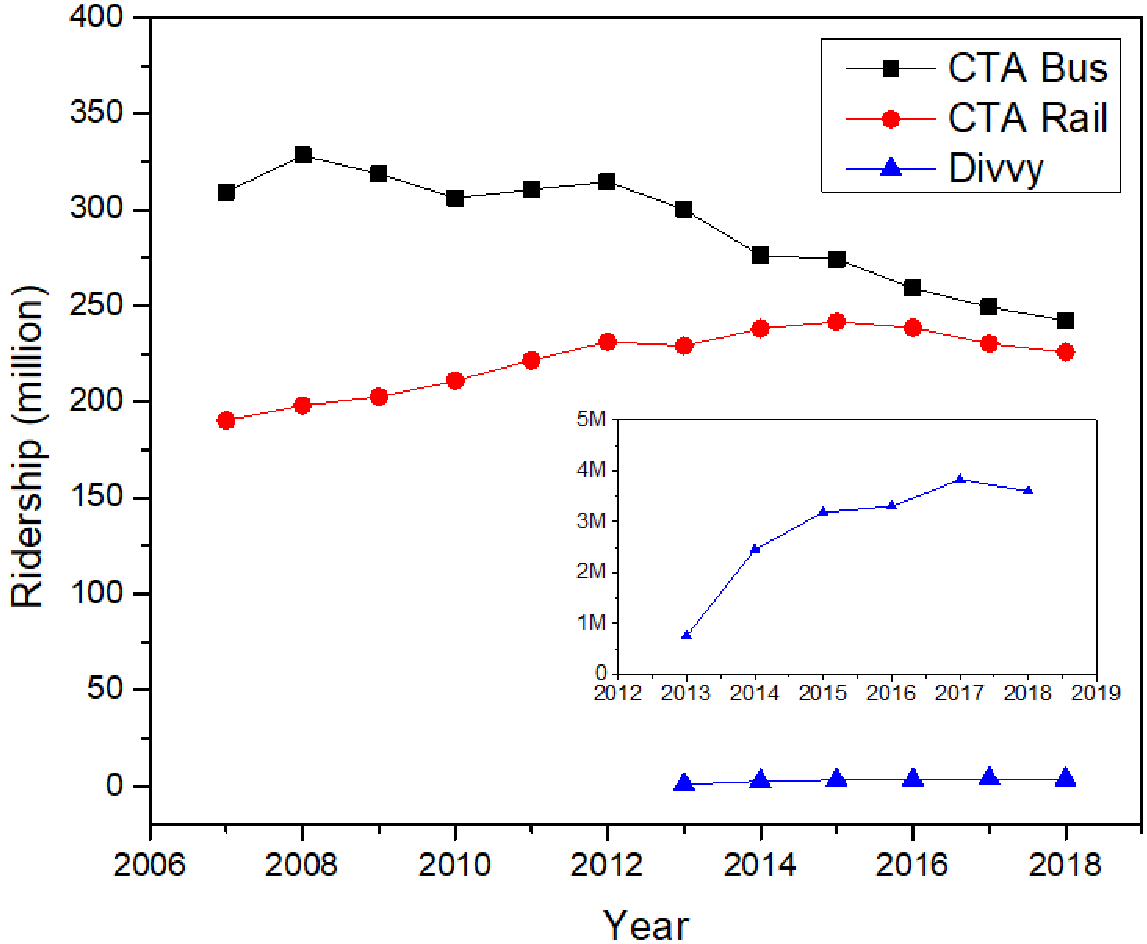


Figure 1: Annual Ridership trends of Bus, Rail and Bike over years.

Figure 2 below shows the trend of change in resident population in the city of Chicago. The population growth shows a steady rise till 2014 but then again drops back to 2018. So, the overall population change between 2010 and 2018 is small (8465). If there is not much population change during this period, then the overall changes in transit ridership as well as the rise in bike ridership is not a result of increase in population. Rather, this shows that the over trend in transit and bike share ridership is a result of people's travel choice. This travel choice can be dependent on many factors such as: access to vehicle, access to transit, access to bikeshare etc. The travel choices may also vary in different population mix such as younger population prefer urban life [29] whereas

for low income population, transit is mainly for commute purpose and their choices are very limited [25]. Consequently, for senior population quality of transit service has a huge impact on their usage [1].

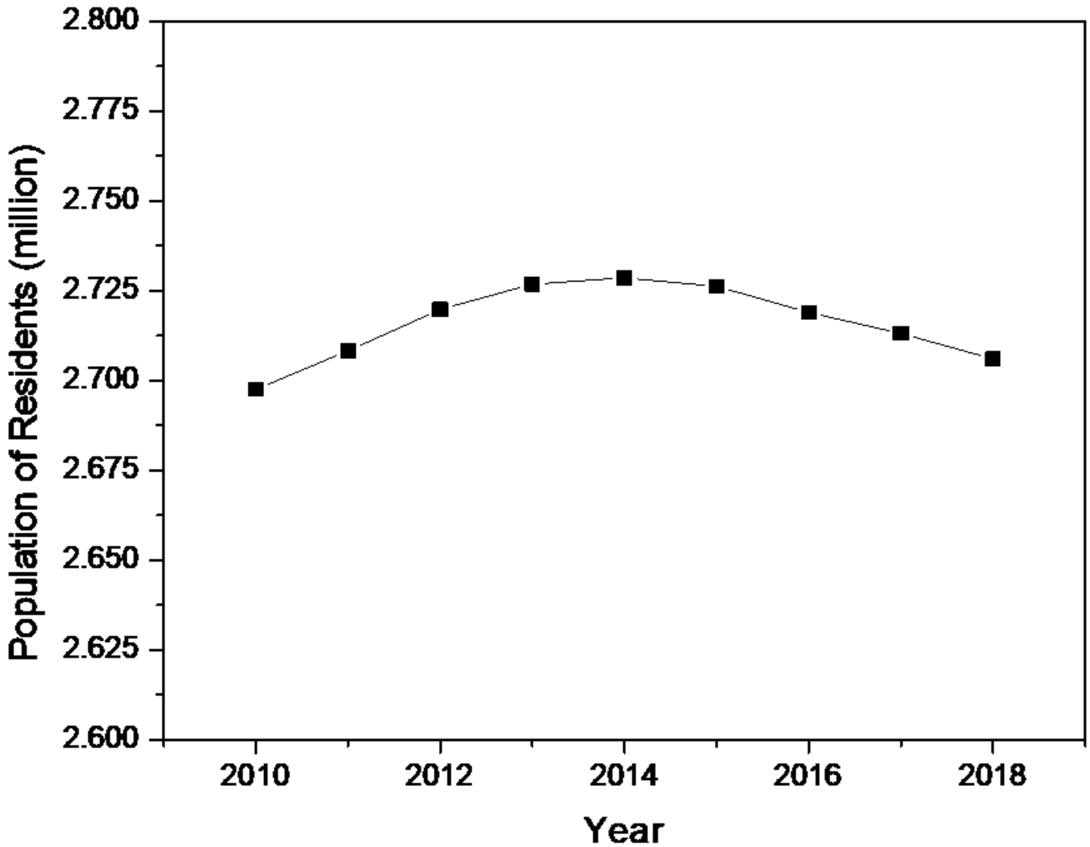


Figure 2: Population change over years (2010-2018)

## 2. Access to Transit and Bike share

Figure 3 compares the density of bus, rail and bike share service per unit area in each community. By comparing the three, bus is most evenly distributed amongst three. However, the bus service access in the Far south west and Far South east community is least in comparison to all the other seven communities. The map showing the rail accessibility, reveals that Central, North Side has the maximum access to rail transit. However, Far North Side has a relatively lower rail service in comparison to North side, Central and West and Near west. But on the other hand, the Far Southeast and Far Southwest side has the lowest rail accessibility in comparison to all the other communities. Finally, Bike share service is mainly concentrated in the Central, Northside and some parts of Far North side. The South west, West and Near west side has very low concentration. Bike share service is almost nonexistent in the Far south east and Far south west side.

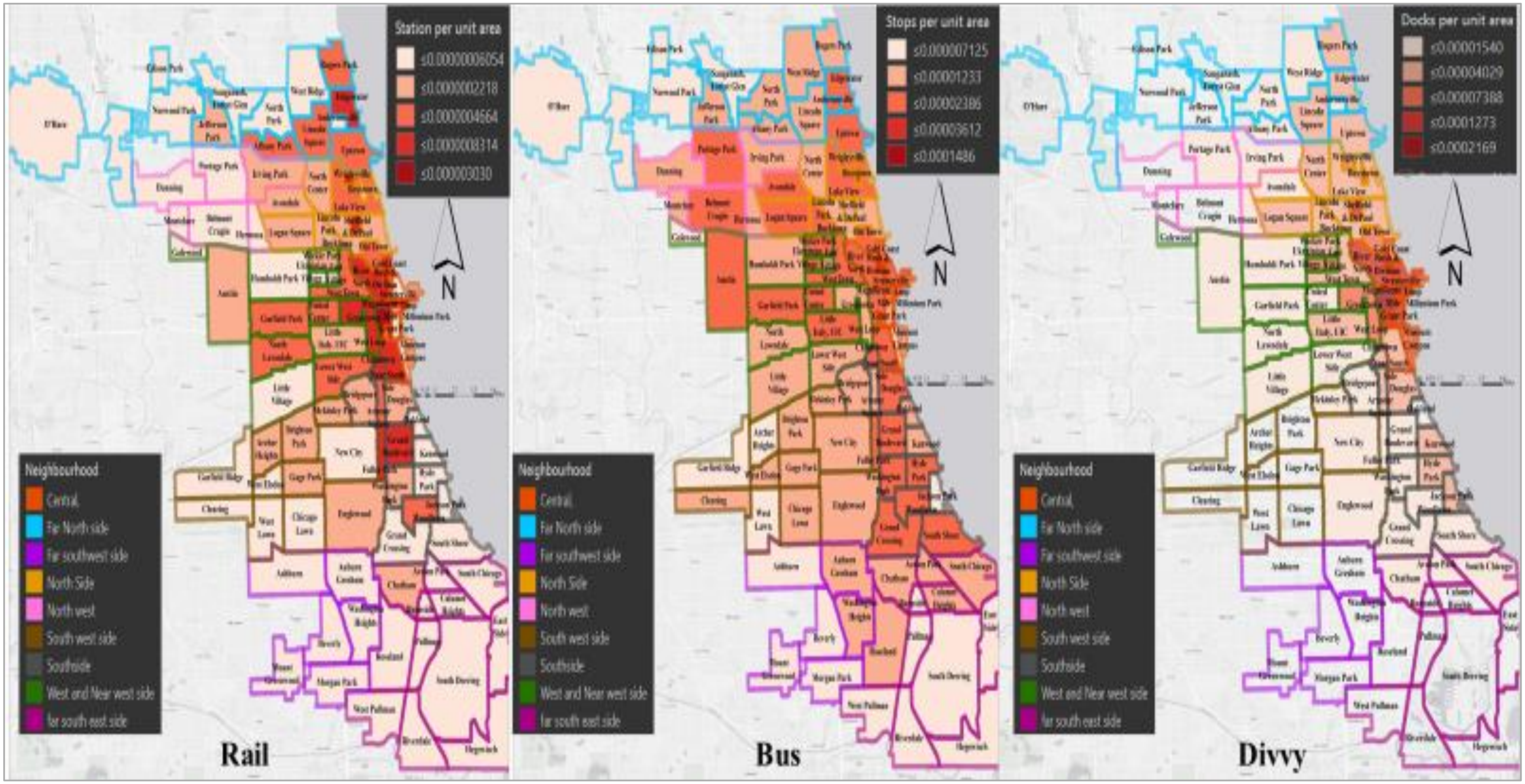


Figure 3:Density of rail, bus and bike service per unit area

# 3. Station/Stop level Ridership Trends

## 3.1. Bus-With and without bike share

Figure 4 makes a comparison between trend in station level bus ridership for bus stops with bike share system and bus stops without bike share system. The total number of bus stops considered is 9756, out of which 54% does not have bike share and 46% has a bike share system within 400m proximity. The mean stop level ridership for stops without bike share is 26.9 and that for the bus stops with bike share is 63.34 making the ratio of average stop level ridership with bike share to average stop level ridership without bike share 2.5times. This is also evident in the visual representation of the plots for average weekday stop level ridership for with and without bike share which shows that the average ridership per station with bike share system is significantly higher in comparison with bus stops without bike share system within a proximity of 400m.

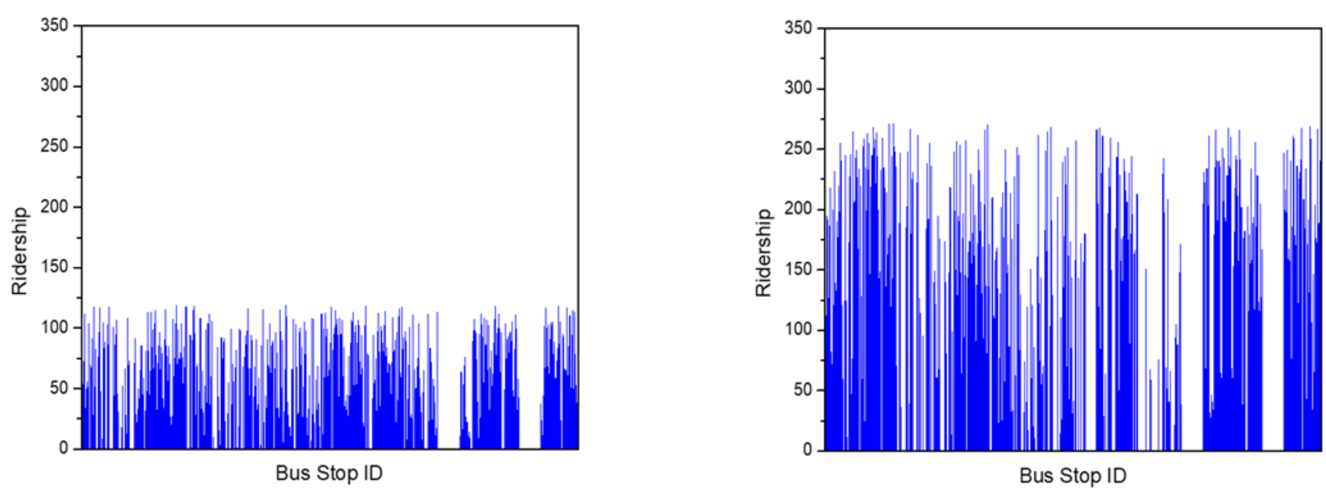


Figure 4: Graph of average annual station level bus ridership with and without bike share.

## 3.2. Rail-With and without bike share

The figure below Figure 5 shows the average weekday station level ridership (October 2018) for rail stations in Chicago with and without bike share. The bar chart on the left represents average weekday ridership of stations without bike share. There are about 26 rail stations which do not have bike share which is about 18 percent of the total number of stations (144 total rail stations). The graph on the right side of Figure 5 visualizes the average weekday station level ridership (October 2018) for rail stations with bike share. There are about 118 rail station with bike share facility within a proximity of 400m which makes about 81% of the total number of rail stations in Chicago. Comparison of the trends of the two bar charts shows that the average ridership of stations with bike are slightly greater than that of the average weekday ridership for rail stations without bike share. The average weekday ridership for all stations with bike share is 3868.84 and that of stations without bike share system 3107.69. Thus, the average weekday station level rail ridership with bike share is 1.3times than that of rail stations without bike share within a proximity of 400m.

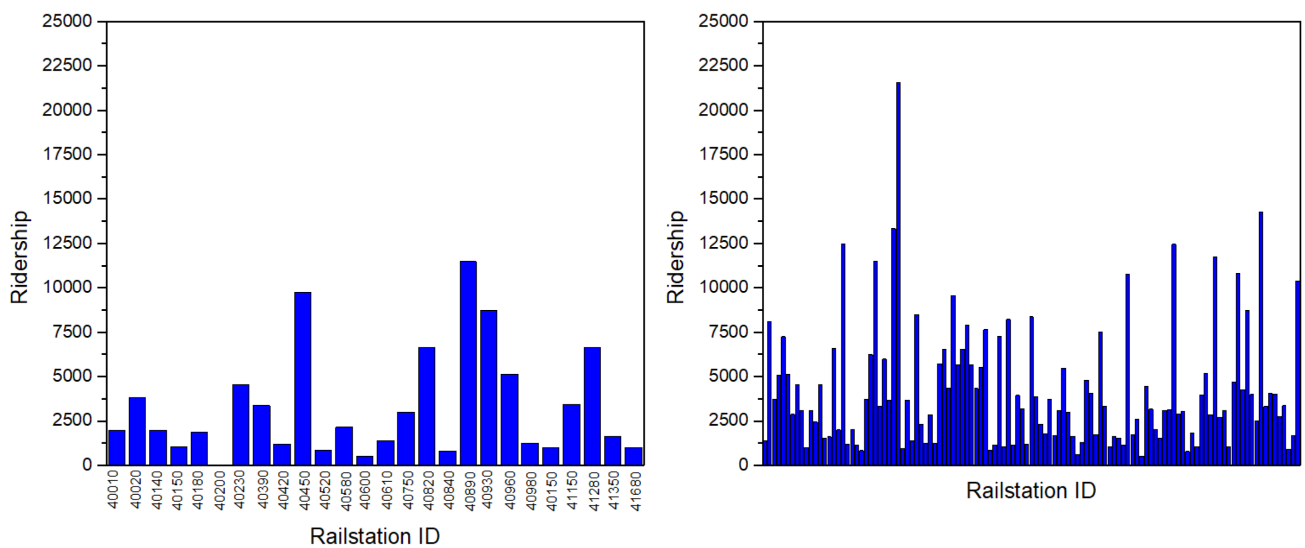


Figure 5: A comparison between average weekday station level rail ridership for stations with and without bike share

## 3.3. Descriptive statistics

Figure 6 and Figure 7 shows the descriptive statistics of the average weekday bus ridership with and without bike share. The horizontal lines of each box represent the first quartile (Q1), median, and third quartile (Q3) values of the variable, while the bottom and top whiskers indicate the minimum and maximum values, respectively.

Figure 6 makes a comparison between the average weekday bus ridership of stations with bike share to average weekday bus ridership of stations without bike share. The minimum value for average weekday bus ridership for both with and without bike share is zero. But the top horizontal line represents the maximum average weekday bus ridership with and without bike share. The maximum ridership for station with bike share is greater than without bike share. Similar trend is also observed on comparing the Q1(25% of the data) and Q3 (75% of the data) ranges for each case. The total samples for stations without bike share are 5282. The mean of ridership for stops without bike share is 26.9rides per day, the median is 15.5 rides per day and maximum ridership is 119.4 per day average weekday ridership. There are 4471 samples of stations with bike share for which the mean ridership is 63.29, the standard deviation is 65.52, the minimum is zero, median is 41.6 and maximum ridership is 271.4 rides per day for average weekday.

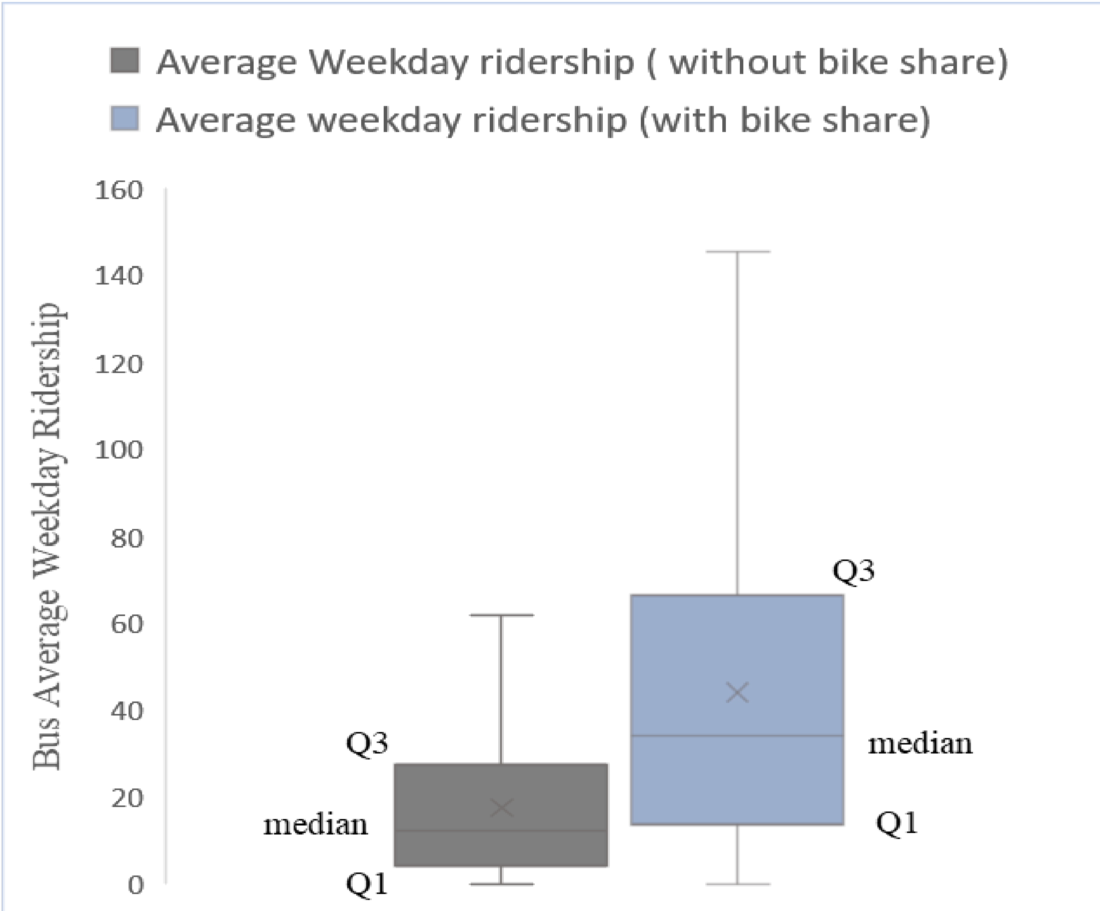


Figure 6: Descriptive statistics of bus ridership with and without bike share.

Figure 7 makes a comparison between the average weekday station level rail ridership of stations with bike share to average weekday bus ridership of stations without bike share. The minimum value for average weekday rail ridership for stations with bike share is greater than that of without bike share. But the top horizontal line represents the maximum average weekday rail ridership with and without bike share. The maximum ridership for station with bike share is greater than without bike share. Similar trend is also observed on comparing the Q1 (25% of the data) and Q3 (75% of the data) ranges for each case.

There are 543 samples (n) for stations without bike share. The mean average weekday ridership is 3107.69 rides per day, standard deviation is 2464.8 rides per day, the minimum ridership is 441

rides per day, the median is 2136 rides per day and the maximum average weekday ridership for station without bike share is 7755rides per day. There are 2544 samples (n) for stations with bike share. The mean of average weekday station level ridership for stations with bike share is 3868.84 rides per day, the standard deviation is 2701.5 rides per day, the minimum ridership is 82 rides per day, the median is 2046.5 rides per day and the maximum station level ridership is 9086 rides per day.

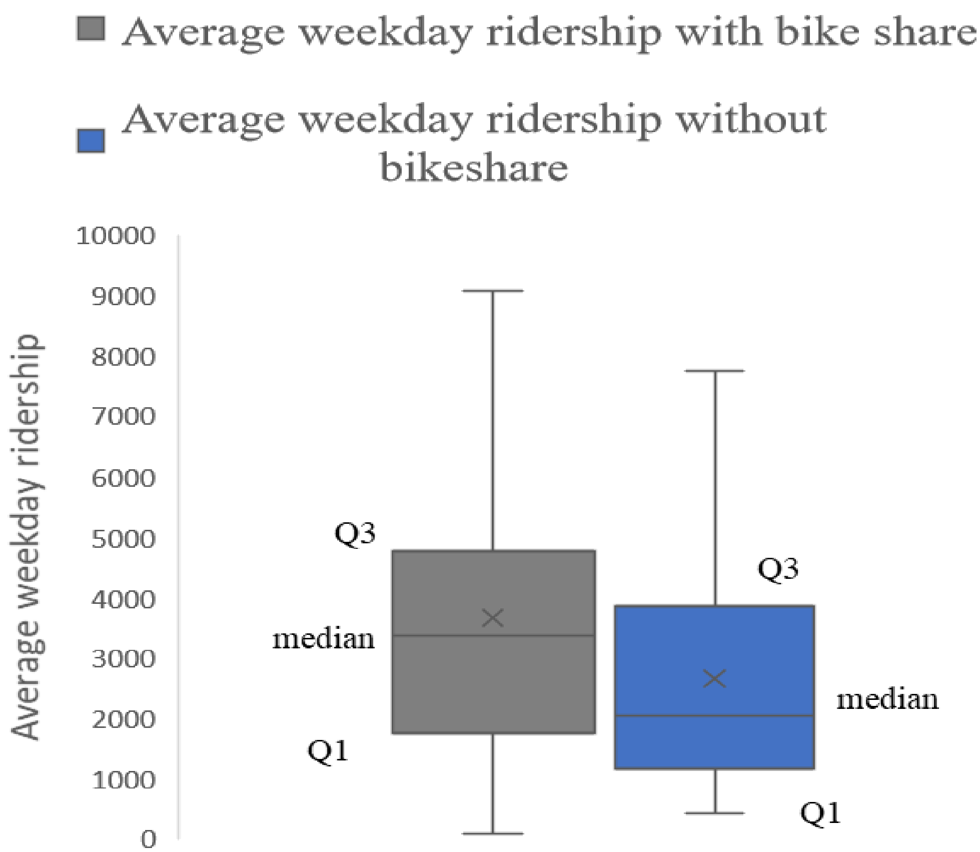


Figure 7:Descriptive statistics of rail ridership with and without bike share.

# 4. Community Level Population Distribution

## 4.1. Ethnicity

The Central community has the highest population of white (47%), followed by North Side (35.6%), Far north west side (31.7%) and North west (30.33%). Black population is highest in the Far South East Side, followed by south side (29.6%) community has the second highest neighborhoods with black population. Hispanic population is highest South west side (16.63%) followed by North west (10.83%) which is the second highest. The rest of the communities in Chicago has Hispanic population under 10%. Asian population is lower than 10% in all communities in Chicago with highest population in Central ( 6.4%) Chicago (Figure 8). This shows that an ethnic segregation clearly exists amongst the communities in Chicago.

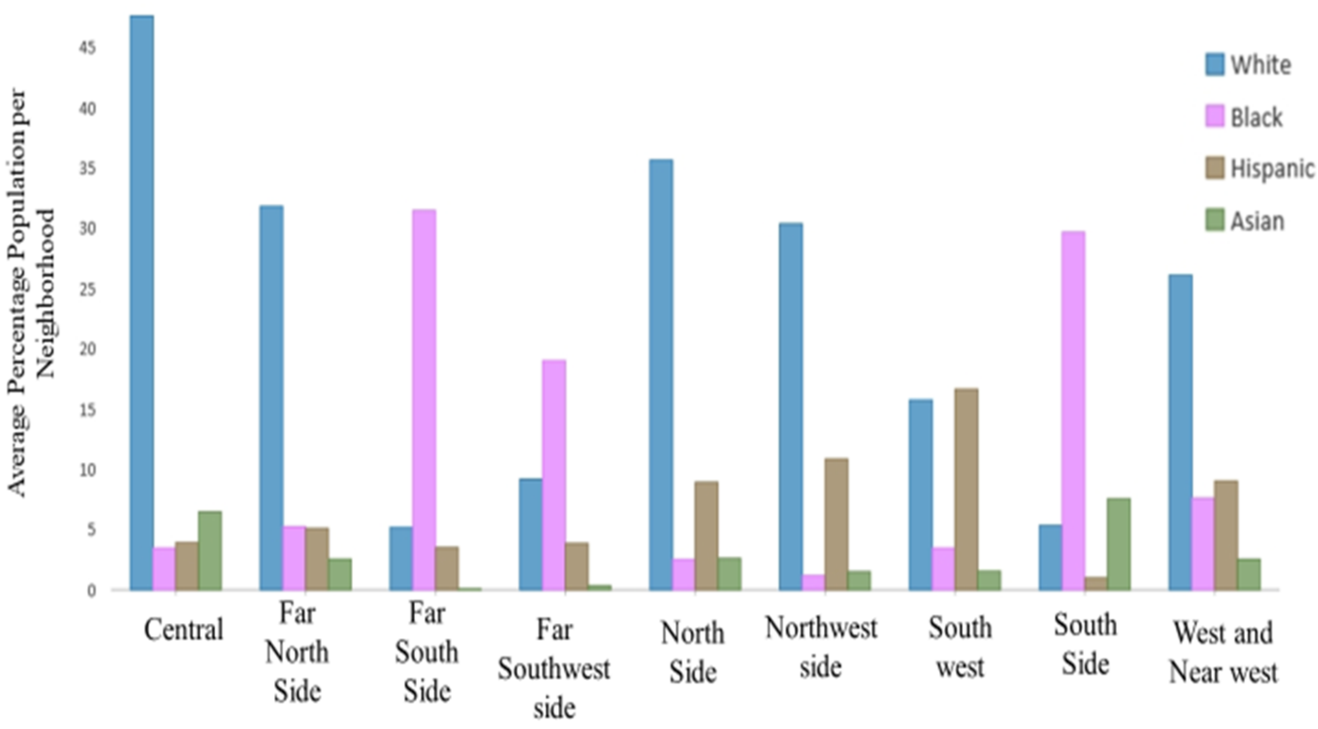


Figure 8: Percent population of Different Ethnic Group in Each neighborhood

## 4.2. Disability

The bar chart below shows a plot of Average Percentage population per neighborhood of population with disability for each community side in Chicago. The highest percentage of the population with disability per community exists in the Far South Side (7.75%) and followed that South Side (7.07%) has the second highest population with disability. The Central (Near north and Near south) community has the least average percent population with disability (2%) (Figure 9).

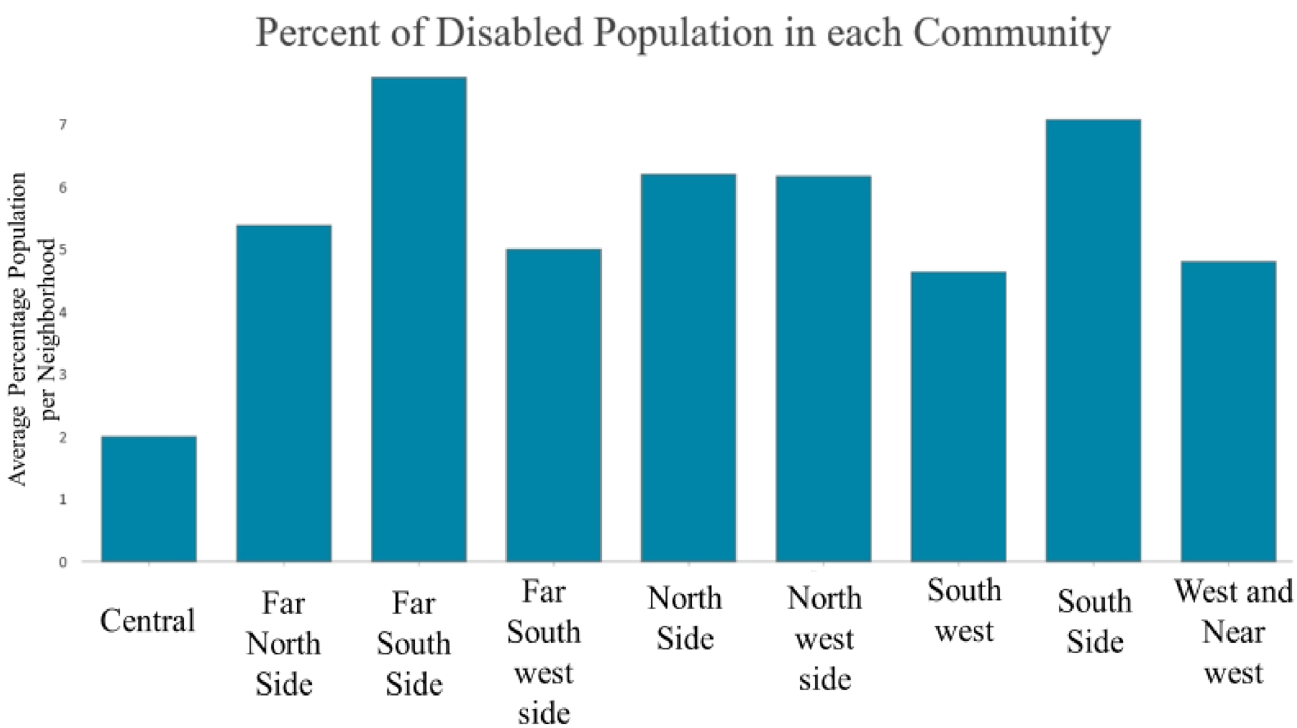


Figure 9: Percentage of Population with Disability in each community in Chicago

## 4.3. Age Groups

The bar chart below shows a plot of Average Percentage population per neighborhood of different age groups for each community side in Chicago. The West and Near west side has the highest average percent of community population within the age range of 15 to 34 years (38.6%) and the Central (Near north and Near south) has the second highest average percent of community

population within the age range of 15 to 34 years (36.8%) and followed by that is North side (35.1%) community. North west community has the lowest average percent of community population within the age range of 15 to 34 years (22%). The percent difference between the highest and lowest percentage is 16.6%.

Northwest community has the highest average percent of community population within the age range of 35 to 64 years (44%) and Far North Side has the second highest (43.46%) average percent of community population within the age range of 35 to 64 years. The lowest average percent of community population within the age range of 35 to 64 years is in the West and Near West Side (35.06%). The percent difference between the highest and lowest percentage is 8.94%. Far South west has the highest population of senior population (18.5%) and then South side community has the second highest (17.69%) average percent of community population within the age range of over 64 or senior. West and Near West side have the lowest average percent of community population within the age range of over 64 (7.53%).The percent difference between the highest and lowest percentage is 10.37% (Figure 10).

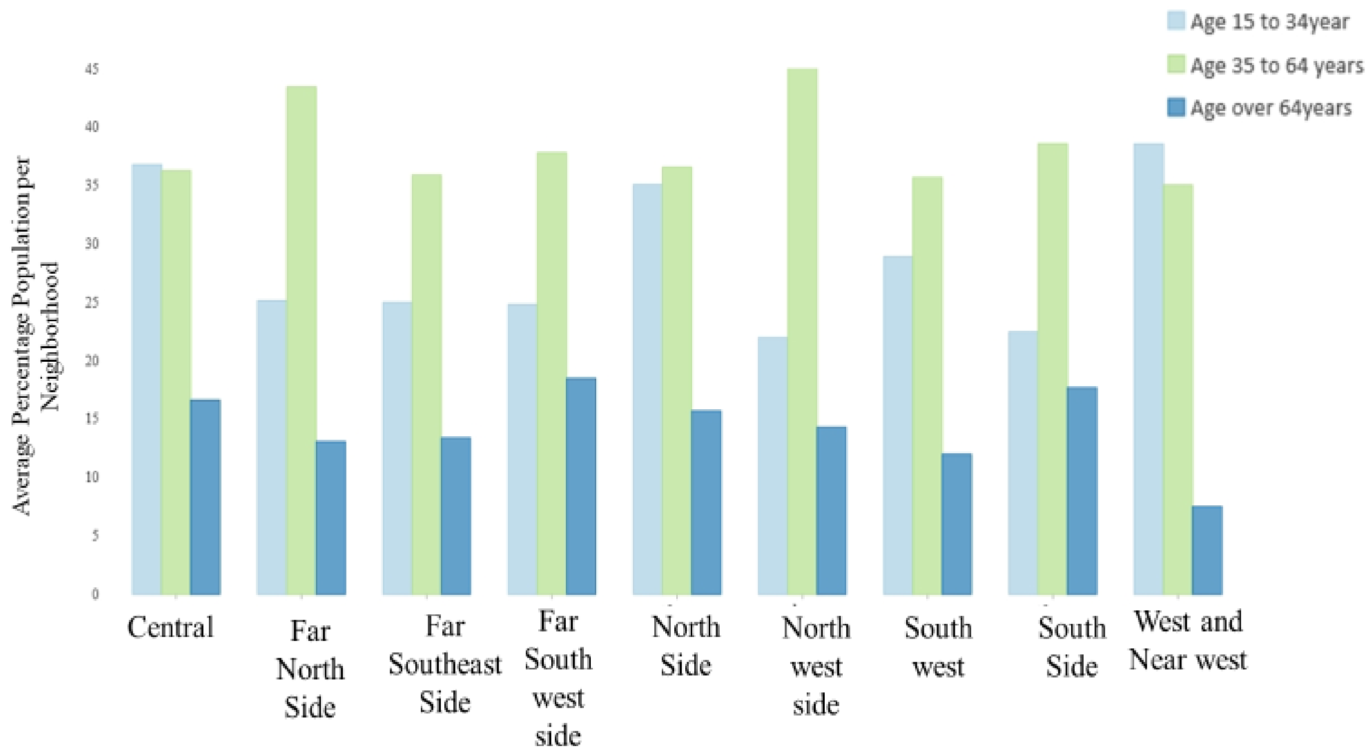


Figure 10: Population distribution of different age group in Chicago Neighborhoods

## 4.4. Income Groups

The bar chart below shows a plot of Average Percentage population per neighborhood of different income groups for each community side in Chicago. The South Side community of the city has the highest average percent population (26.15%) per neighborhood for income under $40,000 and this followed by Far South east community (22.83%) which has the second highest low-income population (<$40,000). Central community has the highest average percent of medium income ($40,000-$99,000) population (18.81%) and this is followed by North West community (15.66%) which has the second highest population in medium income ($40,000-$99,000) . Far South west

(8.66%) has the lowest percent of population with medium income. The Central community (10.27%) also has the highest percent of population with higher medium income ($100,000-$150,000) and this is followed by North Side (7.3%). South Side has the lowest average percent population (3%) per neighborhood for income in higher medium income range. The Central Chicago also has the highest percent of population in high income range (>$150,000) and followed by that North Side has the second highest average percent population of community over high income (9.8%). This shows that an economic divide clearly exists amongst the communities in Chicago.

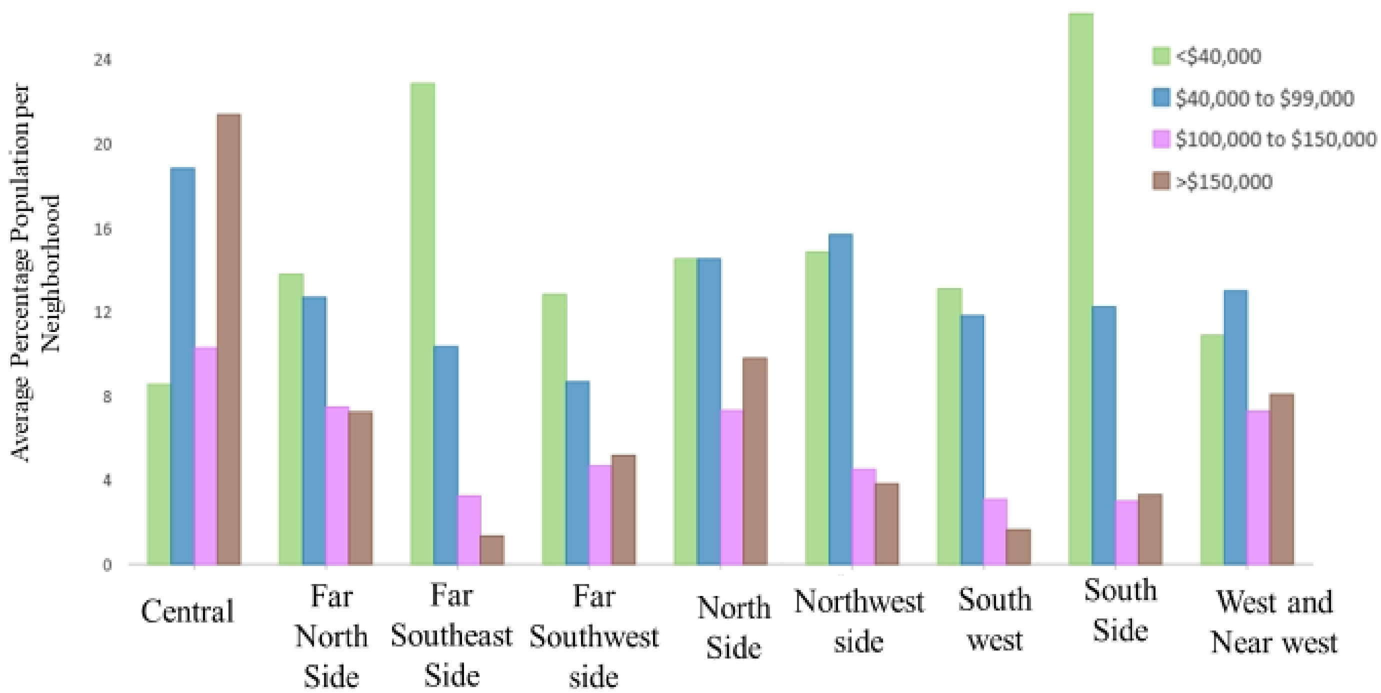


Figure 11: Percent of population in different income groups

## 4.5. Zero Car Ownership

Figure 12 below makes a community level comparison between the average percent population per neighborhood with zero car ownership. The bar chart shows that the Central community of Chicago has the maximum percentage of population per neighborhood with zero car ownership (47%). Comparing with Figure 11, it can be observed that Central also has the highest percent population per neighborhood with highest income range ( >$150,000) and lowest percent within low income (<$40,000) range. This means the zero ownership for auto mobile is not resulting their financial condition but rather than their personal travel choice. Thus, such trend is only possible if a neighborhood has a very good access to alternative transportation mode such as public transportation.

Consequently, Far South east side, far south west side and South side still has a relatively low percent population in comparison to all other communities except for Central. Coincidentally, there communities have the highest percent population per neighborhood with low income population (<$40,000). This could only be a result of inadequate access to transit or their reluctance to using public transportation.

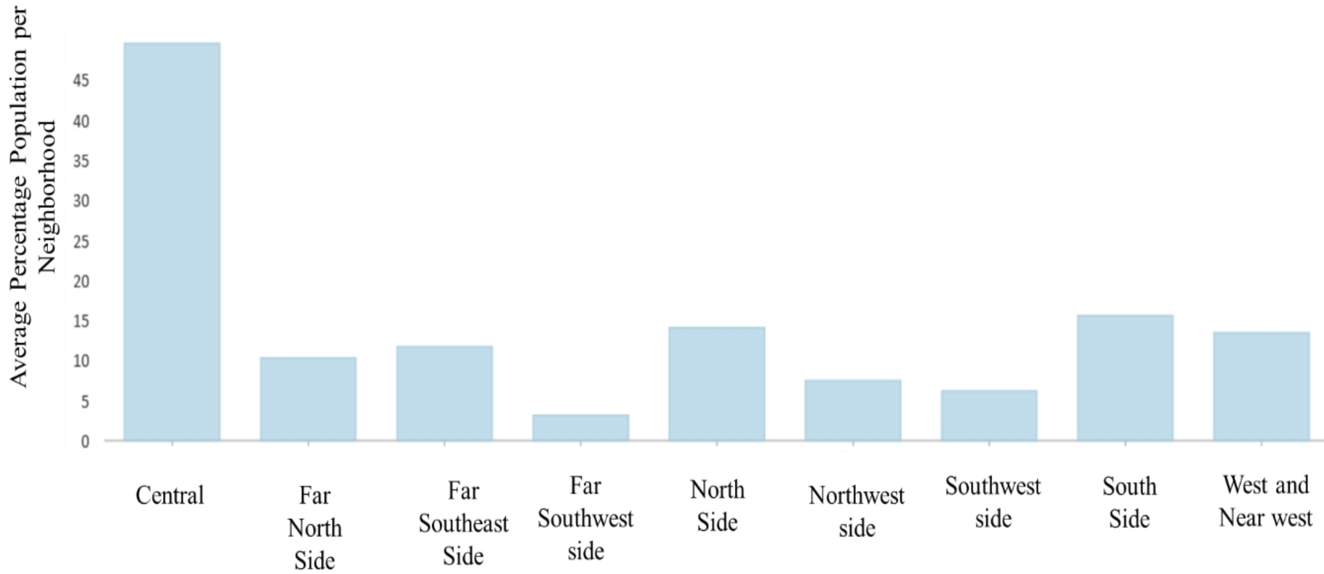


Figure 12: Population with zero auto ownership.

# CHAPTER 3

# IDENTIFY SIGNIFICANT FACTORS AFFECTING RAIL STATION/BUS STOP LEVEL TRANSIT RIDERSHIP: COMMUNITY LEVEL ANALYSES

Each year United States spends billions of dollars resolving congestion issues. It will continue to have serious consequences for national and local economies, businesses and citizens in the years to come. Congestion, pollution, and inactive lifestyles (automobile dependency) is leading transportation professionals and researchers to seek new solutions [53]. Public transportation can not only mitigate congestion issues but also is thought to be a solution to other problems like pollution, health concerns resulting pollution, sustainability in transportation and enabling mobility accessibility to city. Public transportation is an alternative to building new infrastructure to solve congestion issues. This brings into vision a new picture of "bike-and-ride," cycle–transit integration (C-T), or the transportation cocktail [54]. Integration of transportation modes allows for additional flexibility, making multimodal transport more attractive, and expands travel alternatives. Likewise, integration can be advantageous for transit agencies as they develop transit stations' service area at either end of the origin and destination [53]. Bike share has expanded exponentially over the last decade. However, majority of the study concentrated on the factors effecting bike share. The interaction of bike share with preexisting public transit system has not been explored as much.

A study of Washington DC integration of metro rail and Cabi (Bike share) showed that Metrorail stations have been important origins and destinations for CaBi (Washing D.C bike share) trips. It was found that the location of the CaBi stations with the highest ridership are located close to Metrorail stations, and some have decent ease of access to multiple stations. The study also found a relationship between the two , CaBi's effect on Metrorail ridership is statistically significant resulting a 10% increase in CaBi trips to generate a 2.8% increase in transit ridership [44]. Another study which made a comparison between bus ridership in New York and their bike share found that for each thousand bike sharing docks near a bus route is linked with a 2.42% drop in daily

unlinked bus trips on routes in Manhattan and Brooklyn [55]. Another study on Montréal bixi showed the number of bike station within 400 m of home had a small but significant negative effect on frequency of use of bus, which might indicate that BIXI was competing with transit[56]. Bike share systems are becoming more and more acceptable within our community and a growing number of municipal and regional governments acknowledge and wish to experience the advantages of shared bicycle systems. A better insight of factors that trigger or discourage use of the system is necessary for the success of shared bicycle programs and for boosting their capability. [56]. Consequently, if transportation agency and government is shifting towards integration of transit and bike share system considering bike share system as a first or last mile option, it is necessary to also understand the parameters that affect the transit ridership and the impact of bike share on it.

The first two chapters of this study identified the different barriers associated with transit, bike share use and the implementation of bike share as a first and last mile option. This chapter will assess the actual effect of those social, demographic and economic factors on station or stop level transit ridership in presence and absence of bike share. This will help observe the difference in trend as well as estimate the extent to which bike share is associated with changes in transit ridership as an effect of each of the identified social economic and demographic factors. This chapter will Identify how the significant factors affecting rail station/bus stop level transit ridership (with and without bike share) impact each community differently resulting different proportions of population mix. The outcome of this chapter will rank the communities into groups based on transit/bike share access and suggest possible implementation strategies to bridge the identified gap to meet the first and last mile goal.

# 1. Data source, Collection, Processing and Integration

National Historical Geographic Information System (NHGIS) is an ingress to statistical summary and GIS files for U.S. censuses and other nationwide surveys. NHGIS does not provide tools for data analysis, mapping, or reporting rather supplies files designed for use in spreadsheet applications statistical software (*R – Studio Version 3.6.1*) [57] , or GIS. Most NHGIS data files cover all areas in the United States. Data files for census blocks and block groups are available for individual states [58], [59]. The Environmental Protection Agency's (EPA) Smart Location Database (SLD) summarizes several demographics, employment, and built environment variables for every Census block group (CBG) in the United States. The data collected consisted of block group information consisting of sociodemographic data, income data ,vehicle ownership data in the form of shape files [60].Chicago Data Portal is an open data source which was used to obtain the location of train station, bicycle racks, and streets with bicycle routes and Park and Ride locations in the form of shapefile [61]. The average weekday bus ridership data was requested from Chicago Transit Agency. The station level average weekday rail data was obtained for the entire year of 2018 from Chicago Transit Agency website. The data obtained consisted of ridership data (weekdays and weekends) for the year 2018. The total number of bike docks and bike station location was extracted from Chicago Data Portal website [7].

The NHGIS data files were accumulated in form of excel files which comprises of a geo located ID. The excel file was then attached to a shape file of Chicago using ArcGIS Pro [62] so it can be added as a layer to a map. The Smart Location Database data came in form of a shape file and therefore could be downloaded directly from the EPA 's SLD website [60]. The data can either be downloaded for the entire of United Stated or for specific region using the data extraction tool. For

the purpose of this research, data collection was performed using the data extraction tool to obtain data only for the state of Illinois. The bus ridership data was collected from the Chicago Transit Authority. The rail station location and average weekday ridership, park and ride location and Divvy station location was downloaded in form of shape file from the Chicago data portal.

The data sets are then geocoded into a map layer and a 400m buffer layer has been created. This 400m buffer layer around the proximity of the bus stop/rail station will be used to extract data within that area for all independent variable to be tested. This is done by importing all the shape file or comma separated data (divvy ridership) into ArcGIS Pro into one map layer. The buffer layer is then added to the map layer. Then the spatial join feature in ArcGIS Pro is used to extract only the data within the buffer regions. Running this generates a new attribute table consisting of the data set only within the buffer region. For data sets which required counting, such as number of rail station or bike rack within 400m proximity of bus stop, the sum within feature in ArcGIS Pro was used which counts the number of docks located within a buffered region. 400-meter buffer surrounding each station with a sum weighted by the proportion of the area of the intersection of the buffer was used to accumulate the data. The 400-meter buffer intersects multiple Census Block as a result of spatial granularity and in some cases many census blocks may be contained within the buffer [35]. As a result of this fine scale the accumulation process adequately reveals conditions contained by 400 meters of the bike sharing station. Once the new attribute table is created it can export as an excel file by using the feature on ArcGIS Pro (Table to Excel).

# 2. Methodology

Ones the data has been extracted, each of the data sets for rail and bus data were divided into with having and without having a bike share facility within 400m proximity. This was performed by

assigning a score of 1 when a station location has a bike share and a score of 0 when a station location does have a bike station within 400m proximity distance. Once the sets were separated, each of the data sets were checked for multicollinearity by using the pairwise correlation matrix and Variance Inflation Factor.

## 2.1. Model Selection

Several different statistical models were assessed before choosing the appropriate model suitable for this analysis. Ordinary least square regression models have the following assumptions to be met: Error term has a population mean of zero; Independent variables are uncorrelated with the error term; Error term has a constant variance (no heteroscedasticity) and the regression model is linear between the coefficients and the error term. Many of the independent variables considered for this study were highly or somewhat correlated. A box plot and scatter plot were made for each parameter which showed presence of large number of outliers. This is also evident from the variance. For implementing Poisson regression count model, the variance of the data must be approximately equal to the mean. The data used of this study has variance greater than mean. This indicates over dispersion in data which means that the variance of the data is greater than the mean which means results produced could be biased , may have inefficient coefficient estimates and may have greater random error [63]. Zero inflated Negative binomial models often account for excess zeros in the dependent variable. It also accounts for both true or excess zeros and estimates for two equations at the same time, one for count model and one for zeros. The dependent data, the transit ridership data do not have excessive zeros and hence zero inflated models are not applicable [64], [65].

The most appropriate model for over dispersed data is Negatives Binomial Regression models as the statistical models take care of the over-dispersion factor which occurs when the conditional variance exceeds the conditional mean. Negative Binomial regression has the same mean structure as Poisson Regression but also has an added advantage of being able to model the over dispersion factor [65].

Table 6: Comparison between different statistical models.

| Regression model | Conditions | Restrictions |
|---|---|---|
| Ordinary Least Square Regression | The regression model is linear in the coefficients / error term; Error term has a population mean of zero<br>Independent variables are uncorrelated with the error term; Error term has a constant variance (no heteroscedasticity) | Do not meet all assumptions. |
| Poisson Distribution | Count model: The variance of the data must be approximately equal to the mean. | Indicates over dispersion in data; Variance of the data is greater than the mean; May result biased outcome, may have inefficient coefficient estimates and may have greater random error |
| Zero inflated Negative binomial | Accounts for both true or excess zeros and estimates for two equations at the same time, one for count model and one for zeros. | Transit ridership data do not have excessive zeros and hence zero inflated models are not applicable |
| Negative binomial models | Models over-dispersion factor which occurs when the conditional variance exceeds the conditional mean. | More suitable |

## 2.2. Negative Binomial model

Count or frequency models are mostly known as non-parametric model in which model parameter are based on the count observations. The parameters of the underlying distribution are specified as functions of different covariates to capture their influence on count dependent variable. The most

commonly implemented statistical regression method for count data modelling is Poisson and Negative Binomial (NB) model [66]. The Poisson distribution has an assumption that the mean will be equal to the variance of the sample and hence plays the role of a restrictive assumption. This assumption is eased using Negative binomial model. Negative binomial model acts as a suitable condition for both the cases of over dispersion and under dispersion in the data sample.

The probability of observing c count outcome $y_i$ is conditional on the expected mean parameter λ and dispersion parameter Θ> 0. The conditions are expression in the Negative Binomial regression as follows:

$$P(Y = y) = (\frac{\Theta}{\Theta + \lambda})^{\Theta} \times \frac{\Gamma(\Theta + y)}{\Gamma(y + 1)\Gamma(\Theta)} \times (\frac{\lambda}{\lambda + \Theta})^{y}$$

where Γ is the gamma function defined as defined below:

$$\Gamma(\mathrm{t}) = \begin{cases} \int_{x=0}^{\propto} x^{t-1} e^{-x} dx \; for\ positive\ non - intger\ t \\ (t-1)!\, for\ positive\ integer\ t \end{cases}$$

The variance of negative binomial model is $v = \lambda + \frac{\lambda^2}{\Theta}$. The parameter Θ, represents the over dispersion factor and λ is the expected mean [63], [66], [67].

## 2.3. Variables

Based on past literature review and the trends identified in the preliminary analysis (Chapter 2) several independent variables were identified for estimation as many estimators in the statistical analyses was thought to be necessary in order to identify the strongest and most significant predictors of bikeshare activity. However, simultaneously avoiding biases associated with omitting

relevant variables across unique factor groups (e.g., socioeconomic, accessibility, ethnicity, vehicle ownership) was necessary. Thus, variables were sorted using Variance Inflation Factors and Pairwise correlation matrix to avoid multicollinearity. This will avoid over specifying the models with an abundance of independent variables as well as inflated standard errors, sign ambiguity among the regression coefficients and lower predictive power for the entire models as a whole [21], [35].

Table 7 presents definitions of all variables considered for the regression analysis. Unless otherwise specified, variables are based on a 400-meter buffer around each transit (rail or bus) station to account for a catchment area of users likely to walk to the station. In order to evaluate the association between the ridership and the independent variable, the dependent variables (Average weekday bus or rail ridership) and its corresponding independent variables has been classified into treatment(with bike share system within 400m) and control (without bike share within 400m) to analyze each case separately. Hence , The mean and standard deviations for each independent variables regressed for bus stop level ridership (Table 6) and rail station level ridership both with and without bike share system within 400m proximity has been shown (Table 9) for estimation of deviation from mean for each case.

Table 7:Variable Definitions

| Variable | Definition | Source |
|---|---|---|
| **Dependent Variables** | | |
| Bus stop level ridership | Bus ridership data for October 2018, weekday average | Chicago Transit Agency |
| Rail Station level Ridership Daily Total | Daily total rides for the month of October 2018 (excludes Saturdays and Sundays) | Chicago Data Portal |
| Rail Station level Ridership Weekday Average per Month | Weekday average for all the months throughout the year | Chicago Data portal |
| **Independent Variables** | | |
| **Ethnicity** | | |
| Households White | Households with a householder who is white alone | NHGIS (National Historical Geographic Information System); 2017 American Community Survey: 5-Year Data [2013-2017, Block Groups & Larger Areas] |
| Households Hispanic | Households with a householder who is Hispanic or Latino | |
| Household Black | Households with a householder who is Black or African American alone | |
| Household Asian | Households with a householder who is Asian alone | |
| **Income** | | |
| <$40,000<br>$40,000 to $99,000<br>$100,000 to $149,000<br>>$150,000 | Household Income in the last 12 months (in 2017 Inflation adjusted in dollars) | NHGIS (National Historical Geographic Information System); 2017 American Community Survey: 5-Year Data [2013-2017, Block Groups & Larger Areas] |
| **Vehicle ownership** | | |
| Households with zero auto ownership | Number of households in CBG that own zero automobiles, 2010 | ACS, 2010 decennial Census, Smart Location Database |
| Households with one auto ownership | Number of households in CBG that own one automobile, 2010 | |
| Households with two auto ownership | Number of households in CBG that own two automobiles, 2010. | |
| **Population in different age group/Disability** | | |
| Age 15 to 34 years<br>Age 35 years to 64 years<br>Over 64 years | Total population under each age group (Male and Female) | Derived from NHGIS (National Historical Geographic Information System) ;2017 American Community Survey: 5-Year Data [2013-2017, Block Groups & Larger Areas] |
| Population with disability | Total population with disability | |
| **Bike share** | | |
| Total Docks | Total Number of Bike Docks within 400m of each stop or station location | Chicago Data Portal, Total Divvy Station in Service 2018. |
| Park and Rider | Count of Park and Ride facility within 400m proximity to transit stop or station location | Chicago Data Portal, Park and Ride location in Chicago. |

Table 8:Summary statistics of Model Variables for Rail ridership.

| Variables | With Bikeshare | | Without Bikeshare | |
|---|---|---|---|---|
| | Mean | Standard Deviation | Mean | Standard Deviation |
| **Ethnicity** | | | | |
| Household White | 405.1 | 368.3 | 353.90 | 273.69 |
| Household Black | 146.47 | 199.2 | 109.61 | 151.62 |
| Household Asian | 64.033 | 90.40 | 52.47 | 77.28 |
| Household Hispanic | 77.006 | 10.688 | 97.871 | 132.34 |
| **Vehicle Ownership** | | | | |
| Household zero car | 244.35 | 227.64 | 64.70 | 71.36 |
| Household 1 car | 335.55 | 264.15 | 250.32 | 189.97 |
| Household 2 car | 149.23 | 106.78 | 159.17 | 86.014 |
| **Income** | | | | |
| <$40,000 | 239.57 | 156.67 | 176.38 | 122.841 |
| $40,000 to $99,000 | 203.377 | 188.449 | 204.85 | 140.035 |
| $100,000 to $149,000 | 107.020 | 125.877 | 70.538 | 67.501 |
| 150,000 and above | 158.73 | 219.286 | 74.547 | 89.597 |
| **Age** | | | | |
| Age 15-34years | 660.55 | 603.98 | 466.88 | 439.77 |
| Age 35-64years | 519.65 | 284.53 | 540.82 | 257.00 |
| Age over 64years | 172.73 | 171.95 | 5.095 | 121.44 |
| **Others** | | | | |
| Population with Disability | 91.027 | 82.21 | 79.852 | 52.12 |
| Park and Ride | 0.059829 | 0.2372 | 0.4049 | 0.4913 |
| Total Bike Dock | 17.50 | 6.807 | Not Applicable | Not Applicable |

Table 9:Summary statistics of Model Variables for Bus ridership

| Variables | With Bikeshare | | Without Bikeshare | |
|---|---|---|---|---|
| | **Mean** | **Standard Deviation** | **Mean** | **Standard Deviation** |
| **Ethnicity** | | | | |
| HH White | 334.99 | 370.39 | 219.29 | 203.92 |
| HH Black | 307.91 | 205.91 | 149.311 | 181.76 |
| HH Asian | 54.925 | 97.088 | 19.673 | 45.33 |
| HH Hispanic | 83.991 | 111.73 | 112.4960 | 133.316 |
| **Vehicle Ownership** | | | | |
| HH zero car | 224.08 | 206.17 | 100.819 | 91.919 |
| HH 1 car | 306.75 | 190.25 | 202.840 | 113.383 |
| HH 2 car | 148.64 | 93.517 | 189.47 | 104.68 |
| **Income** | | | | |
| <$40,000 | 167.25 | 116.38 | 190.75 | 121.685 |
| $40,000 to $99,000 | 163.7083 | 80.81 | 159.95 | 86.900 |
| $100,000 to $149,000 | 60 | 40.95 | 54.8500 | 45.688 |
| >$150,000 | 73.20 | 79.08 | 42.916 | 62.425 |
| **Age** | | | | |
| Age 15-34years | 507.41 | 432.5 | 348.644 | 274.84 |
| Age 35-64years | 504.66 | 316.02 | 494.552 | 219.29 |
| Age over 64years | 150.164 | 117.342 | 178.07 | 132.73 |
| **Others** | | | | |
| Population with Disability | 75.622 | 69.657 | 73.846 | 52.778 |
| Park and Ride | 0.019678 | 0.13890 | 0.015524 | 0.12363 |
| Total Bike Dock | 15.3253 | 6.355 | Not Applicable | Not Applicable |

# 3. Results and Analysis

This section describes the results obtained by regressing dependent variable (average weekday ridership) for all the independent variables to estimate the effect of each variable on station level ridership with and without bike share using negative binomial regression The coefficient represents the extent of the expected log count increase or decrease of the dependent variable based on whether its positive coefficient or negative coefficient. The coefficients and the level of significance represents the association between the dependent variable and the independent variable in order to estimate the effect on the dependent variable (average weekday transit ridership) based on the presence of bike versus no bike share. A negative sign on the coefficient means the factor contributes towards decreasing transit ridership and a positive sign means that the factor contributes towards increasing transit ridership. The glm (generalized linear model) package of R-Studio (version 1.2.5033) has been used to model the Negative Binomial model.

## 3.1. Analysis of bus ridership

The total data set of average weekday bus stop level ridership for the month of October 2018 has been classified into treatment and control group. The treatment group sample (n) of 4473 and control sample (n) of 5283. The level of significance if strongest at 0.1%, somewhat significant at 1% and low significance at 5%. Any p value greater than 5% is insignificant. The regression results of the associations between the independent variables and the average weekday station level bus ridership with and without bike share have been summarized in Table 10. Figure 13 to

Figure 27 shows the geographic distribution of each factors to compare with the statistical results. This section interprets results for each factor based on what impact it may have on the transit ridership in presence or in absence of bike share and the possible reason for it.

Table 10:Summary of statistical results for bus ridership with and without bike share

| | **With Bikeshare** | | **Without Bikeshare** | |
|---|---|---|---|---|
| | **Coefficients** | **$P_r(>\|z\|)$** | **Coefficients** | **$P_r(>\|z\|)$** |
| **Intercept** | 4.191 | < 2e-16 *** | 3.908 | < 2e-16 *** |
| **Ethnicity** | | | | |
| HH White | 0.0002345 | 0.000956 *** | -0.0001926 | 0.140855 |
| HH Black | 0.0003400 | 0.000476 *** | 0.0001683 | 0.218502 |
| HH Asian | -0.0009517 | 1.54e-05 *** | 0.001220 | 0.004167 ** |
| HH Hispanic | -0.00008962 | 0.623191 | 0.0006429 | 0.0000617*** |
| **Vehicle Ownership** | | | | |
| HH zero car | 0.0005027 | 6.06e-06 *** | -0.0002098 | 0.348752 |
| HH 1 car | -0.000009488 | 0.90001 | 0.001234 | 1.60e-12*** |
| HH 2 car | -0.0004550 | 0.033299 * | -0.001718 | < 2e-16 *** |
| **Income** | | | | |
| Less than 40,000 | 0.0005668 | 0.0000702*** | 0.0005742 | 0.000940 *** |
| Between 40,000-99,000 | -0.0001673 | 0.397559 | 0.0007773 | 0.002750 ** |
| Between 100,000-149,000 | -0.0003827 | 0.320562 | -0.0007115 | 0.186704 |
| 150,000 and above | 0.0009117 | 0.000000828*** | -0.002170 | 2.74e-09 *** |
| **Age** | | | | |
| Age 15-34years | 0.0001054 | 0.041811 * | 0.00005189 | 0.547430 |
| Age 35-64years | -0.00003541 | 0.705555 | -0.0003503 | 0.006683 ** |
| Age over 64years | 0.00009066 | 0.569209 | -0.0005991 | 0.000168 *** |
| **Others** | | | | |
| Population with Disability | -0.001515 | 0.00000541*** | 0.001065 | 0.008623 ** |
| Park and Ride | 0.09589 | 0.444461 | -0.1617 | 0.261480 |
| Total Bike Dock | 0.01487 | 0.00000786*** | Not Applicable | Not Applicable |

*** p<0.001; **p<0.01; *p<0.05

### 3.1.1. Age as a factor

The younger population (15-34 years) have slight positive (0.0001054, $p<0.01$) impact on the ridership for bus stations which has bike share in proximity and for bus stops without bike share has no significant impact ($p>0.05$). This means that for each one-unit increase on population within age range 15-34 years the expected log count of rail ridership increases by 0.0001054.The distribution of bus stop is even and therefore based on the statistical analysis result there is possibility of increase in ridership if there was adequate supply of bike share system close to bus stops amongst this age group. The trend shown is an average effect considering the entire Chicago population. The map shows an uneven distribution of transit service as well as bike share and the trends could be reflective of the scattered geographic distribution of the population (Figure 10). The distribution of bus stop is even and therefore based on the statistical analysis result there is possibility of increase in ridership if there was adequate supply of bike share system close to bus stops amongst this age group.

Table 10 shows that middle aged group (35 to 64 years) has an insignificant ($p>0.05$) effect on the bus ridership with bike share. The population however has a relatively strong negative effect (-0.0003503, $p<0.01$) on the average weekday stop level bus ridership for locations with bike share system within proximity of 400m. This can be interpreted as for each one-unit increase on population within age range 35 to 64 years the expected log count of rail ridership decreases by -0.0003503 provided the bike station does not have access to any bike share system within 400m proximity. Population for age over 64 has a strong negative effect (-0.0005991, $p<0.001$) when they have no bike share facility near 400m proximity. However, Seniors who does not have access to bike share has negligible effect on the average weekday bus ridership.

The associations between transit ridership and age is different for each age range. Young age individuals are more inclined towards transit friendly area and urban area. So, if there are not sufficient micro mobility options (bike share) within 400m of young age group population then there may be an insignificant effect ($p>0.05$). On the other hand, a strong negative could either mean the populations unwilling to use micro mobility options or rather in case of younger population, a substitutional effect on bus ridership due to the short trip distance between the stop locations. The choices of middle-aged group (35 to 64 years) may be dependent on their income (Figure 20,

Figure 21, Figure 22, Figure 23), vehicle ownership (Figure 16, Figure 17, Figure 18) or geographic location (Figure 14). However, for senior population the strong ($p<0.001$) negative effect may be a result of reluctance to use transit due to transit being unable to provide the services needed by the senior. Bike share use amongst senior depends on their level of acceptability of micro mobility option, safety or their disability status.

### 3.1.2. Income

The results show that population with income below $40,000 has a significantly positive effect on the average weekday station level bus ridership for both bus stops with bike share (0.0005668, $p<0.001$) as well for stops without bike share (0.0005742, $p<0.001$)Table 10. The population with medium income range ($40,000 to $99,000) shows only a positive impact (0.0007773, $p<0.01$) on average weekday bus ridership when there is no bike share. The population within higher middle-class ($100,000 - $150,000) group does not show any significance towards average weekday station level bus ridership. On the other hand, the results show that high income population (> $150,000) demonstrates a positive impact (0.0009117, $p<0.001$) on average bus ridership for bus

stops with bike share system and a strong negative effect on stops without bike share (-0.002170, $p<0.001$) (Table 10).

The trends for population falling under different income ranges are based on other social, economic or personal choice based on the range of the income (low (<$40,000), medium ($40,000 - $99,000), medium high ($100,000 - $150,000), High (> $150,000)). Low income population has very limited options of transportation modes and are based on their financial constraint. They are more likely to use transit whether they have access to bike share or not. Trends for the medium income ranges both high ($100,000 to $149,000) or low ($40,000 to $99,000) is dependent on many factors such as age, auto ownership(Figure 16), access or even physical limitations (Figure 19). The associations between average weekday bus ridership and high-income population ($150,000) is based on their personal choice, they may be only willing to use transit if there is a micro mobility option (convenience). Therefore, also affected by their residential location choice, if they decided to live in a transit-oriented neighborhood or rather far away from urban area (Figure 23).

### 3.1.3. Ethnicity

White population shows a significant positive effect on bus ridership (0.0002345, $p<0.001$)) when there is a bike share within 400m of the stop location. Bus stops without bike share system has an insignificant effect on the average weekday stop level ridership. Hispanic population shows an insignificant effect on the bus ridership in presence of bike share system within 400m proximity of stop location. However, bus stops without bike share shows a strong positive effect on the bus ridership (0.0006429, $P<0.001$). The Black population shows a strong positive contribution (0.0003400, $p<0.001$)) on the bus ridership when located within 400 proximity of a bike share

facility. Bus stop without any bike share system does not have any significant($p>0.005$) impact on the average weekday station level bus ridership.

Majority of the area where the Black population or Hispanic population resides don't have adequate supply of bike share as shown by the total number of bike docks neighborhood (Figure 26). This may be a reason for Hispanic population to not have a significant effect of bike share on station level bus ridership. However, for areas with higher Black, few stops where there is some bike share within proximity of bus stop, it has a significant increase in stop level bus ridership(Figure 25). This implies that bus ridership may increase in the Black populated area. Asian population has a strong significant negative effect (-0.0009517, $p<0.001$) on bus ridership on station locations with bike share. The population also has a somewhat positive significant effect (0.001220, $p<0.01$) on the bus ridership of stations without bike share. The overall population of Asian origin residing in Chicago is relatively smaller in number. Their geographic location is clustered in specific regions (Figure 27).

### 3.1.4. Car Ownership

According to results from Table 10 population with zero car ownership has a significant positive (0.0003907, $p<0.001$) impact on increasing the average weekday station level bus ridership. However, the population with one car household has a positive effect (0.0004003, $p<0.001$) and population with two car household has a negative effect (on the average weekday station level bus ridership for bus stop which has bike share facility within 400m proximity of the stop location.

### 3.1.5. Disability

Disabled population has a strong negative effect (-0.001515, $P<0.001$) for ridership of bus stops which are close to a bike share facility. On the other hand, disabled population has somewhat positive effect (0.001065, $p<0.01$) on the bus ridership for locations without bike share. This trend may reflect the accessibility of disabled population to bike share to transit (Table 10, Figure 19).

### 3.1.6. Park and ride

Park and ride location have an insignificant effect ($p>0.005$) on the average weekday station level ridership for bus. This is evident form the park and ride location shown on the maps (Figure 16). Majority of the park and ride location are not located in an area accessible to bus service. However, the limited number of bus stops which have park and ride locations within proximity has a relatively higher ridership compared to those of the surrounding bus stops (West Elson, Gage park, Engle wood, Bridgeport, Albany park). Also, most of those bus stop with park and ride either has no or limited bike share facility within 400m proximity and introducing bike share facility to those areas may increase transit use more.

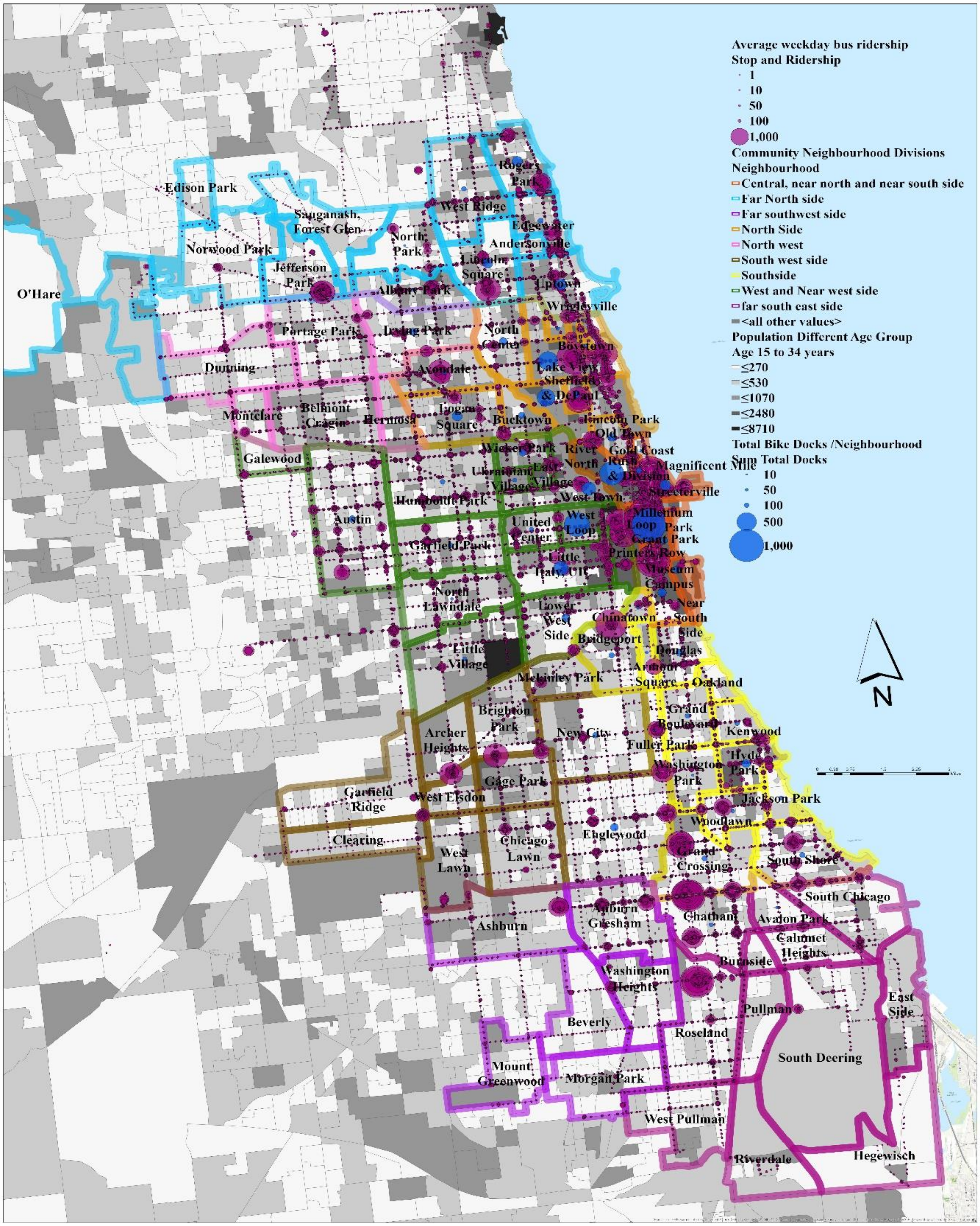


Figure 13: Population between ages 15 to 34 years in different Chicago communities with access to bus transit and bike share.

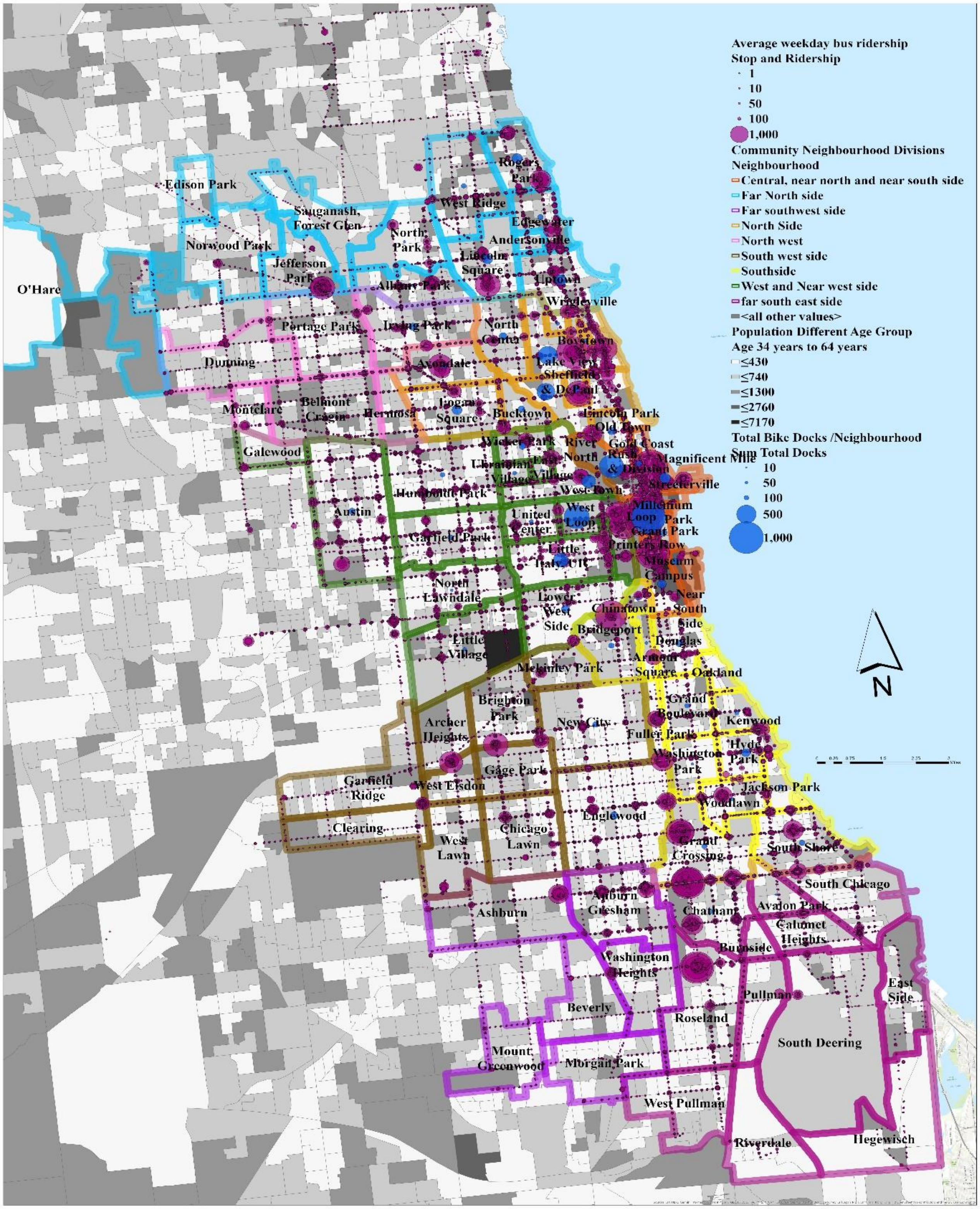


Figure 14: Population in between ages 35 to 64 years in different Chicago communities with access to bus service and bike share.

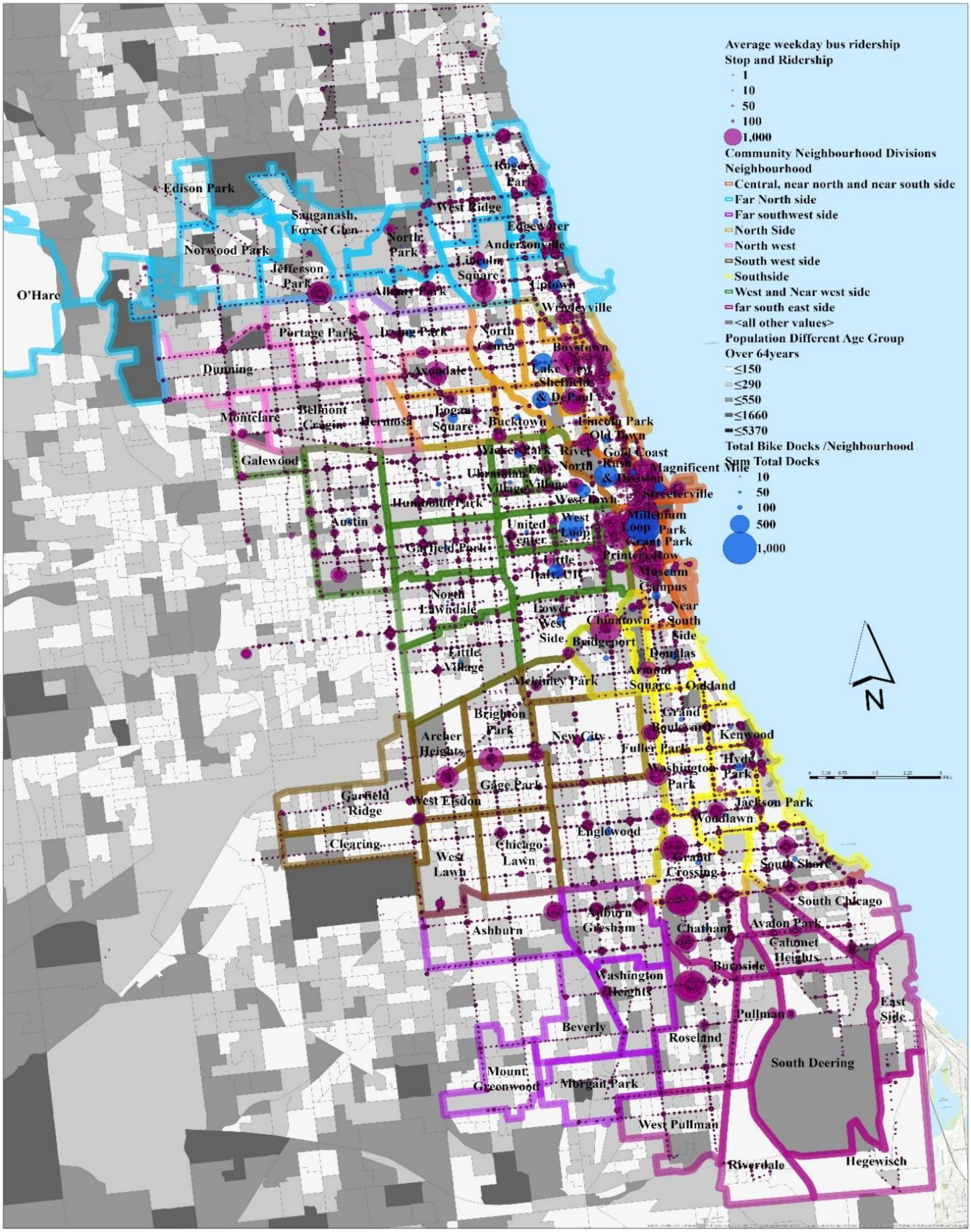


Figure15:Population in between age over 64years in different Chicago communities with access to bus service and bike share.

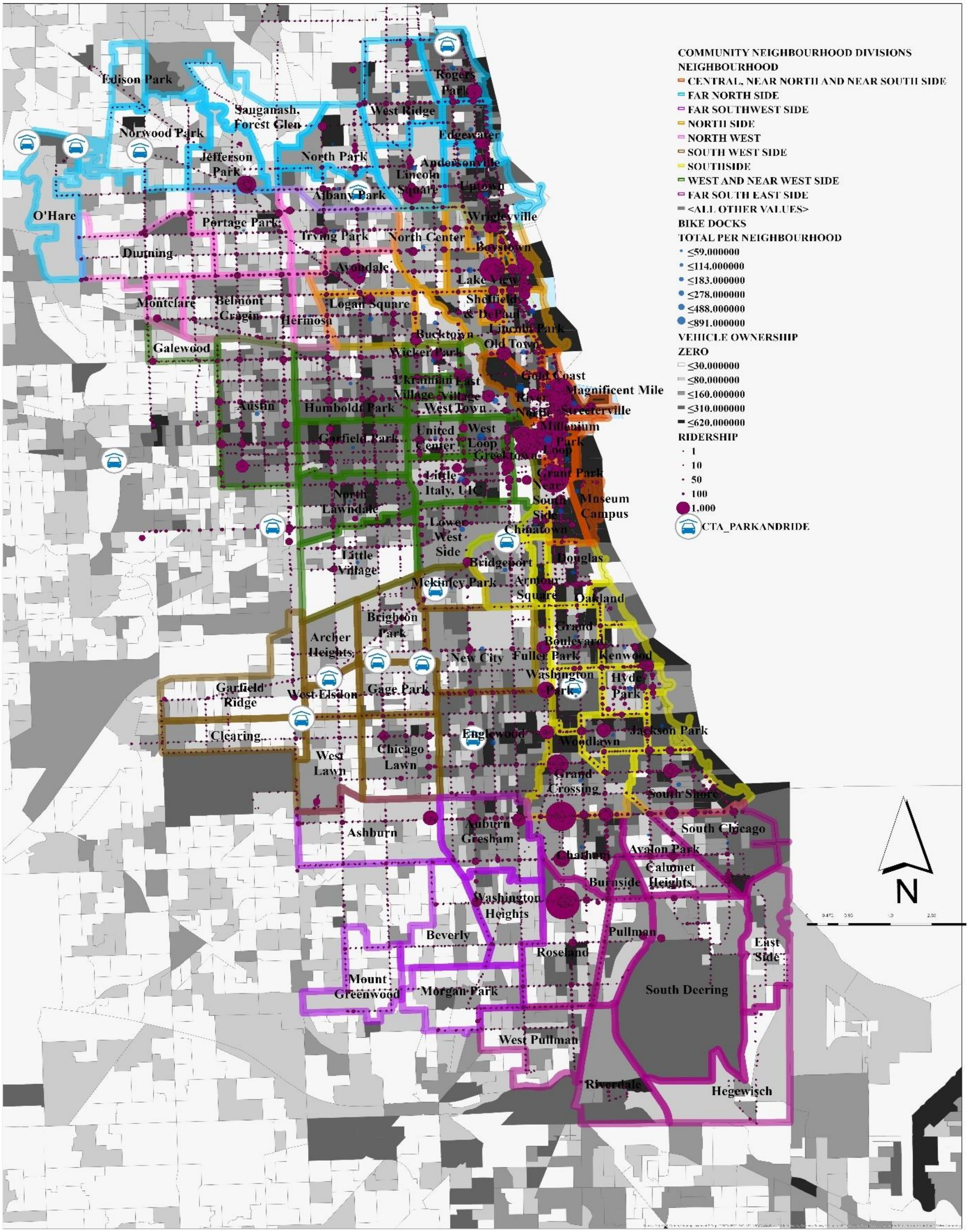


Figure 16 : Population with zero vehicle ownership and access to bus service

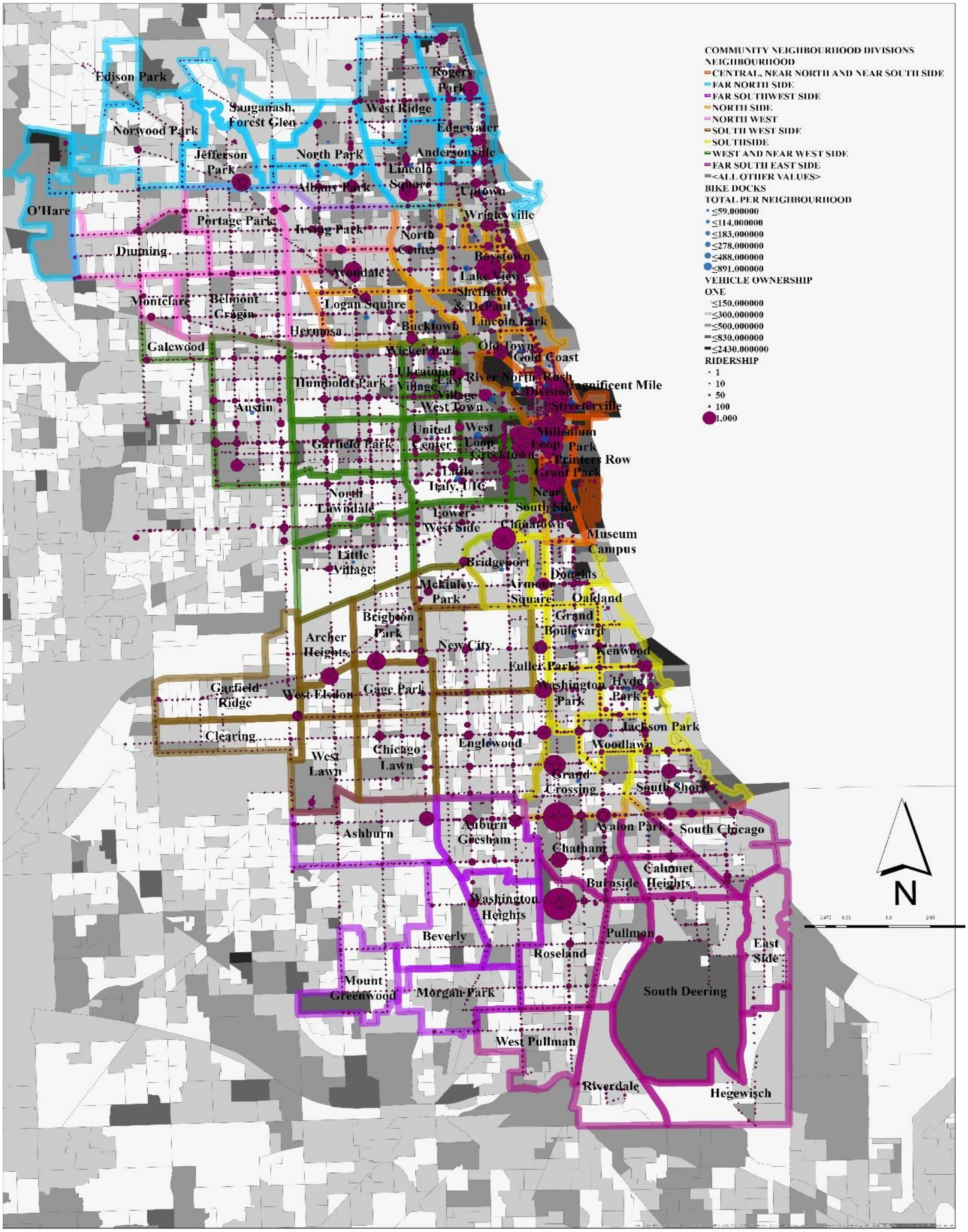


Figure 17: Population with one vehicle ownership and access to bus service

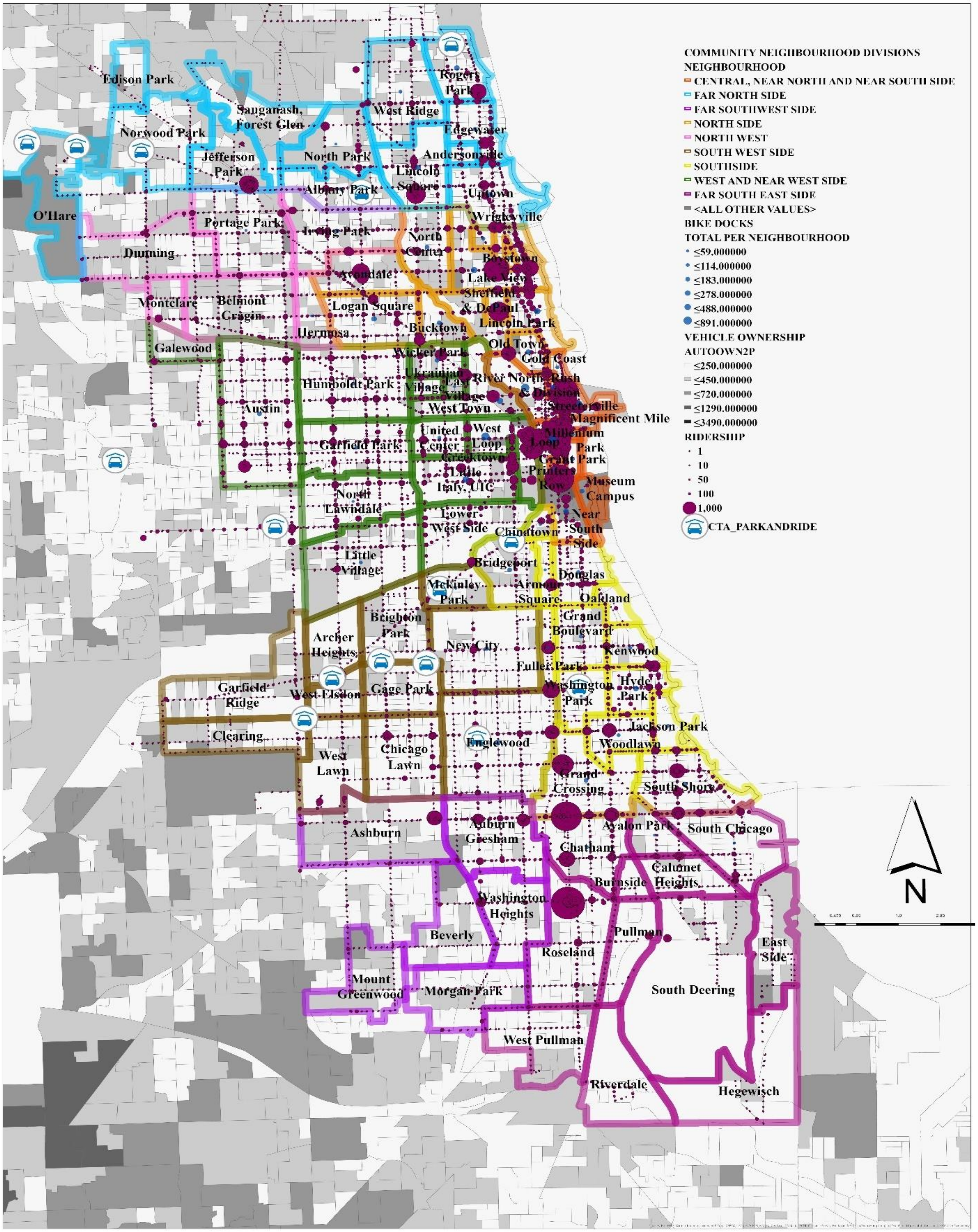


Figure 18:Population with two vehicle ownership and access to bus service

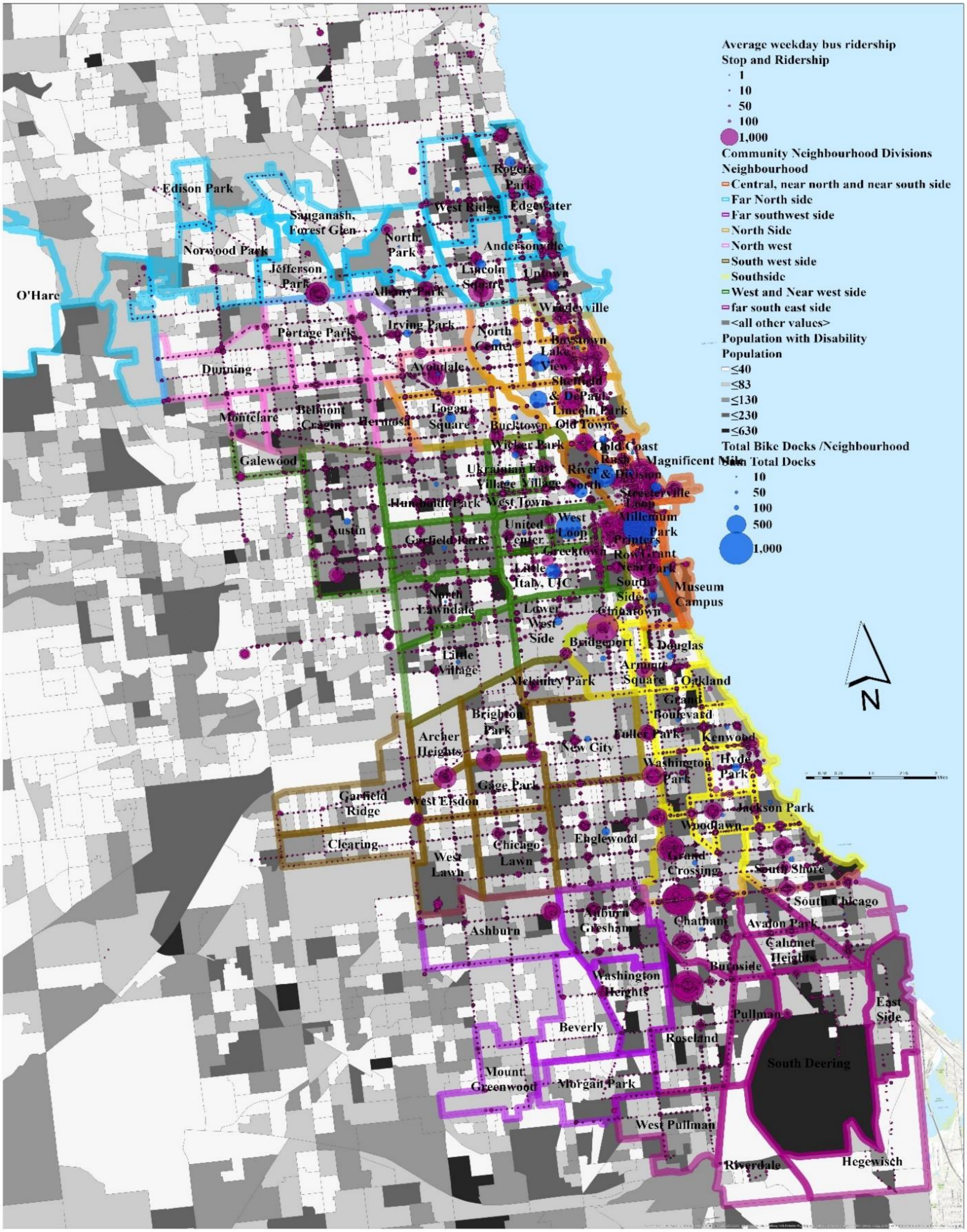


Figure 19: Population with Disability and access to bus.

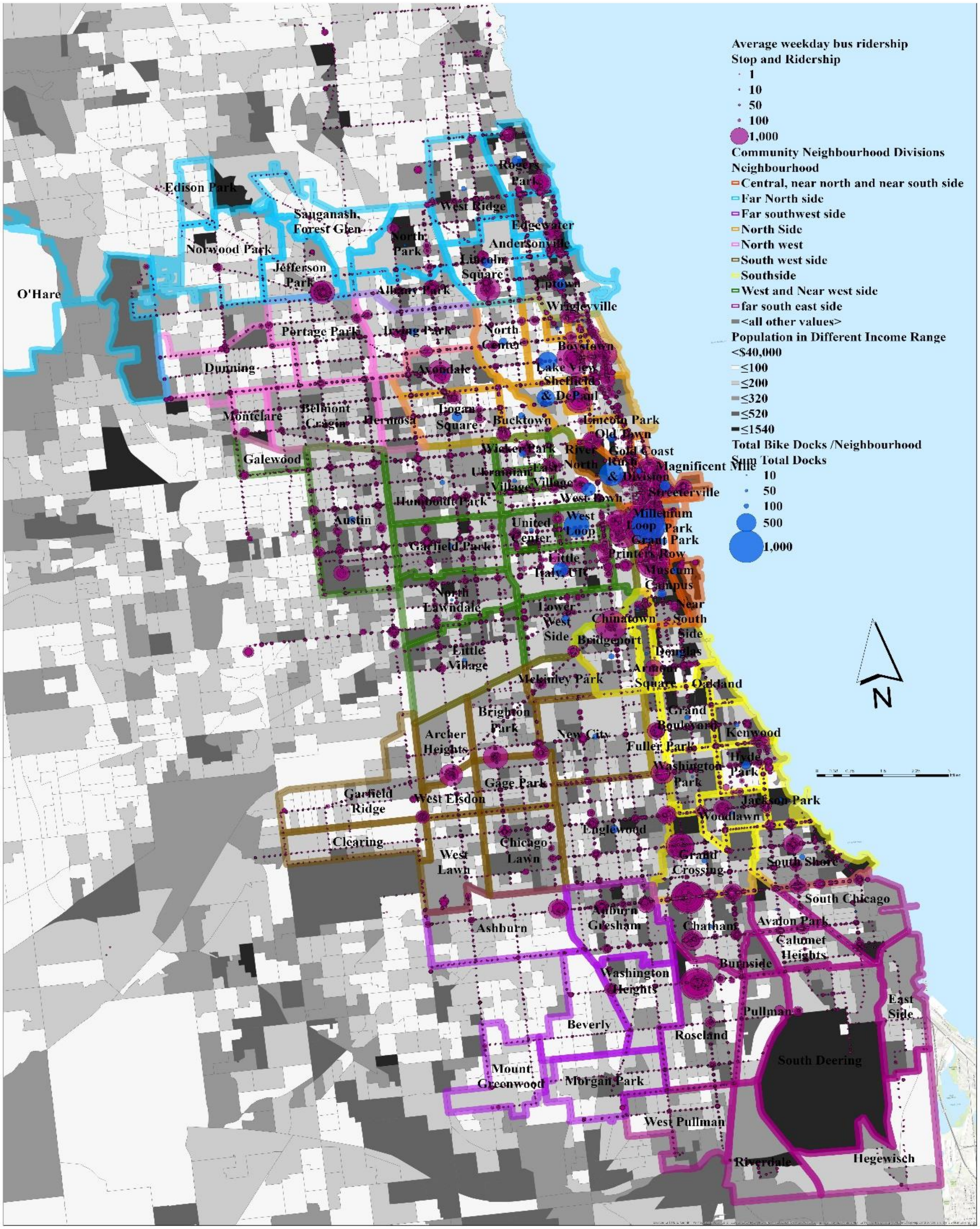


Figure 20:Access to bus service and bike share service for population with income below $40,000.

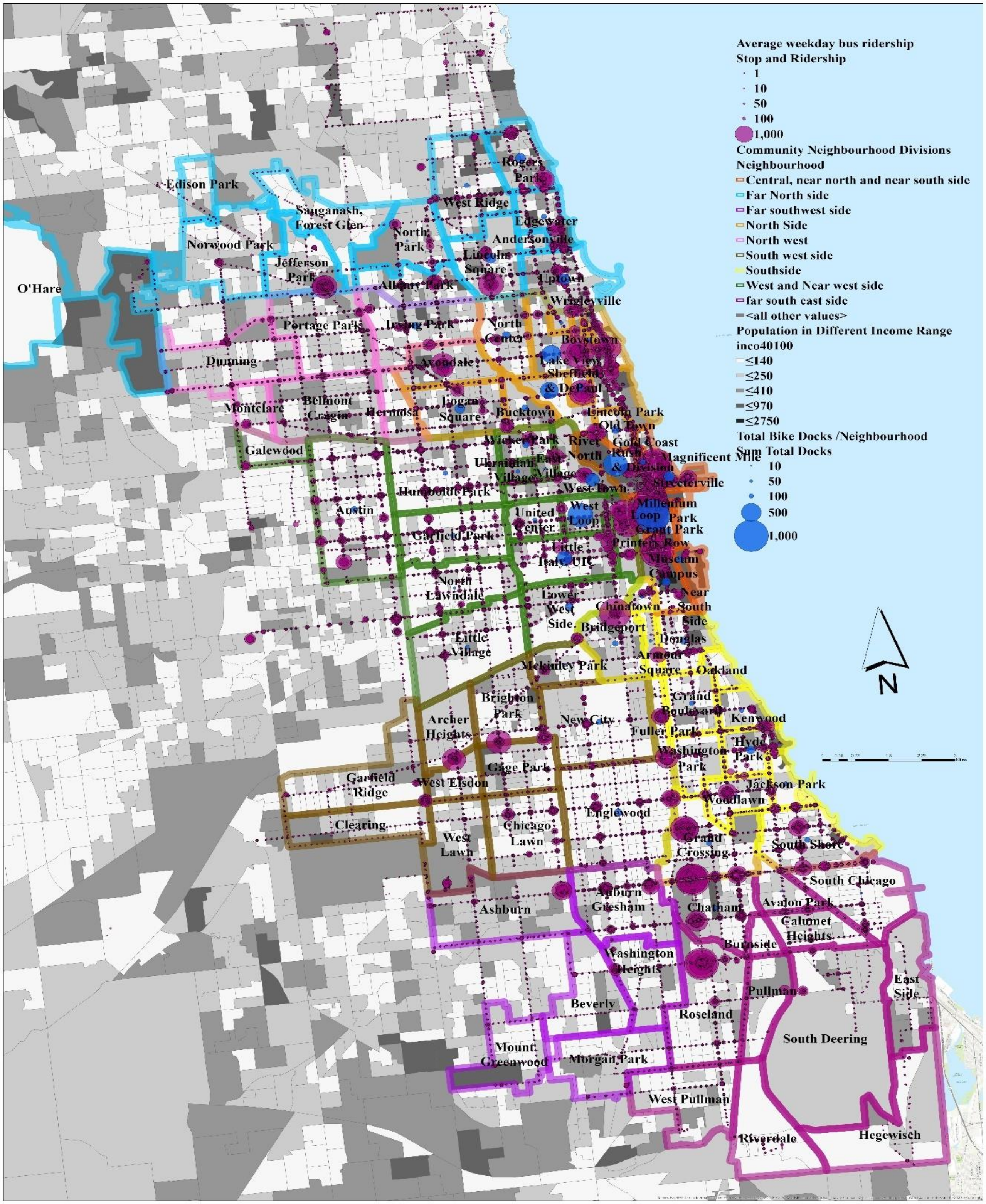


Figure 21:Access to bus service and bike share service for population with income between $40,000 to $99,000.

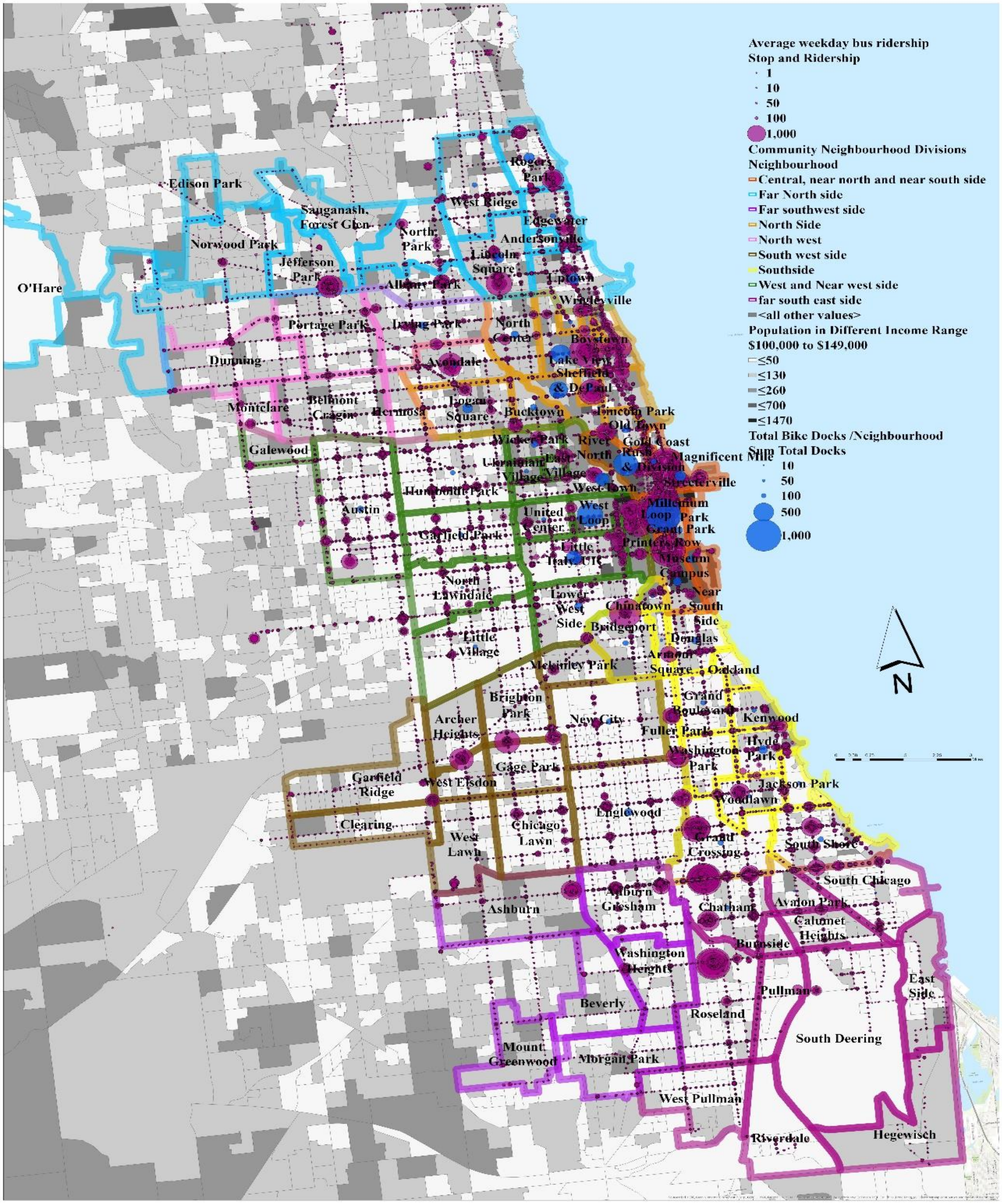


Figure 22:Access to bus service and bike share service for population with income between $100,000 to $150,000.

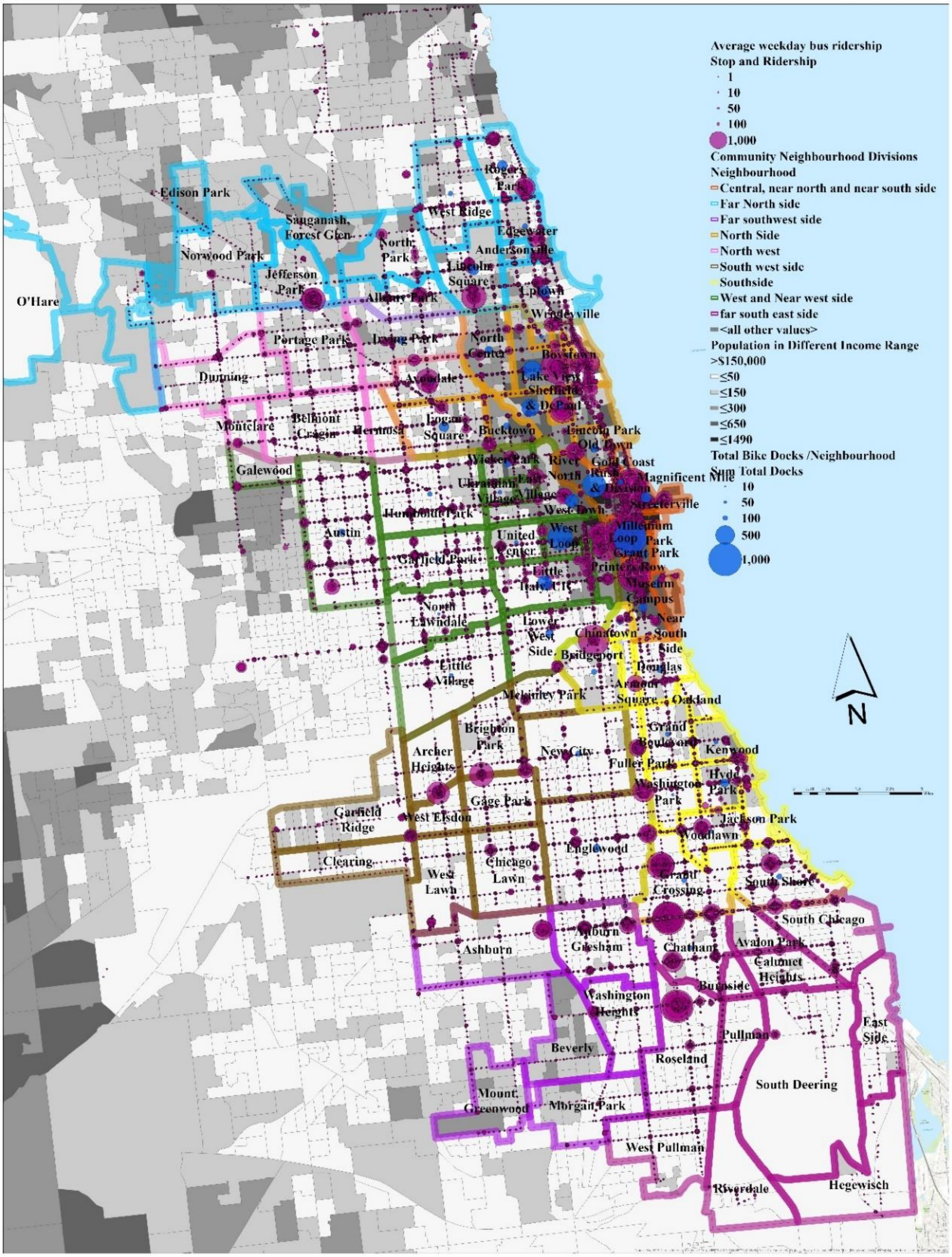


Figure 23:Access to bus service and bike share service for population with income over $150,000.

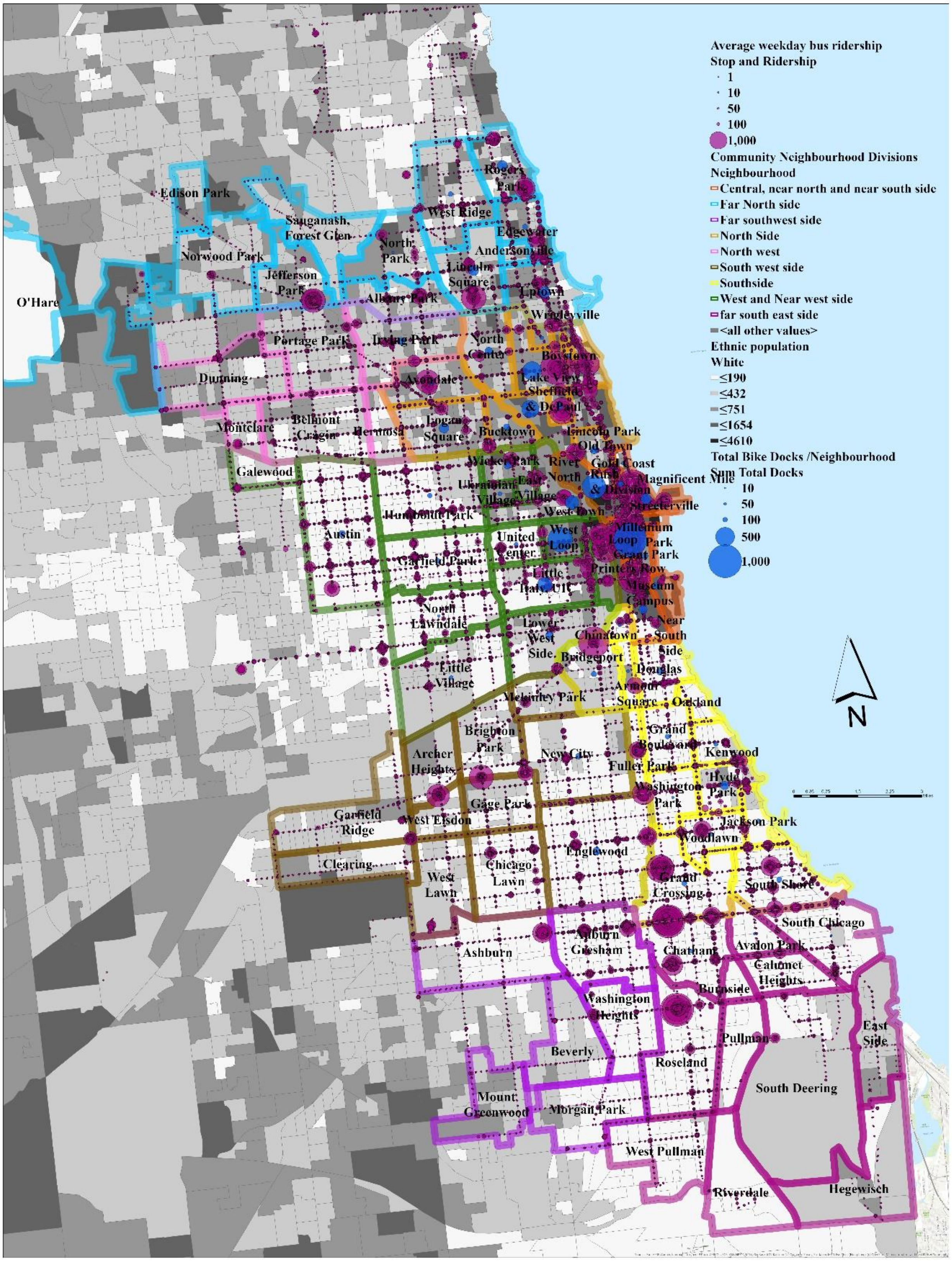


Figure 24: Access to bus service and bike share for population of white origin.

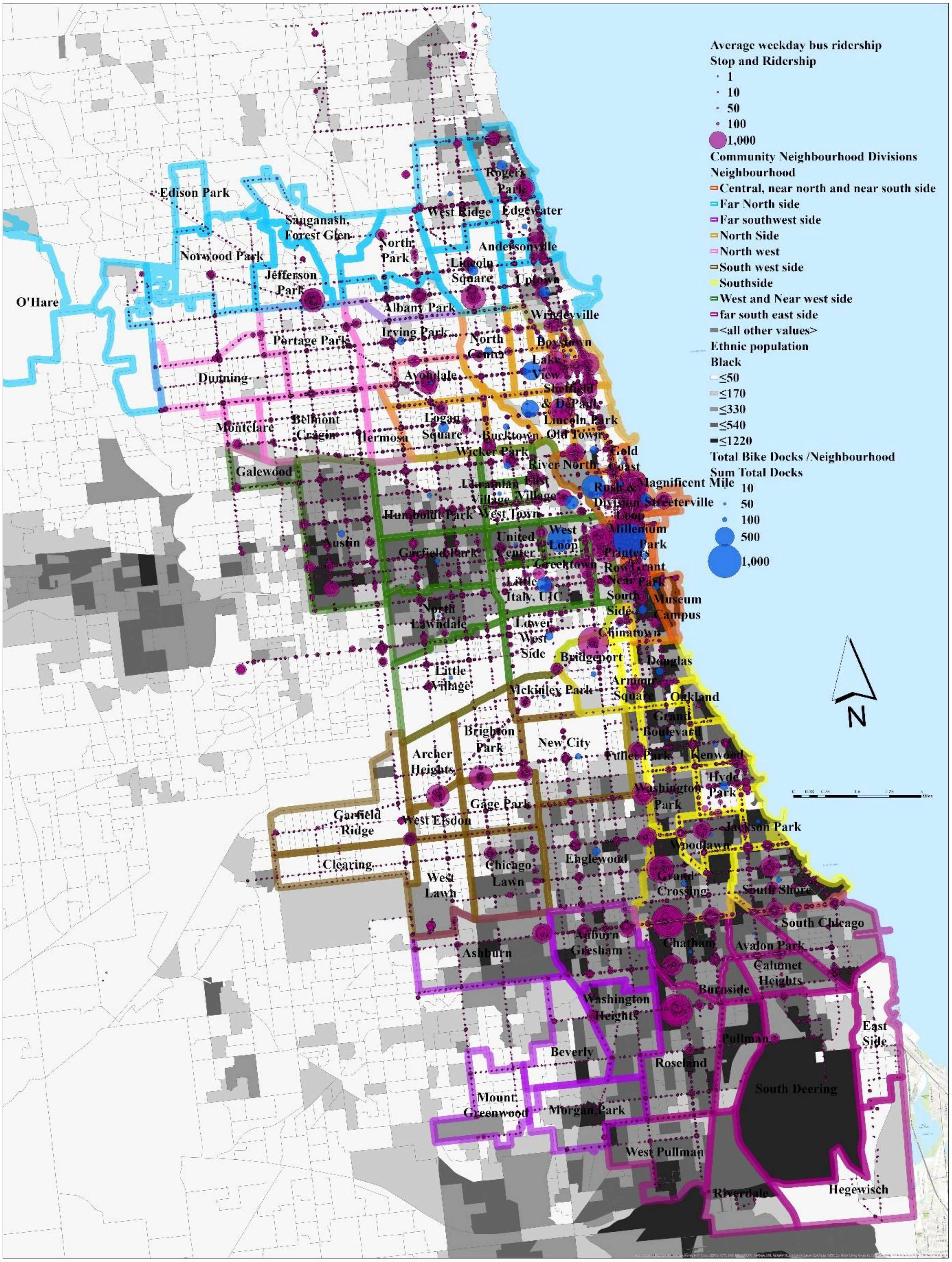


Figure 25:Access to bus service and bike share for population of black origin.

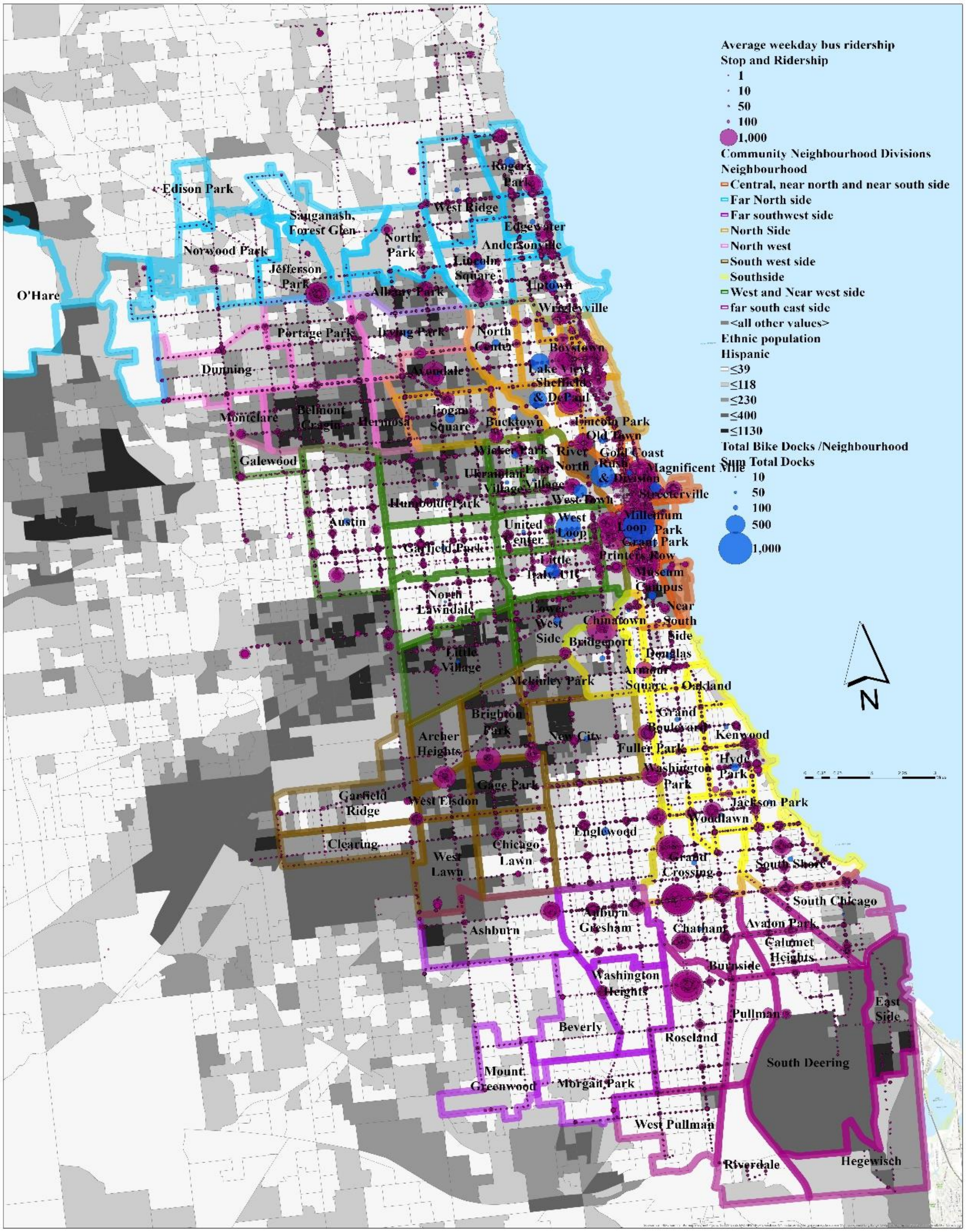


Figure 26:Access to bus service and bike share for population of Hispanic origin.

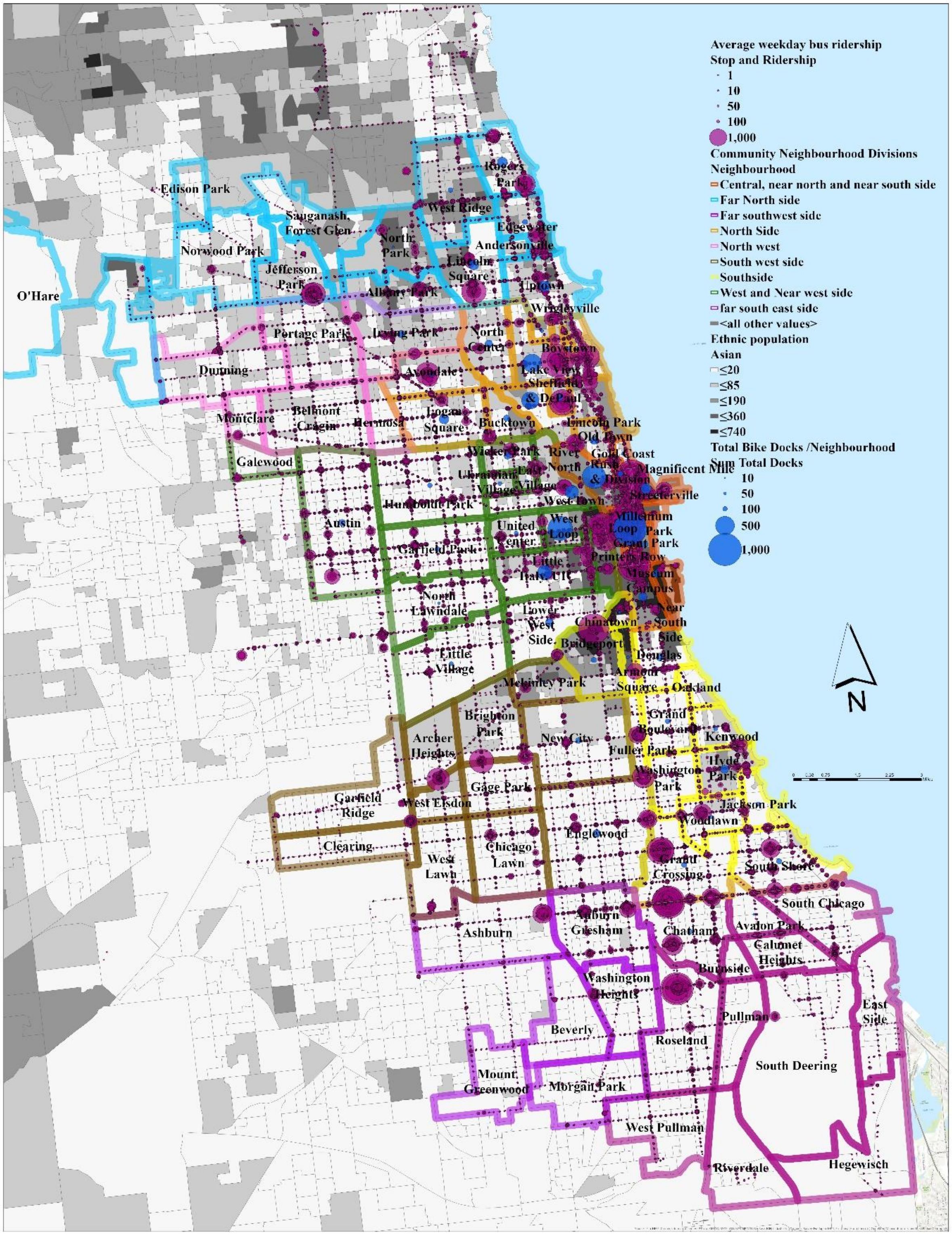


Figure 27:Access to bus service and bike share for population of Asian origin.

## 3.2. Analysis of rail ridership

The total data set of average weekday rail station level ridership for the month of October 2018 has been classified into treatment and control group. The treatment group sample (n) of 2544 and control sample (n) of 543. The level of significance is strongest at 0.1%, somewhat significant at 1% and low significance at 5%. The regression results of the associations between the independent variables and the average weekday station level rail ridership with and without bike share have been summarized in Table 11. Figure 28 to Figure *42* shows the geographic distribution of each factors to compare with the statistical results.

Table 11:Summary of statistical results for rail ridership with and without bike share.

| | **With Bikeshare** | | **Without Bikeshare** | |
|---|---|---|---|---|
| | **Coefficients** | **$P_r(>\|z\|)$** | **Coefficients** | **$P_r(>\|z\|)$** |
| **Intercept** | 7.687 | < 2e-16 *** | 9.021 | < 2e-16 *** |
| **Ethnicity** | | | | |
| HH White | 0.0009209 | < 2e-16 *** | 0.0009449 | 0.029384 * |
| HH Black | -0.0001066 | 0.28419 | -0.0009427 | 0.042621 * |
| HH Asian | 0.001226 | 6.39e-14 *** | -0.004468 | 1.61e-09 *** |
| HH Hispanic | -0.0003749 | 0.00814 ** | -0.0003078 | 0.455130 |
| **Vehicle Ownership** | | | | |
| HH zero car | 0.0003907 | 1.33e-12 *** | 0.004987 | 2.44e-12 *** |
| HH 1 car | 0.0004003 | 1.38e-09 *** | 0.002494 | 1.81e-12 *** |
| HH 2 car | -0.0000126 | 0.92033 | -0.004374 | 2.41e-11 *** |
| **Income** | | | | |
| Less than 40,000 | -0.0002930 | 0.00540 ** | -0.002785 | 0.000208 *** |
| Between 40,000-99,000 | 0.00006684 | 0.60137 | 0.003202 | 6.58e-10 *** |
| Between 100,000-149,000 | -0.0005947 | 0.00610 ** | -0.004835 | 6.36e-09 *** |
| 150,000 and above | 0.0004316 | 0.0000351*** | -0.007926 | < 2e-16 *** |
| **Age** | | | | |
| Age 15-34years | -0.0000442 | 0.04202 * | -0.0008293 | < 2e-16 *** |
| Age 35-64years | -0.0006830 | 5.98e-16 *** | 0.001684 | 0.00000117*** |
| Age over 64years | -0.0007064 | < 2e-16 *** | -0.009257 | 0.005358 ** |
| **Others** | | | | |
| Population with Disability | 0.0002866 | 0.17851 | -0.008872 | < 2e-16 *** |
| Park and Ride | 0.2923 | 9.29e-10 *** | -0.3780 | 0.000264 *** |
| Total Bike Docks | 0.02503 | < 2e-16 *** | Not Applicable | Not Applicable |

*** p<0.001; **p<0.01; *p<0.05

### 3.2.1. Age as a Factor

The younger age group has negative impact on the rail ridership both with (-0.0000442, $p<0.01$) and without bike share (-0.0008293, $p<0.001$). However, the magnitude of negative impact is greater for rail stations with bike share facility. The population 35 to 64year age group demonstrates a strong negative effect (-0.0006830, $p<0.001$) and a strong positive effect on stations without bike share facility (0.001684, $p<0.00$). For the senior population ( over 64 years), bike share has a stronger negative effect(-0.0007064 ,$p<0.001$) on station level rail ridership than rail stations without bike share (-0.009257,$p<0.01$) (Table 11) .

Rail stations are normally used for longer distances and the station distance between one rail station to another is relatively large and beyond walking or biking capacity. As a result, the trends in different age group may not only be resulting the geographic distribution of transit and bike share in coordination with each other, rather also the limitations of travelers biking long distances between rail stations. Younger generation under the age of 30 till adulthood consider urban area to be their preferable choice for residence such as downtown areas with a mix of land use or urban residential neighborhoods [30]. The decision making may be influenced by many different factors such as income, employment etc. [31]. A growing acceptability of bike share has been found amongst millennials in various research [32]. Past study on the Divvy bike share system found that age under 30 years consists of 7% of female subscribers and 17% of the male subscribers with total number of subscribers making 66% of the total population [68]. The same study found 27% of the male between the age of 30 to 50 and 7% percent of the female subscribers (66%) are using bike share [68] which shows acceptability to micro mobility options. The statistical analysis results found were based on the entire Chicago population and the trends could be effected by several

factors in general such as younger population not having access to combination or bike share and rail station or it could also be that bike share has a substitutional effect on rail transit ridership. Divvy bike share has been found to have a total percentage of bike share trips by senior population over 50 years to be 2% of the female subscribers and 7% of the male subscribers. The study found that the majority of trips are contributed by registered “subscribers” (66% of total trips)and 34% by the “customers” with one-day pass [68] .For senior population, the trends could not only reflective of generation gap rather their willingness to use bike share resulting their physical limitations. The negative trends could also be because rail transit needs to be improved to meet the needs of senior population.

### 3.2.2. Income

Population with income less than $40,000 shows a negative effect on rail ridership of both stations with bike share (-0.0002930, $P<0.01$) within 400m proximity as well station that does not have bike share within 400m proximity (-0.002785, $p<0.001$). Population in the medium income range has an insignificant effect ($p>0.05$) on rail ridership with bike share whereas has a significant positive effect (0.003202, $p<0.001$) on rail ridership for station locations without bike share. The higher medium group shows strong negative effect for both rail stations with (-0.0005947, $p<0.01$) and without (-0.004835, $p<0.001$) bike share within the proximity of 400m. The negative effect is greater for the case of rail stations without bike share and could be reflective of the population who has access to rail stations with bike share. Finally, the higher income population shows a strong positive effect (0.0004316, $p<0.001$) for stations with bike share and a strong negative effect for

stations without bike share (-0.007926, p<0.001). This may infer that high-income group may only use rail transit only in combination with bike share.

Transit is the only option for low income group (<$40,000). It is notable that the negative effect on rail ridership is greater in case of stations without bike share than that with bike share. This means that this population group is more likely to use rail as transit if there is a bike share and may reflect their acceptability to bike share as a first and last mile option. On the contrary, the negative effect on the rail ridership could reflect poor transit accessibility to low income group(Figure 35) which could refer to both physical accessibility or financial accessibility. On the other hand, the behavior of the medium income group ($40,000 to $99,000) may be affected by their accessibility or their willingness to use transit which can be estimated by comparing their auto mobile use (Figure 31;Figure 32)and transit access (Figure 36). This is also true for the higher medium income group ($100,000 to 150,000). Finally, the population in the high-income group having an income of over $150,000 shows a clear acceptability of rail transit only if there is bike share present within 400m proximity of rail station. The strong positive (p<0.001) effect on the average weekday rail ridership of stations with bike share shows their high acceptability of bike share as a first and last option. Consequently, the strong negative effect (p<0.001) on rail ridership for stations without bike share shows that they are less likely to even use rail as transit if there is no bike share within 400m proximity of station location (Table 11).

### 3.2.3. Ethnicity

White population shows a stronger positive effect on the rail ridership (0.0009209, p<0.001) in comparison to rail stations without bike share in close proximity of 400m (0.0009449,P<0.05).This

could imply that white population are more likely to use rail as transit and the propensity to use rail as transit increases if bike share is available within 400m proximity. This means bike share can serve as a last mile option for white population. However, this could also infer that majority of bike share facility are located close to rail station in locations where there is greater concentration of white population (Figure 39).

On the other hand, black population demonstrates a significant negative effect (-0.0009427, $p<0.005$) on the rail average weekday ridership for stations without bike share within proximity of 400m. The population has an insignificant effect ($p>0.05$) on the rail station ridership with bike share in proximity of rail station location. Access to rail station and bike share system is very limited in the areas where the black household population high (Figure 40). The trends are also in line with areas populated by low income group and therefore budget constraint may be another reason for the negative effect on rail transit use (Figure 35).

Hispanic population has an insignificant effect ($p>0.05$) on the rail ridership when there is no bike share system within 400m proximity. However, it has a relatively significant negative effect on the ridership (-0.0003749, $p<0.01$) of rail stations close to bike share system. Most of the rail station locations where Hispanic population are concentrated don't have access to bike share system (Figure 41). The negative effect on rail ridership for stations with bike share may either reflect that Hispanic population are not likely to use bike share or point out that Hispanic population does not have bike share within 400m of the rail station location in their area or it may suggest that bike share has a substitutional effect on rail ridership.

The Asian population makes a smaller percent of the total population. However, the models result shows a strong positive effect on rail ridership for station with bike share and a strong negative ($p<0.001$) effect on rail stations without bike share. This could firstly indicate that Asian

population are mainly located in areas with good transit connection (Figure 42). The positive effect on rail station with bike share and negative effect on station without bike share shows that Asian population are more likely to use rail station in combination with bike share and less likely to use rail transit if no bike share is present. This shows that they have a strong acceptability of transit micro mobility for bike share.

#### 3.2.4. Car Ownership

The results from Table 11 shows that zero car ownership has a significant positive effect on both rail stations with bike (0.0003907,$p<0.001$) and rail stations without bike share(0.004987,$p<0.01$). This trend is supported by the location of population density of car owners. Majority of them are either located close to transit rich area (Figure 31) or low-income areas (Figure 35). Zero car ownership could be either due to not needing car due to high availably of transit or low transit use due to financial barrier. One car owner shows a strong positive impact on rail ridership for both stations with bike share (0.0004003, $p<0.001$) as well as without bike share (0.002494, $p<0.001$). Finally, two car owners show a strong negative effect on rail ridership for both stations with bike (-0.0000126, $p<0.001$) share as well as stations without bike share (-0.004374, $p<0.001$). Majority of the two car owners do not reside close to transit oriented area (Figure 31) and may use transit if they had access to good transit connectivity as well as bike share. This can be assessed by addressing the age group, income and ethnicity to which those population belong to.

### 3.2.5. Disability

Population with disability shows an insignificant effect ($p>0.05$) on rails station location with bike share. This could mean that most of the bike share facilities are not located close to rail station where population with disability are located. On the other hand, population with disability are limited to bike use due to their physical limitations and therefore the trend may not be affected presence of bike station. It is notable that rail stations without bike share shows a strong negative effect on rail ridership. This could mean that rail transit facility needs to be further improved to meet the needs of the population with disability. Referring to the map for population with disability (Figure 34) it can also be observed that disabled population are also concentrated in areas with high senior (Figure 30) or low-income (Figure 35) population concentrated regions which are barely accessible to transit.

### 3.2.6. Park and Ride

Park and ride location have a significant positive effect on average weekday station level ridership for rail stations with bike station within 400m proximity. On the other hand, park and ride locations located close to rail station which has bike share system within 400m proximity has a significant negative effect. A seen on the map, most of the park and ride locations are located synchronized with the location of the rail station (Figure 31). The results indicate that rails stations which has both park and ride and bike share facility has a significant positive effect of increase in rail ridership. Travelers are more likely to use rail transit if they have a park and ride facility and a bike share within 400m proximity. This means that transit users will use bike share as a first and last mile options for the rail transit.

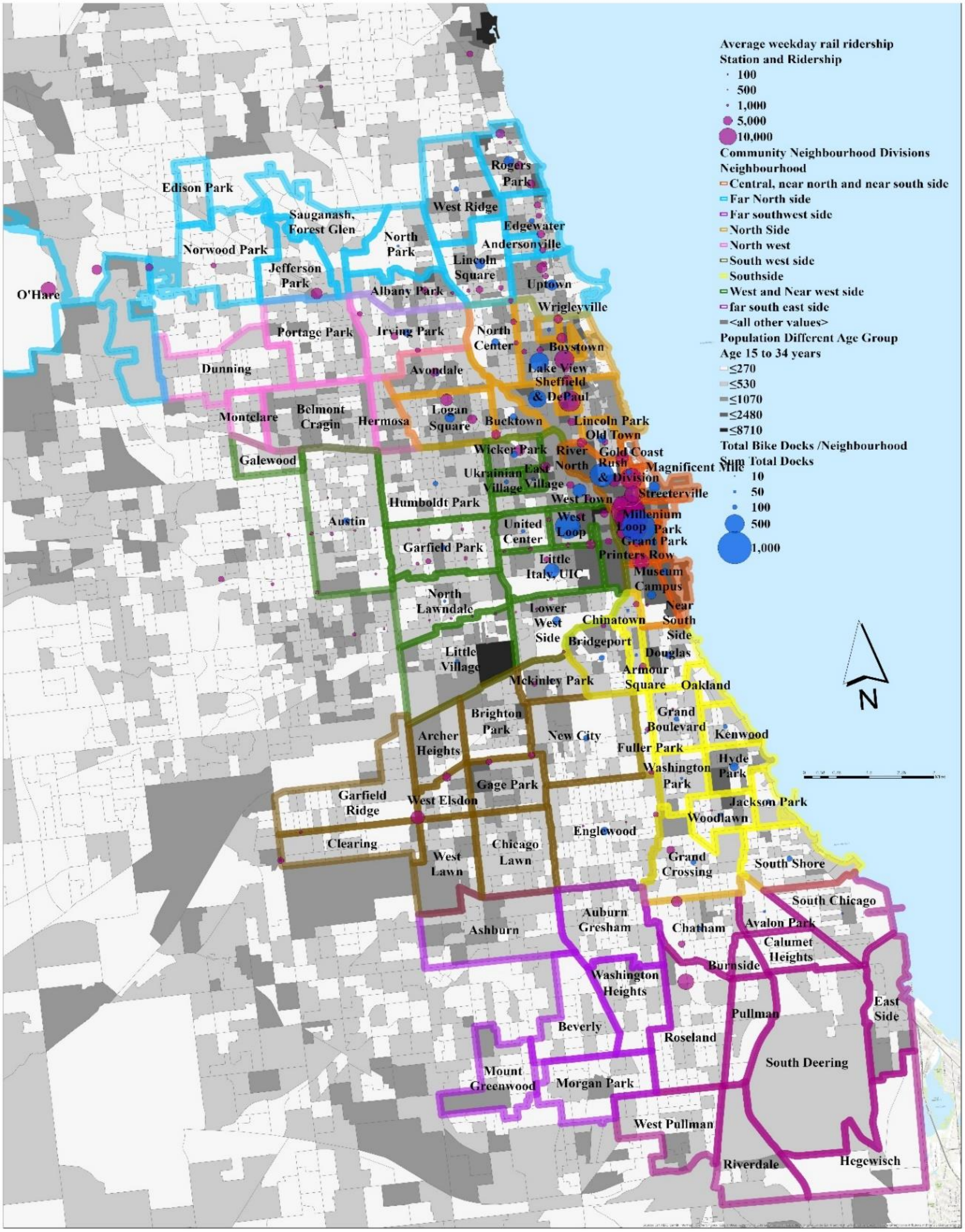


Figure 28:: Population between ages 15 to 34 years in different Chicago communities with access to rail transit and bike share.

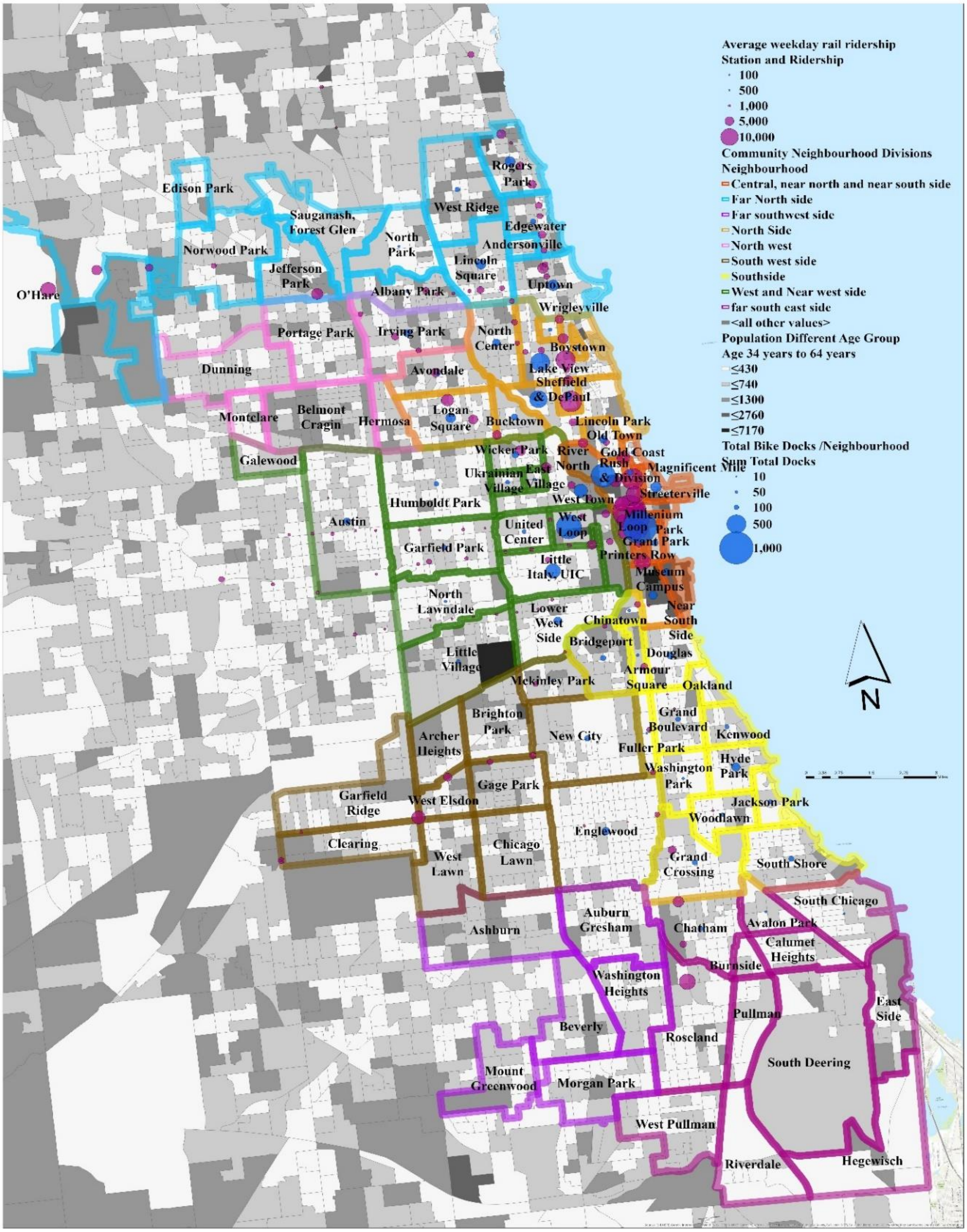


Figure 29: Population between ages 35 to 64 years in different Chicago communities with access to rail transit and bike share.

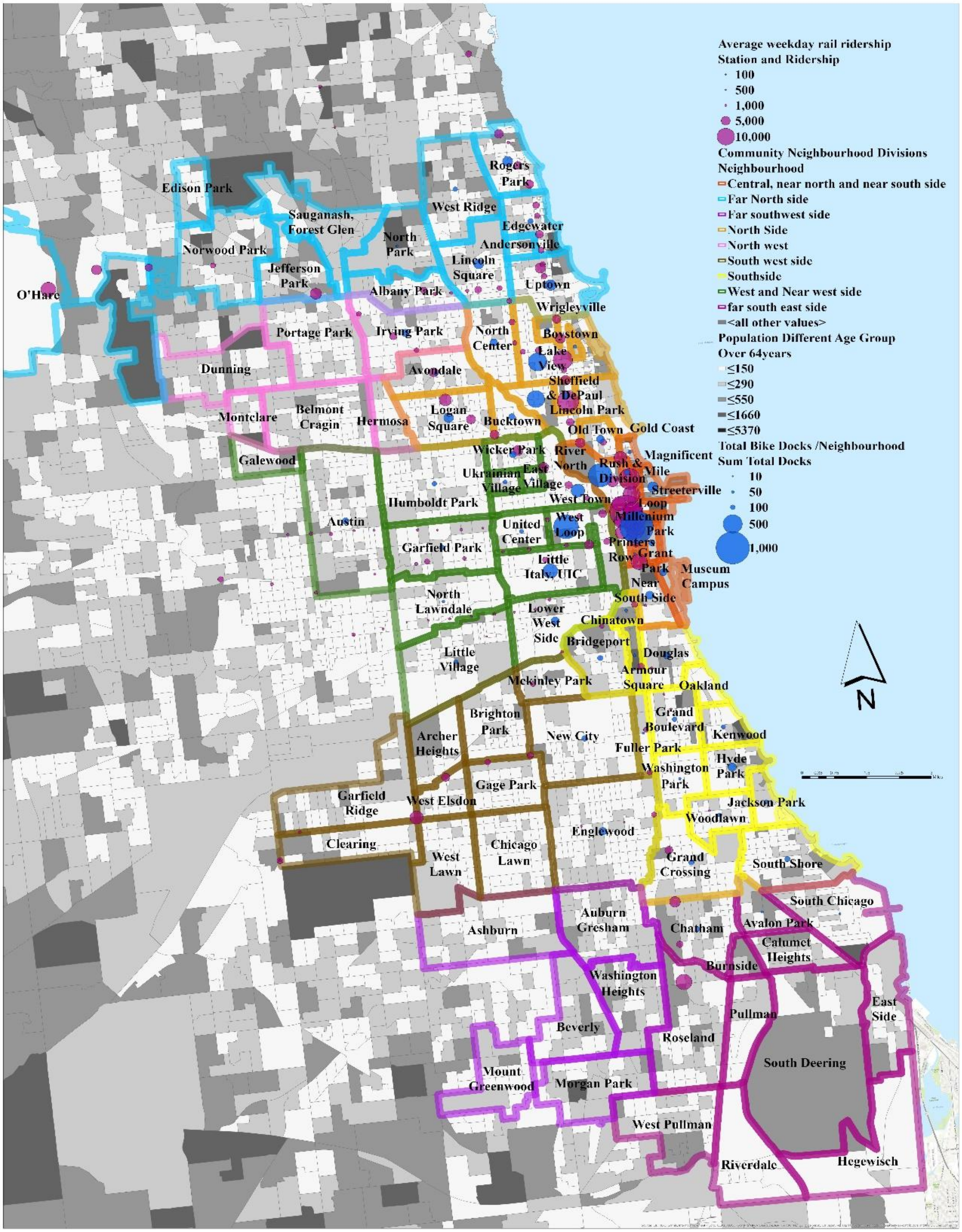


Figure 30: Population between ages over 64 years in different Chicago communities with access to rail transit and bike share.

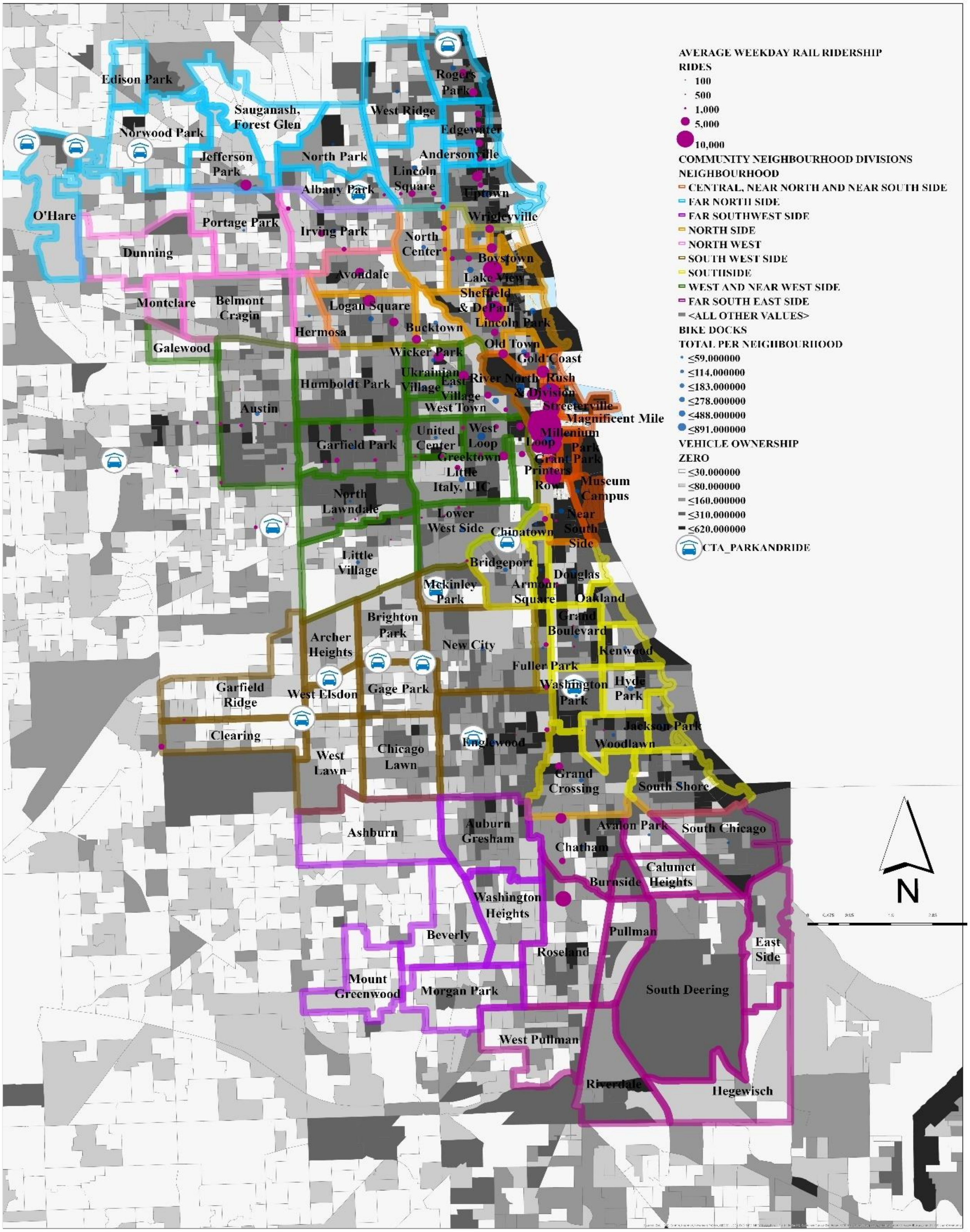


Figure 31: Population with zero vehicle ownership and access to rail transit.

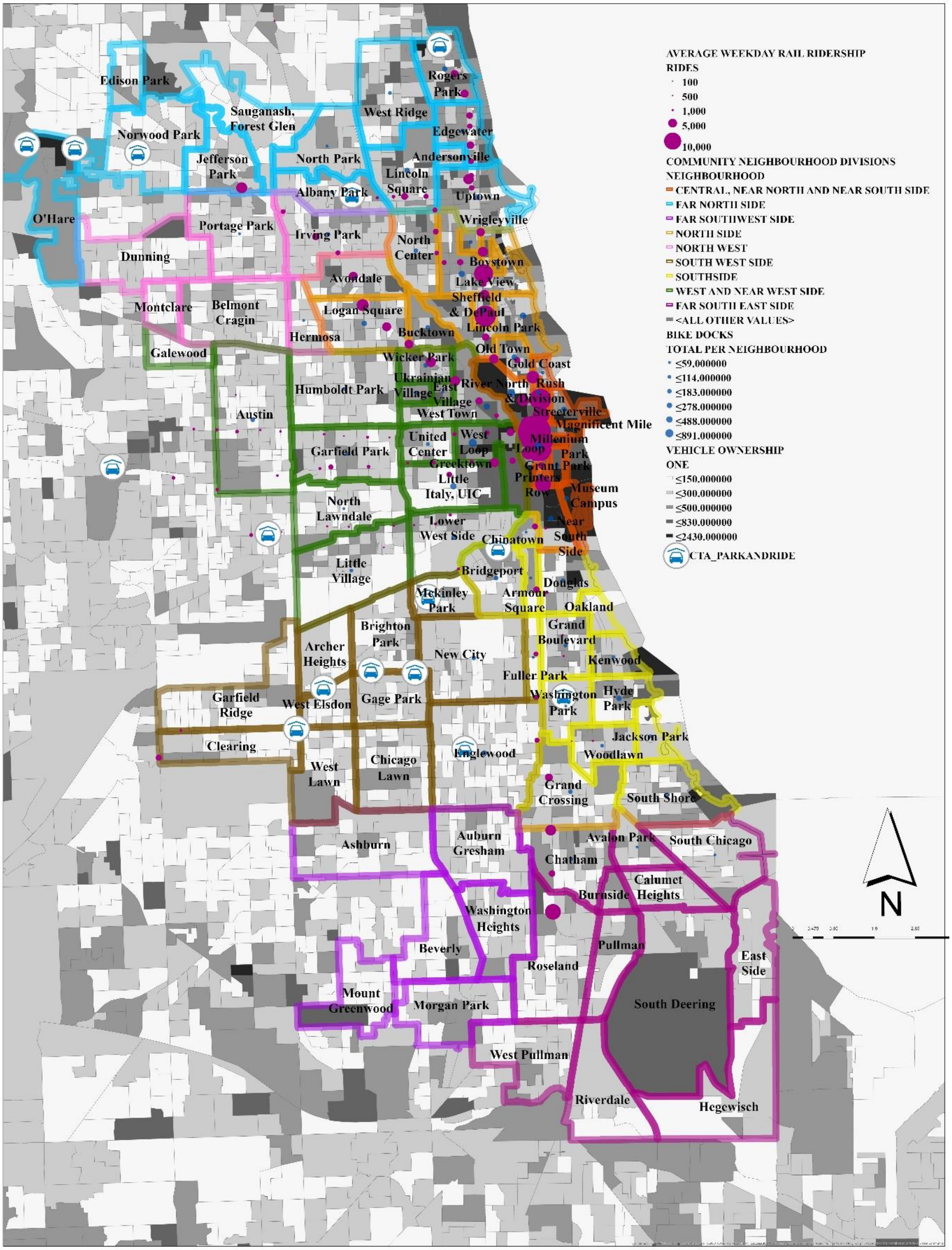


Figure 32: Population with one vehicle ownership and access to rail transit.

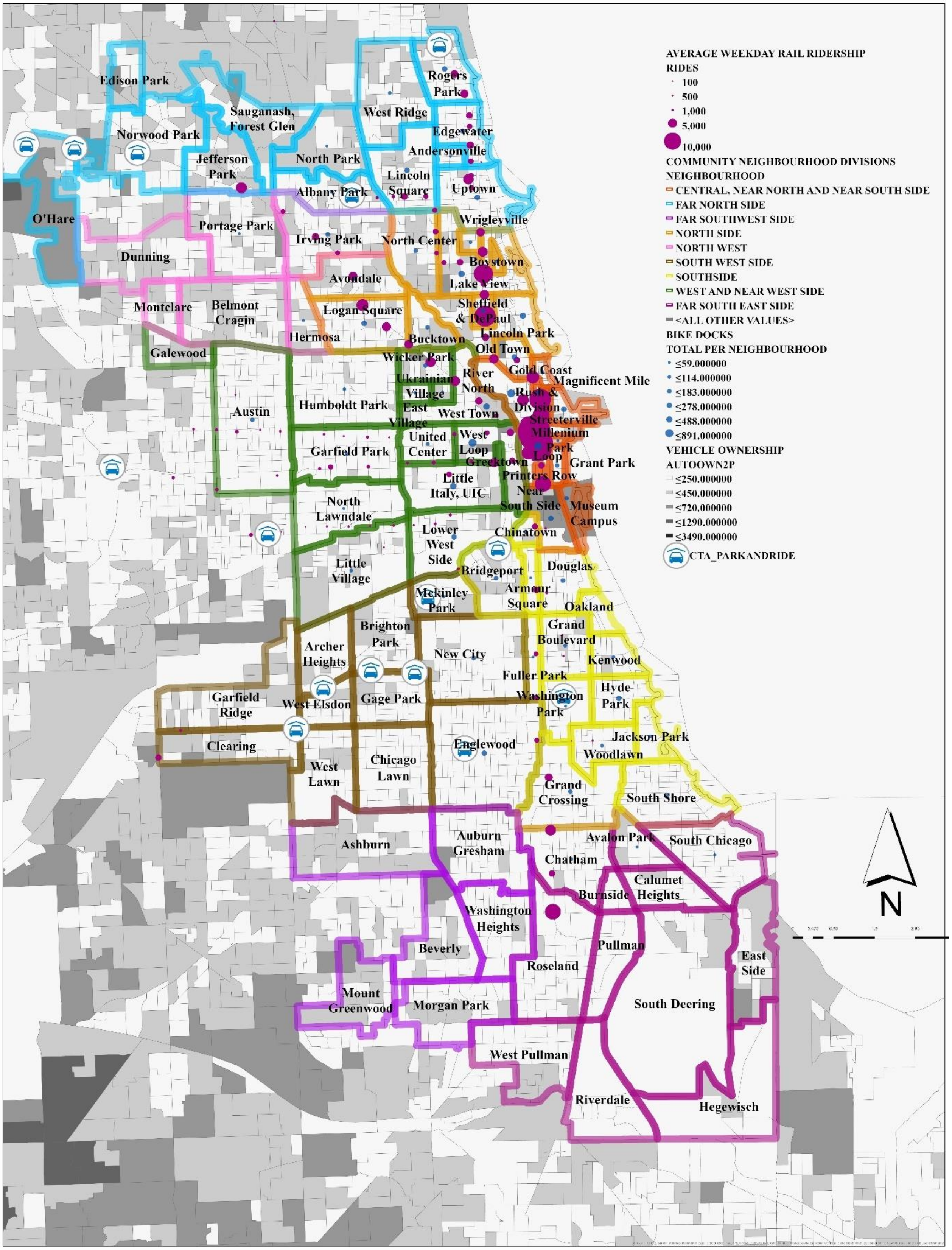


Figure 33: Population with two vehicle ownership and access to rail transit.

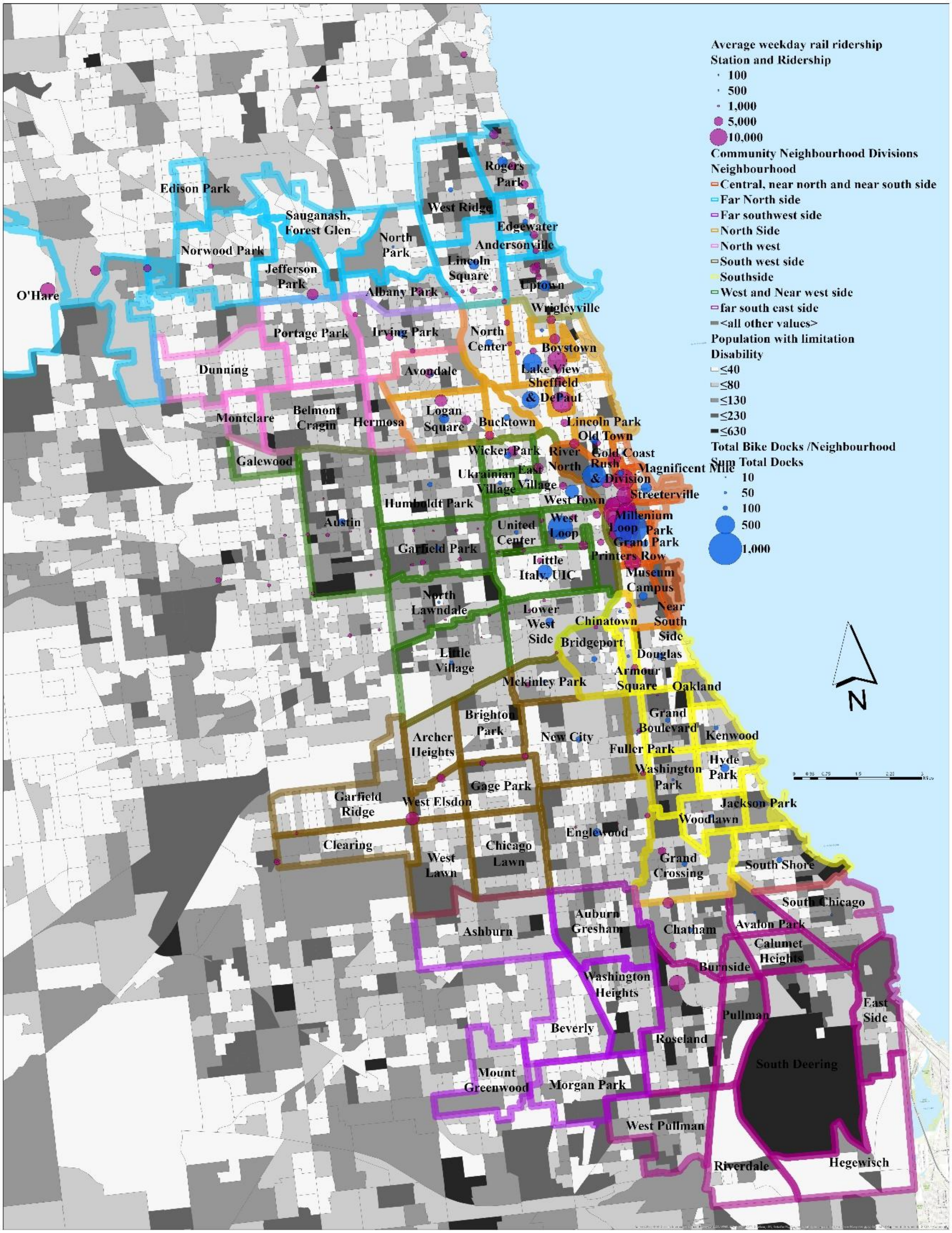


Figure 34: Population with disability and access to rail transit.

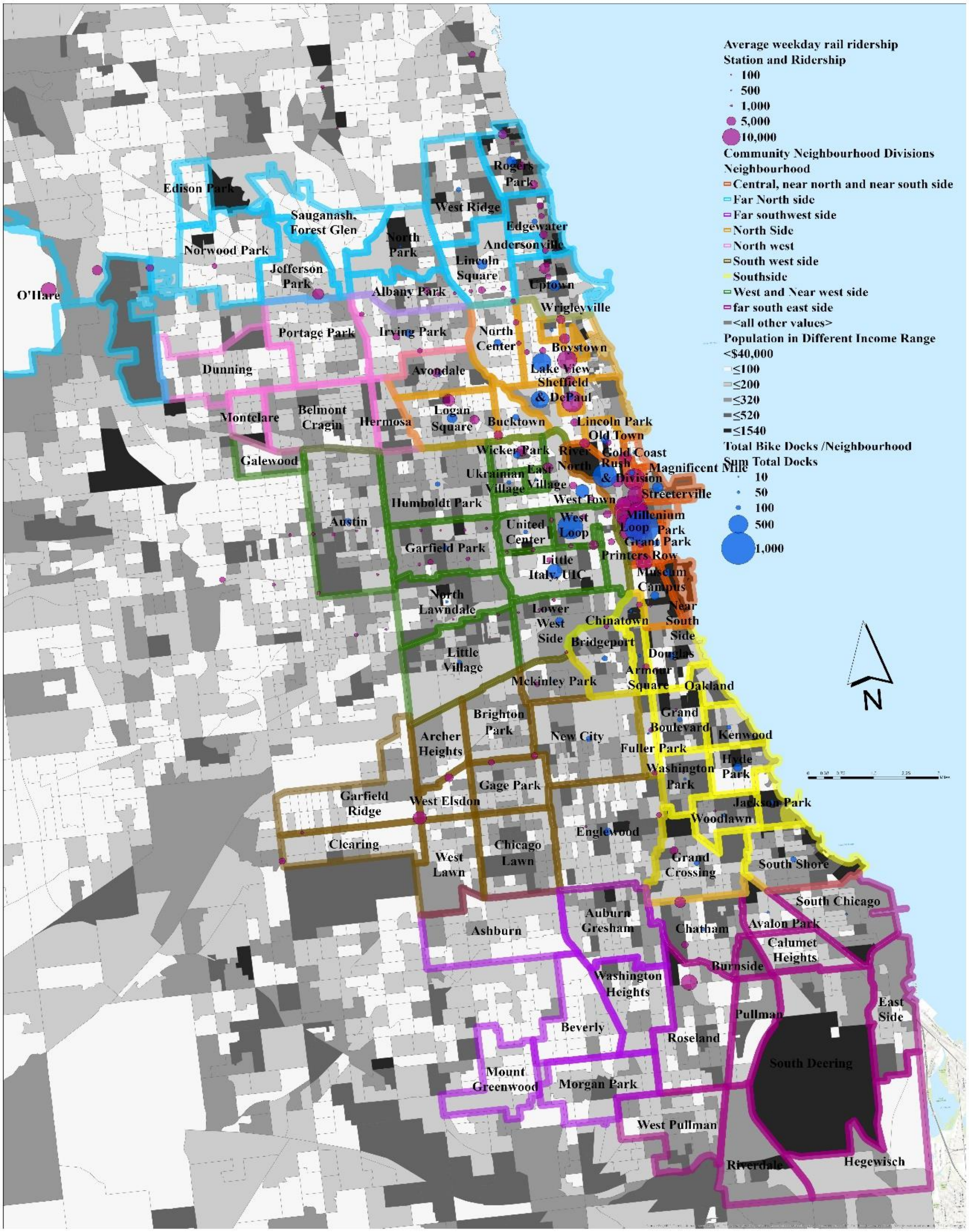


Figure 35: Access to rail transit and bike share service for population with income below $40,000.

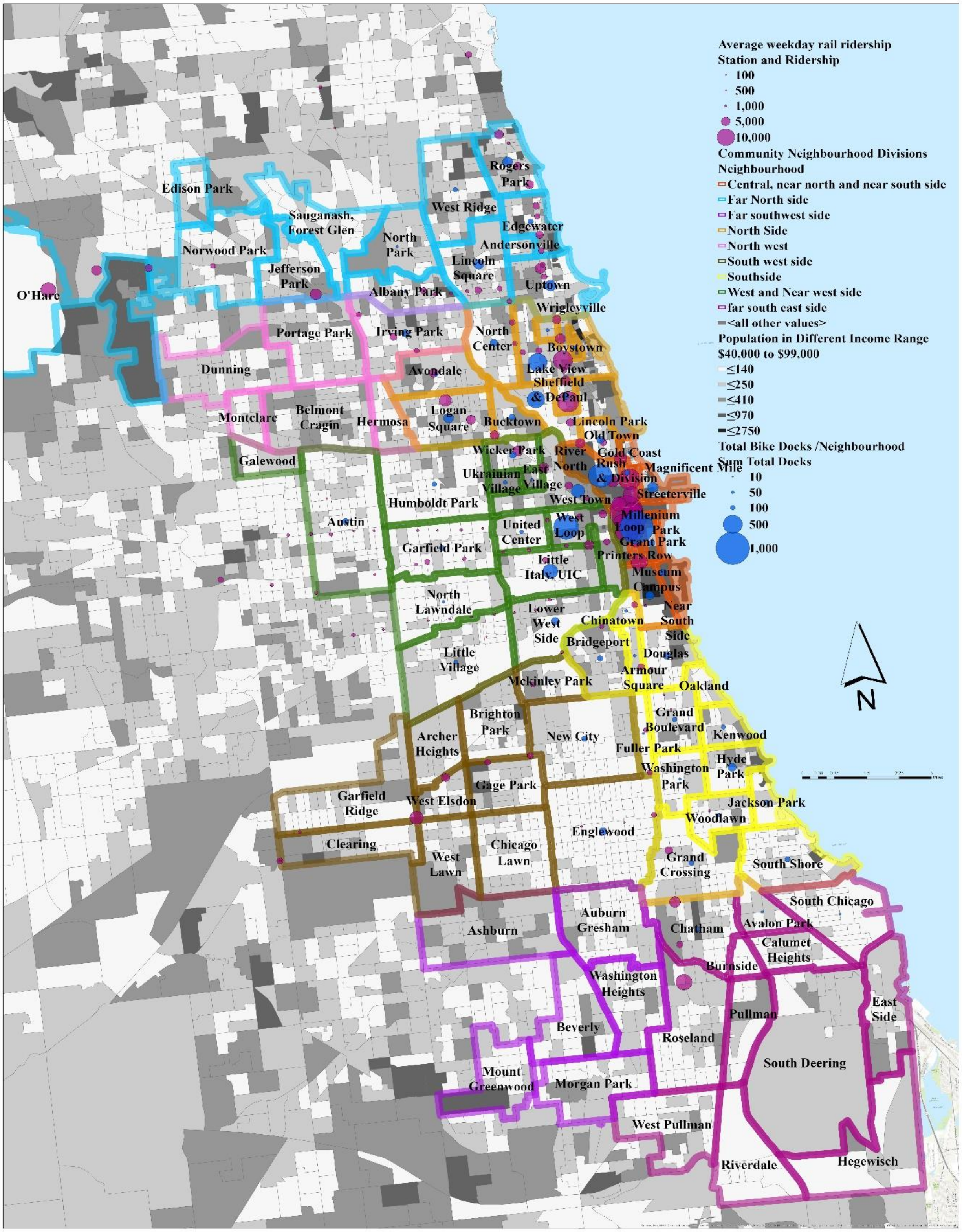


Figure 36: Access to rail transit and bike share service for population with income between $40,000 to $99,000.

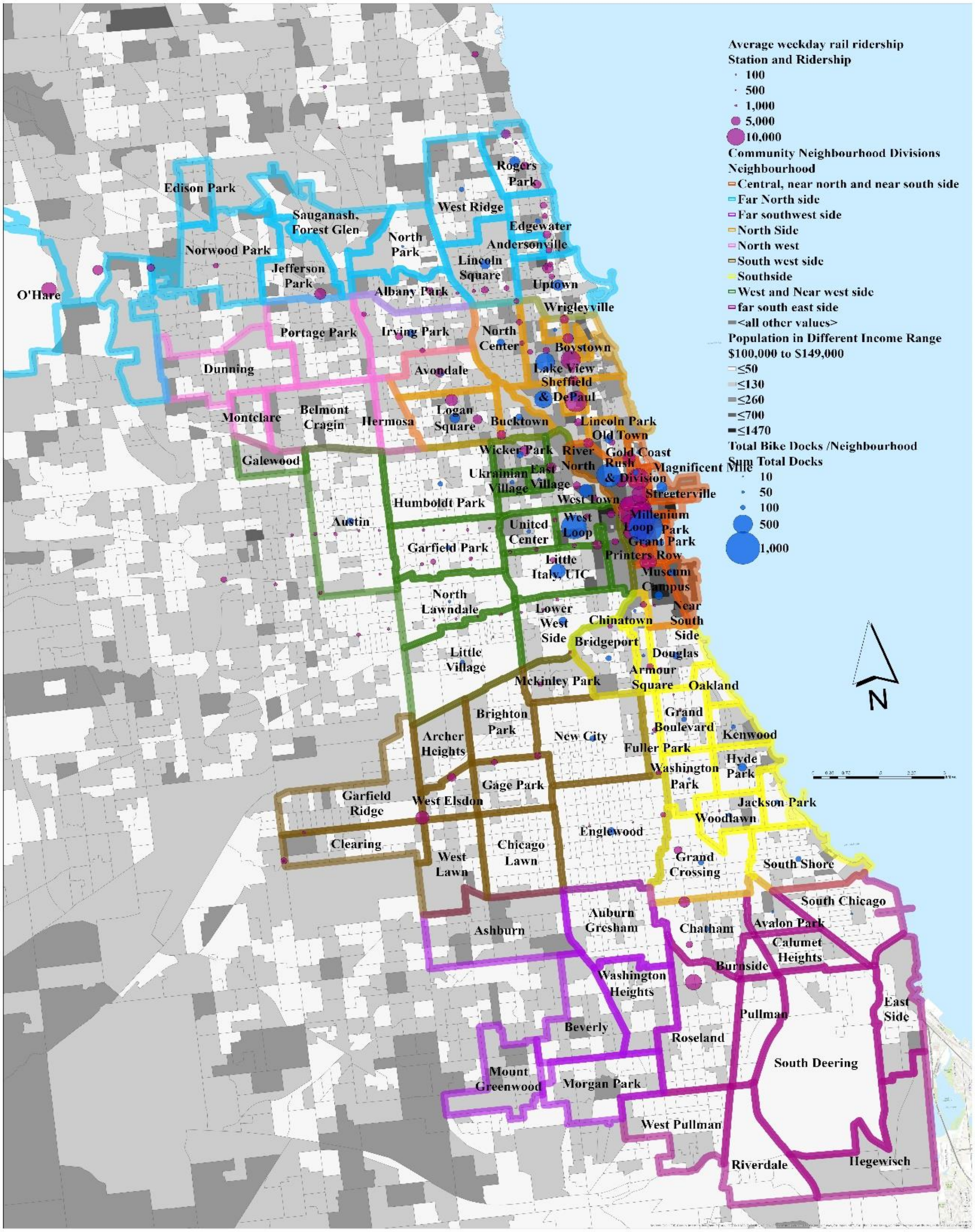


Figure 37: Access to rail transit and bike share service for population with income between $100,000 to $150,000.

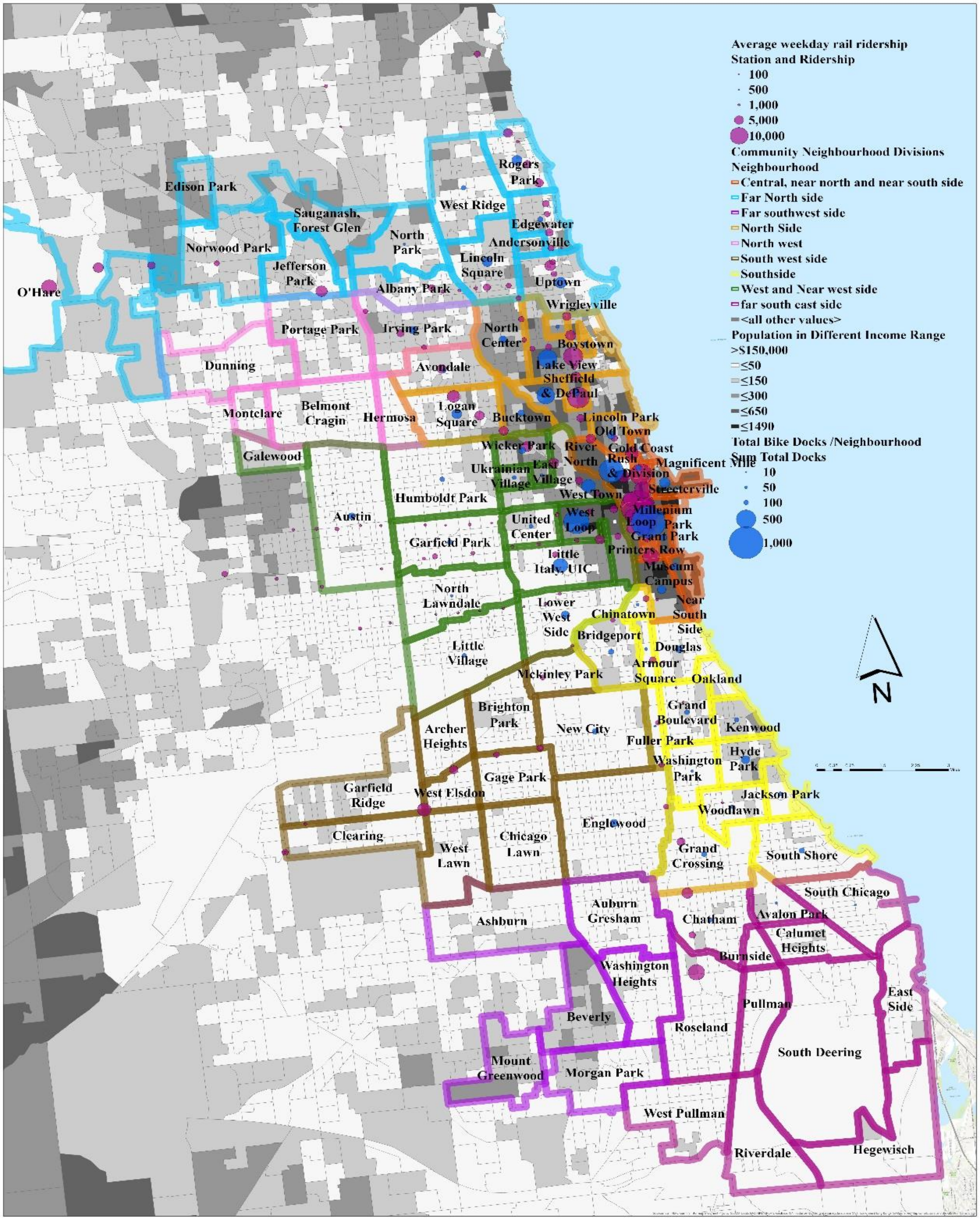


Figure 38: Access to rail transit and bike share service for population with income over $150,000.

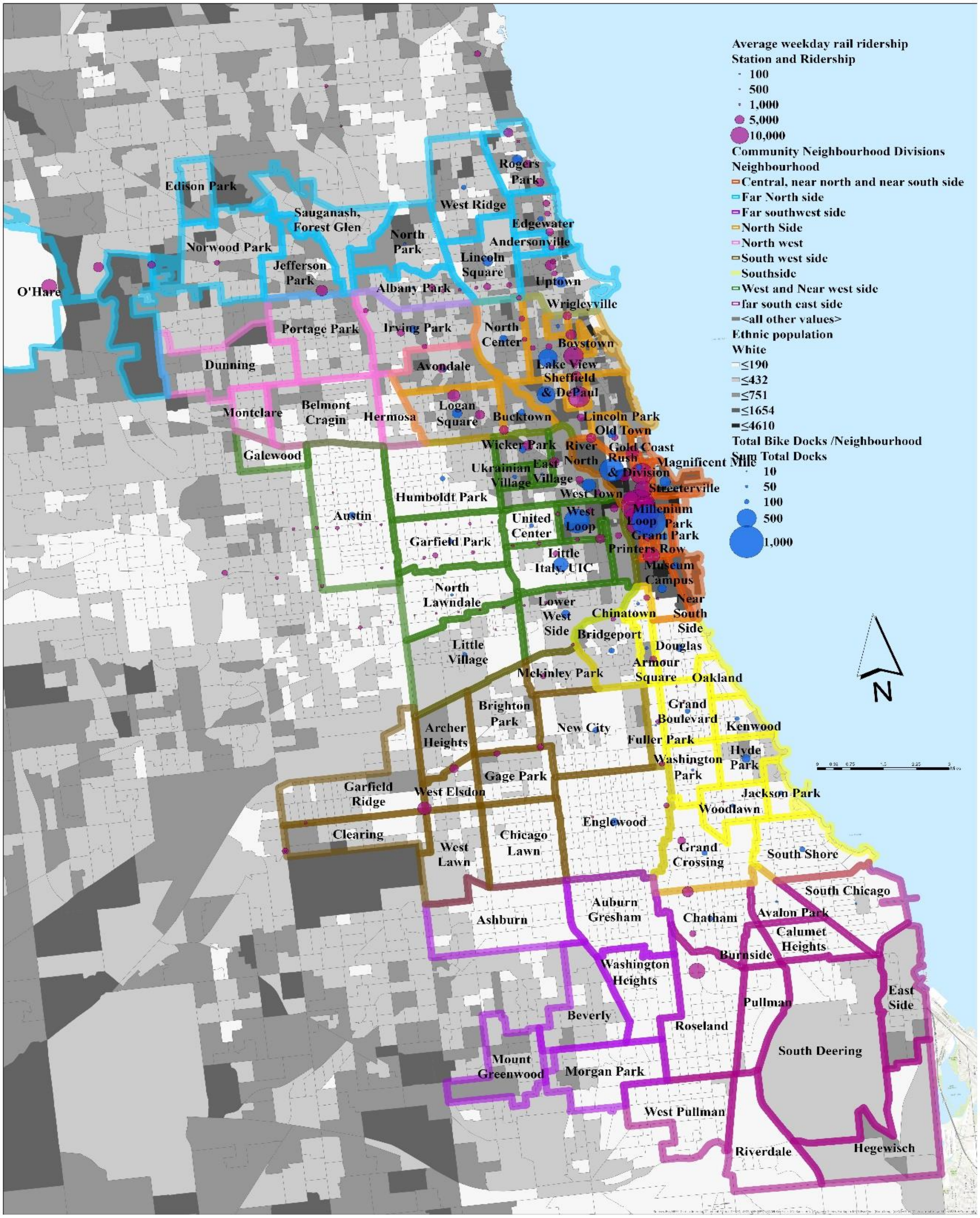


Figure 39: Access to rail transit and bike share for population of white origin.

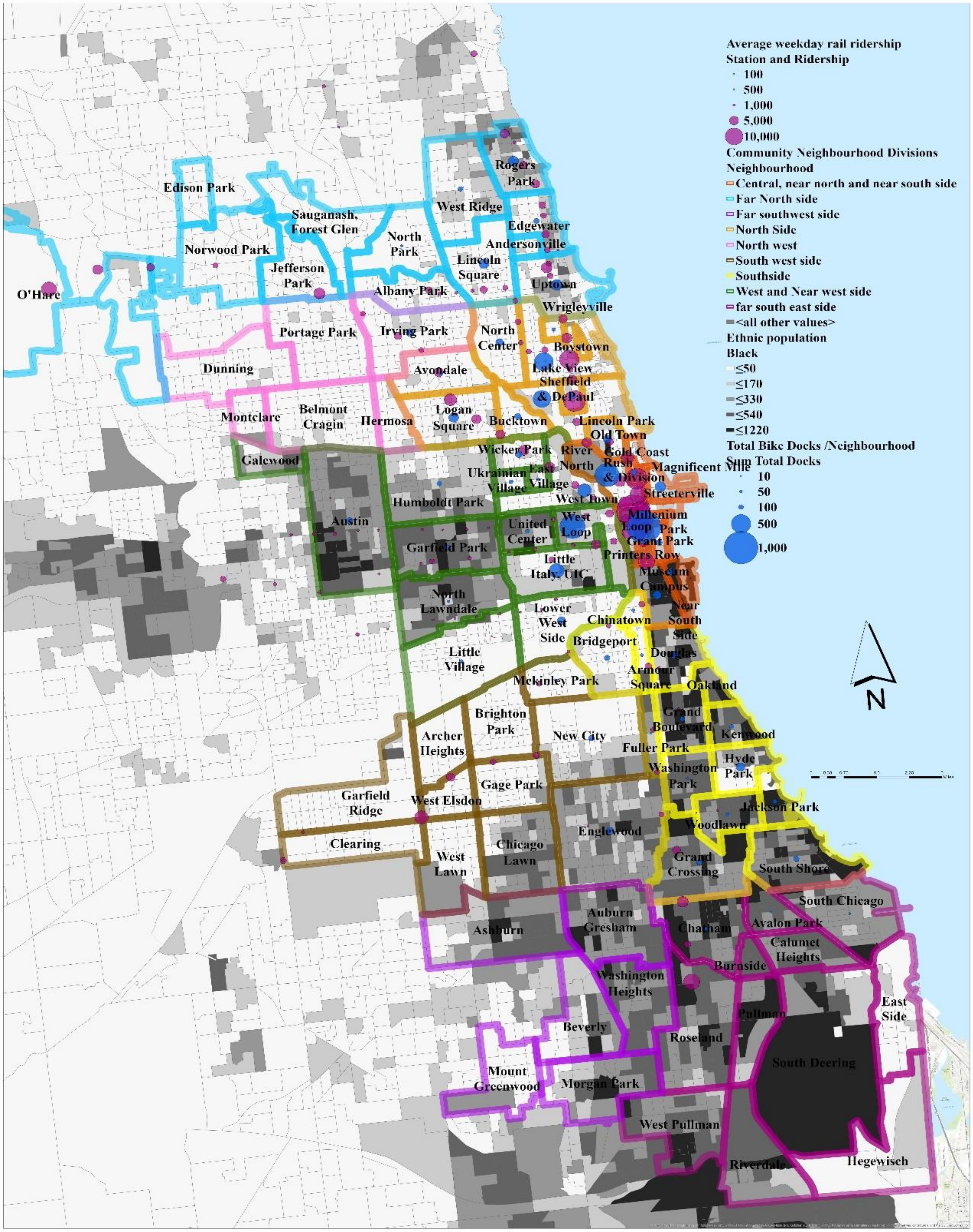


Figure 40: Access to rail transit and bike share for population of Black origin.

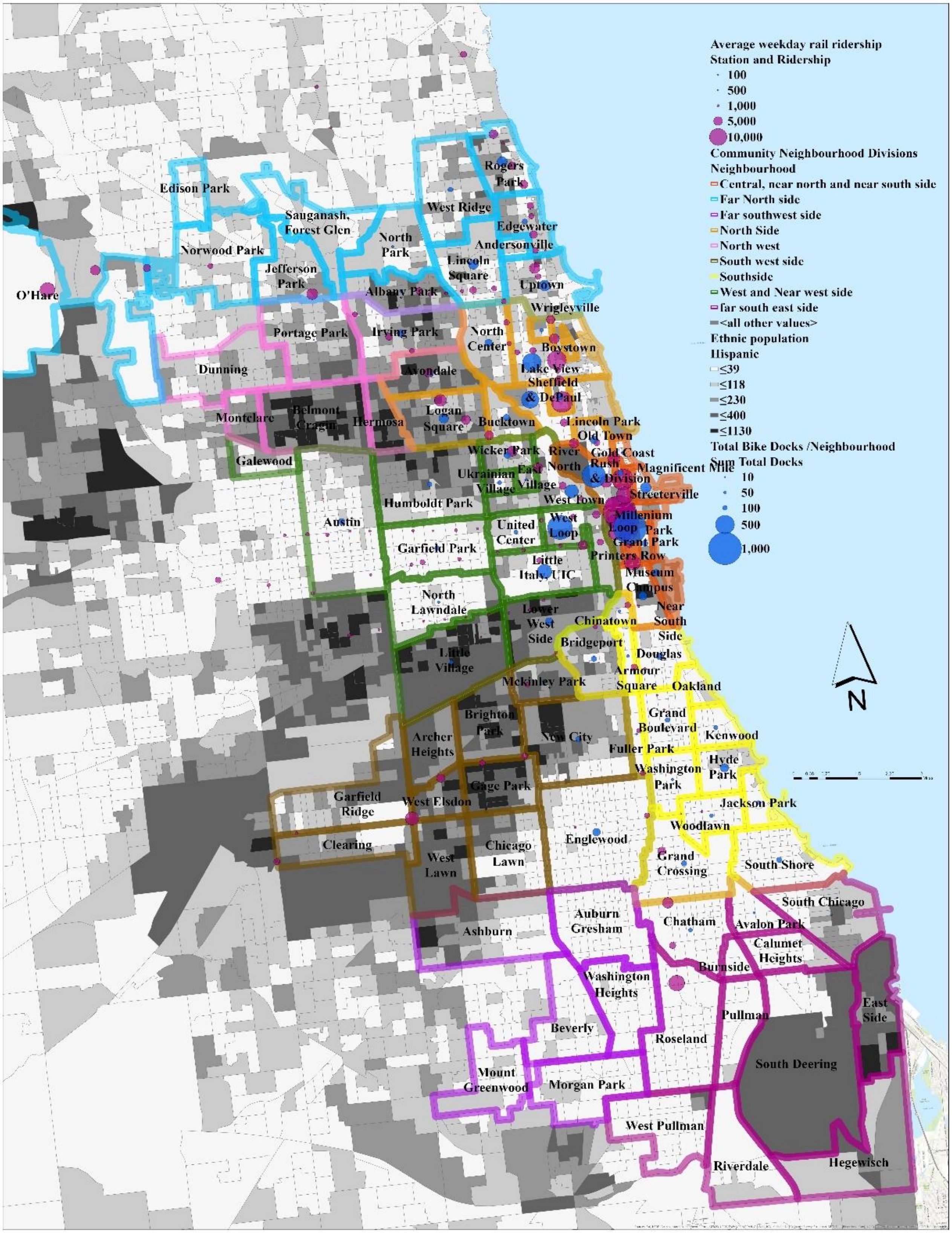


Figure 41: Access to rail transit and bike share for population of Hispanic origin.

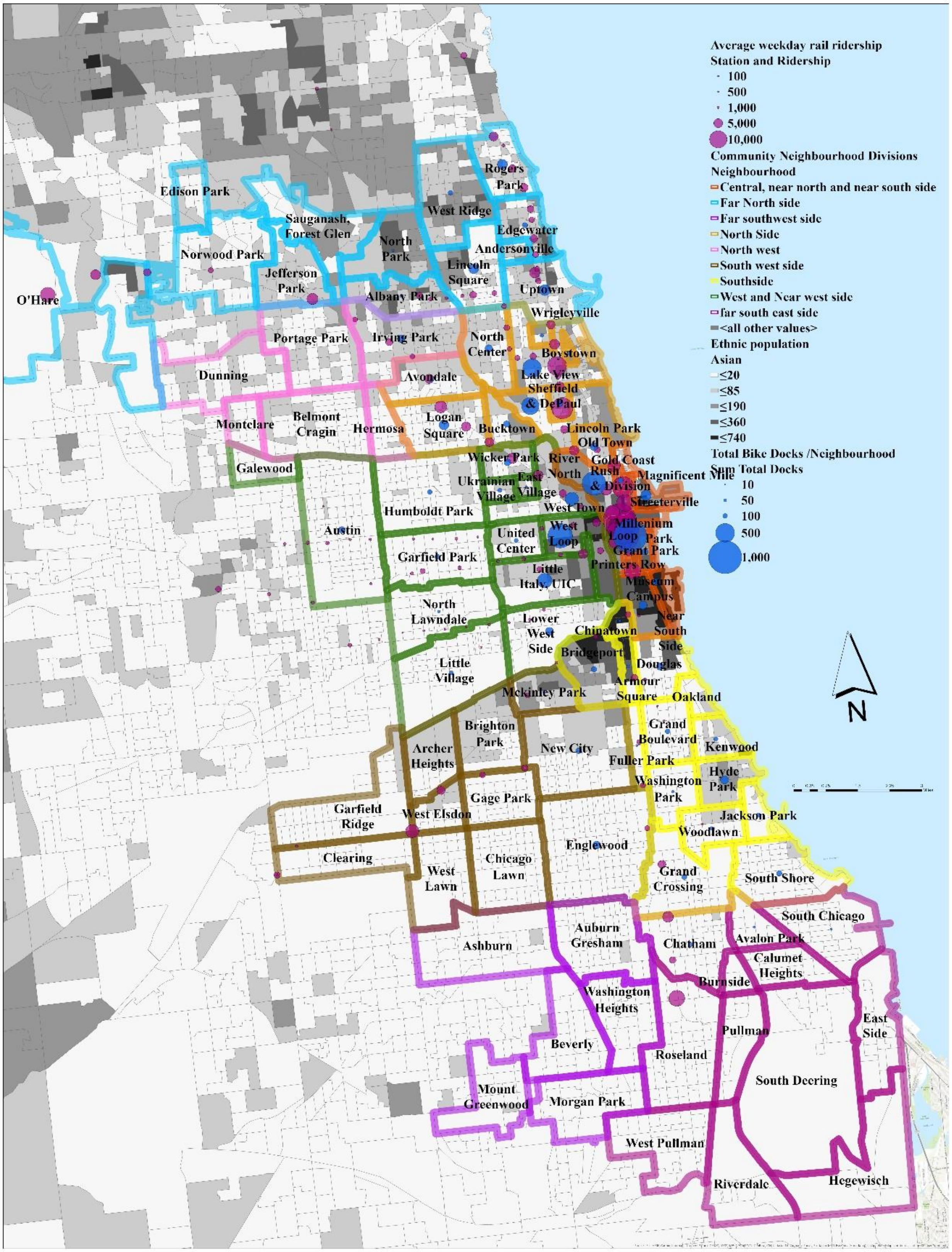


Figure 42: Access to rail transit and bike share for population of Asian origin.

# 4. Discussion

Based on the preliminary analysis results in Chapter 2 and the proportion of different population mix amongst different community, Chicago clearly shows an ethnic divide amongst its communities. Based on past literature review in Chapter 1 and preliminary analysis in Chapter 2, several variables from social, economic and demographic had been identified which affects transit ridership as well as bike share trips. Chapter 3 Section 4, then regressed the identified variables with the transit ridership(rail/bus) in order to assess the effect of these factors on ridership in presence and absence of bike share system. The analysis results helped identify : 1) does the factor have help increase or decrease transit ridership; 2) if the effect is insignificant then why it may be insignificant; 3) If the negative effect is there a possibility that more bike access can improve micro mobility or is bike share having a substitutional effect on transit ridership;

Each community in Chicago has different proportions of population mix (by age, income, ethnicity, auto ownership) which was also identified in Chapter 2.  As identified in the previous section, different population variable affects transit differently. Different proportion of population mix will affect the transit ridership and bike share use or their combined association differently or may need improved transit bike share access to improve or introduce micro mobility as a first and last mile option. Based on the findings from Section 0 as well as the geographical distribution of each factor, the following section divides the communities in Chicago into five different groups. In the following few sections, the findings from the preliminary analysis from Chapter 2 and the results from statistical model in Section  0 will now be analyzed to extract the travel behavior, gaps in transit or bike share service in each community in Chicago. This allows an insight into the possibility of transit micro mobility in different social, economic or demographic group in Chicago

allowing an assessment of transit micro mobility amongst the different communities in Chicago. Hence, based on similarity in ethnic and economic distribution the communities in Chicago has been distributed into five groups with different level of transit or micro mobility needs. In the following sections the travel behavior, transit and bike share use/needs will be assessed in terms of the population mix that is mainly concentrated in each of those regions.

## 4.1. Central

The central community of the city is mainly dominated by white population (An average of 47% population per neighborhood). The community has about an average 21.36% of population per neighborhood with income over $150,000. The community also has a relatively high (10.2%) upper medium income (100,000-150,000$) and medium income group (Average 18.8%) and very low average percentage (8.54%) of low-income group (<$40,000). The community has a low percentage of Black and Hispanic population, an average per neighborhood of 3.45% and 3.9% respectively. The community has the highest access to bus stops, rail stations and bike share system. The community also has a high population within young generation age group (15 to 34 years) and age between 35 to 64 years. Younger age group are more inclined towards urban community as well as area with well-integrated transit system which is available in the central community in Chicago. The station level transit ridership as well as access to bike share amenities is very good in this area.

#### 4.1.1. Statistical results bus

The community has about average percent per neighborhood population of 21.36% with income over $150,000. The statistical analysis shows a significant positive effect (on bus stop ridership with bike share. Whereas bus stop without bike share demonstrate a strong negative effect. This trend also persist amongst the white population shows a significant positive effect (coefficient=0.000000828, $p<0.001$) on bus ridership when it located near bike share system, whereas absence of bike share shows an insignificant effect on bus ridership. However , this is not true for lower medium income ($40,000-$99,000) group which only shows a positive effect (0.0007773, $p<0.001$)on bus ridership for stops without bike share and higher medium group who shows an insignificant effect on the statistical result as well as contributes to a smaller percent of the average neighborhood populations in the community. Therefore, it can be implied that bike share will play the role of first and last mile option for higher income group in the Central Chicago community neighborhoods and white population may be the major contributor towards increase in bus ridership (Figure 24). Asian population shows a significant negative effect (-0.0009517, $p<0.001$) on the bus ridership when near bike share and shows a somewhat positive effect (0.001220, $p<.01$) on bus ridership without bike share. This means, when bus is the transit mode for Asian population it does not act as a first and last mile option. In this case bike share may also have a substitutional effect as the Central part of Chicago has good bike share connectivity and resource (Figure 27).

4.1.2. Statistical Results rail

The white population again shows a significant positive impact (0.0009209, $p<.001$) on the rail ridership where there is a bike share system within proximity to rail station and slight positive effect (0.0009449, $p<0.05$) on the rail stations without bike share. Higher income population (> 150,000) shows a strong positive effect (0.0004316, $p<0.001$) on station level ridership for stations within bike share and a strong negative effect (-0.007926, $p<0.001$) without bike share. Since the central part has a significant population in the high-income range then it can imply that the high-income population are more likely to use bike share as a first and last mile option and hence have a positive effect on the rail ridership(Figure 38). Consequently, the high-income population are less likely to use rail if there is no bike share within proximity. Young population (age 15-34years) has a significant negative effect on rail ridership for both with (-0.0008293, $p<0.001$) and without (-0.0008293, $p<0.01$) bike share. The statistical result in Section 0 considers the results on average on the entire population of Chicago as other regions of the city a high percent of young population who doesn't have access to rail and bike share in other regions. The effect of regression model may have been distributed. Younger generation under the age of 30 as well as adults report that their "ideal" neighborhood type is in an urban area—either downtown areas with a mix of land use or urban residential neighborhoods [30]. The central community of Chicago has high access to bus transit and bike share service. Comparing the density of younger age population on the map it is found that most of the population is in the central region which is urban area. Therefore, it cannot be implied based on this result that young population are less likely to use rail as public transit whether with or without bike share. Although, Asian population contributed to a smaller percentage of the average neighborhood population, but the population has a significant positive impact on the rail ridership when near bike share system and has a significant negative effect in

absence of bike share. Thus, bike share acts as a first and last mile option for the Asian population otherwise they are less likely to use rail transit. The central community also has the highest concentration of population with zero car ownership and the reason behind that may be because the transit and micro mobility options are sufficient to compete with auto mobile ownership (Figure 16; Figure 31).

Hence, Central community can be defined to have enough access to transit as well as micro mobility options. Majority of the population has zero auto ownership and station level ridership is very high in this region. The community has already become the hub for younger population as it can meet their urban life needs. Finally, the strong positive acceptability of bike amongst different majority of population (ethnic, age or income) shows that this community has somewhat already established bike share as a first and last mile option.

## 4.2. North Side

North Side of the population has a large percent of white population household per neighborhood on average (35.6%) compared to other ethnic groups. The North side communities has a relatively high percent of average population per neighborhood (14.5%) of low-income group (<$40,000) and about 14.5% of medium income group ($40,0000-$99,0000). A large percent of the population per neighborhood lies in the age group 35-64 years on average (36.6%) and young (15-34years) percent (36.8%).

4.2.1. Statistical results bus

The white population shows a significant positive (0.0002345, p<0.001) effect on bus ridership when it located near bike share system, whereas absence of bike share shows an insignificant effect (p>0.005) on bus ridership. However , this is not true for lower medium income group which only shows a positive effect (0.0007773,p<0.01) on bus ridership for stops without bike share and higher medium group who shows an insignificant effect (p>0.05) on the statistical result as well as contributes to a smaller percent of the average neighborhood populations in the community. On the other hand, low income (<$40,000) population also has a significant positive effect on bus ridership whether there is presence of bike share or not in proximity. The station level magnitude of bus stop is relatively high in majority of the stops for this community. Hence it can be implied that bus ridership is high in these areas and bike share may already be playing the role as the first and last mile option. The North Side (8.9%) has a comparatively higher average percent Hispanic population per neighborhood. The analysis results show that Hispanic population has a significant positive effect on bus ridership for stop locations which does not have bike share within proximity. But the map shows that bike share is not very accessible to most areas where Hispanic population is high. The overall bus ridership and bike share accessibility is high in this region. Majority of the population does not have access to car ownership (Figure 13). Thus, improving bike share access a little more can further contribute to bus ridership.

### 4.2.2. Statistical result rail

The north side community has a high access to rail transit and good distribution to bike share system. The community has a high average percent white population per neighborhood. The white population again shows a significant impact (0.0009209, $p<.001$) on the rail ridership where there is a bike share system within proximity to rail station and slight positive effect (0.0009449, $p<0.05$) on the rail stations without bike share. The community has 9.8% of high-income population which has a significant (0.000431, $p<0.001$) positive effect on bike ridership. The population 35 to 64 years has good accessibility to rail transit but has a strong negative effect on station location with bike share (-0.000683, $p<0.001$) and a positive effect on rail ridership for stations without bike share (0.001684, $p<0.001$). This could imply that this age group either prefers bike share to rail when available and therefore bike share has a substitutional effect on rail ridership. The community has 35.1% of average percent younger population per neighborhood. But the age range 15-34 year has a strong negative effect in both with (-0.0000442, $p<0.05$) and without (-0.0008293, $p<0.001$) bike share for rail transit ridership which may imply that this age group does not prefer rail as transit. The population with zero car ownership has a strong positive effect on both bus and rail when in proximity to bike share which imply that they are transit dependent and the map shows a high concentration of zero car owners in this region

North Side has high White population in the Lake View, Sheffield and DePaul, Lincoln Park, Edge water and Rogers Park area (Figure 39). There is high percent young population distributed relatively evenly around the community such as Lincoln Park, Boys town Wrigley vile and Sheffield and DePaul (Figure 13;Figure 28). The map shows a high population of zero auto ownership population well distributed in the community. The community does not lack access to

transit or bike share and hence the ridership trends reflect the population mode choice characteristics. But some population with younger concentration does not have access to adequate bike share. The North side communities has a relatively high percent of average population per neighborhood (14.5%) of low-income group (<$40,000) and about 14.5% of medium income group ($40,0000-$99,0000). The North side community has a high accessibility to bus service and rail and but gap in accessibility of bike share services and a very good connectivity to park and ride services. Improving bike share will improve accessibility for young, low and medium group. The community has very high concentration of zero hence is highly transit dependent. Overall, the population composition is more like to accept bike share as a first and last mile option only in case of bus in comparison to rail.

## 4.3. Far North Side

The Far north side of the population has a large percent of white population household per neighborhood on average (31.7%) compared to other ethnic groups. The Far North Side communities has a relatively high percent of average population per neighborhood (13.76%) of low-income group (<$40,000) and about 12.9% of medium income group ($40,0000-$99,0000). A large percent of the population per neighborhood lies in the age group 35-64 years on average (Far North Side 43.46%) and young (15-34 years) percent (36.8%).

### 4.3.1. Statistical results bus

The white population shows a significant positive effect on bus ridership when it located near bike share system, whereas absence of bike share shows an insignificant effect on bus ridership. However , this is not true for lower medium income group which only shows a positive effect on bus ridership for stops without bike share and higher medium group who shows an insignificant effect on the statistical result as well as contributes to a smaller percent of the average neighborhood populations in the community. On the other hand, low income (<$40,000) population also has a significant positive effect on bus ridership whether there is presence of bike share or not in proximity. The station level magnitude of bus stop are relatively high in majority of the stops for this community. Hence it can be implied that bus ridership is high in these areas and bike share may already be playing the role as the first and last mile option. The North Side (8.9%), has a comparatively higher average percent Hispanic population per neighborhood. The analysis results show that Hispanic population has a significant positive effect on bus ridership for stop locations which does not have bike share within proximity (Figure 41, Figure 26).

### 4.3.2. Statistical result rail

The North side is mainly dominated by white, young and low to medium income population. White population shows a stronger positive effect on the rail ridership (0.0009209, $p<0.001$) in comparison to rail stations without bike share in close proximity of 400m (0.0009449, $P<0.05$).

Most of the younger population are located close to the lake side where the transit connectivity is good (Rogers Park, Edgewater, Anderson Ville, Lincoln Square and Uptown)(Figure 28;Figure

13). This is also the region where most of the low-income population of the community are located and has a fair share of the bus service accessibility (Figure 20). Areas like North Park, West Ridge has lower access to bike share and rail service and is also populated by a lot of the medium income ($40,000 to $99,000) population (Figure 21; Figure 36). Moving westward in the community, younger population density goes down but white population density goes up (Figure 24, Figure 39). On the other hand, the western side of the community is home to most of the middle-aged population (35 to 64 years). This region does not have adequate bike share service. The Far North side community has a high accessibility to bus service and rail.  The area has limited access to bike share and it nearly not present moving west and hence there is spatial gap in the distribution of bike share service.

## 4.4. North west, West and Near west side and South west

Moving from North west towards West and Near west community towards South west community, the average percent population of white decreases (from 30.33% to 15.7%) and average percent Hispanic population increases (between 9% to 16.6%). Majority of the White population in West and Near west side are clustered towards the Central community. Both bus, rail and bike share facility in the areas with large white population is very accessible (Figure 24).

The highest average percent of Hispanic population per neighborhood is in the Southwest community (16.6%) especially along the border of West and Near west and South west side. Both these areas have had good access to rail service (Figure 41) and limited access to bike share. Bus service access to these areas are very high (Figure 26). However, stop or station level ridership is low in most of the rail stations and bus stops. Hispanic population is also high in the north west

community (10.83%). This population has very good access to bus service but very poor access to bike share service. The access to rail service is more inclined along the border of the North side community and does not exist moving west.

### 4.4.1. Statistical Analysis Bus

The analysis results show that Hispanic population has a significant positive effect (0.0006429***) on bus ridership for stop locations which does not have bike share within proximity. The white population shows a significant positive effect on bus ridership when it located near bike share system, whereas absence of bike share shows an insignificant effect on bus ridership. However, most of the white population are located close to the Central community (Ukrainian Village, West Town, East Village, Wicker Park), the trend from White population only may apply to certain neighborhoods in the West and Near west side (Figure 24). On the contrary an average of 7.6% of population per neighborhood is black in the West and Near west Community (Figure 25). The areas where the black population resides (Austin, Garfield Park, North Lawndale, United Center) has good accessibility to bus service with some limited access to bike share. The map shows that even though the bike share facility is limited, the nearby bus stops shows some greater magnitude of bus ridership. This is supported by the statistical results which show that Black population has a significant positive effect bus stop ridership when located close to a bike station (0.00034, $p<0.001$). Comparing this to the bike share accessibility to Hispanic population, majority of the areas where Hispanic population are concentrated (North west, West and Near west side and South west) both has limited or no bike share facility (Figure 26). Therefore, the positive effect (0.0006429, $p<0.001$) on the bus ridership without bike share may be due to service gap. This

implies that increasing bike share system in areas where there is higher concentration of Hispanic population may significantly improve bus ridership and hence bike share may serve as a first and last mile solution for this ethnicity.

### 4.4.2. Statistical Analysis Rail

Black population located in the West and Near west side and South west community has fair access to rail transit (Figure 40). Black population has a positive effect (-0.0009427, $p<0.05$) on the rail ridership when there is no access to bike share service. There was some low availability of bike share facility in West and Near west side and parts of south west side where there is concentration of black population. Most of these locations also have high concentration of low-income population (Figure 35). The rail stations with bike share in proximity did not increase the station level rail ridership. This may imply that bike share will not serve as a first and last mile solution for black population or the mode of payment or the fare price is out of their reach. Most of the neighbor hoods in North west, West and Near west side and South west where Hispanic population are concentration (Belmont Craigin, Hermos, Portage Park, Archer Heights, Brighton Park, Mckinlet Park, Gage Park and West Lawn) doesn't have adequate access to bike share but has access to rail (Figure 41). Despite that some of the limited number of rail station which has access to bike share did not show any significant increase in station level rail ridership in comparison with ones which did not. This is reflected by the statistical analysis result (-0.0003749, $p<0.01$) which shows that Hispanic population has a negative effect on rail ridership when in proximity to bike share. This trend could also be due to the substitutional effect of Bike share.

The North west, West and Near west side and South west community has a mix of different ethnic population concentrated in different regions of the neighborhood. Majority of the Hispanic community are in this area with some population density of low income as well as a high concentration of population with zero auto ownership. This area, however, does not have a high population density of senior population. Based on the overall trend of different ethnic , social , economic group and vehicle ownership it can be said that most of North west, West and Near west side and South west community, bike share accessibility may need some major improvements and may not be ready to be accessed for first and last mile possibility unless improved.

## 4.5. South Side, Far South West Side and Far South East side

South Side (29.6%), Far South West Side (19%) and Far South East side (31.41%) has the highest average percent population black population per neighborhood. The average percent of white and Hispanic population per neighborhood significantly falls in South Side, Far South West Side and Far South East side. South Side still has the highest percent Asian population per neighborhood (7.53%) but are all clustered along the border of the Central community. All three these communities have the highest percent population of low income (South side 3%, Far South West Side 4.66%, Far South East 3.25%). The average percent population in the medium high (South side 26.5%, Far South West Side 19%, Far South East 31.41%) and high-income group (South side 3.3%, Far South West Side 5.16%, Far South East 1.33%) is very low.

### 4.5.1. Statistical analysis bus

The black population shows a positive effect on the bus ridership when close to a bike share facility (0.0003400, $p<0.001$) and has an insignificant effect($p>0.05$) without bike share. This aligns with the trend in the south side as south side has a decent distribution of bike share as well as bus. The higher magnitude of average weekday station level bus ridership in the bus stops close to bike share system shows that bike share serves as a first and last mile option within the black population (Figure 25). Thus, introducing more bike share system can increase bus ridership of the other two communities with no or insufficient bike share system and low bus ridership (Far South West Side and Far South East side). As most of the population in these communities are low income population (Figure 20) this conclusion is further supported by the positive effect of low income on stop level bus ridership both with (0.0005668, $p<0.001$) and without bike share (0.0005742, $p<0.001$).

### 4.5.2. Statistical analysis rail

The black population shows a negative effect on the rail ridership (-0.0009427, $p<0.001$). This is further supported by the influence of low-income population on rail ridership both with (-0.0002930, $p<0.01$) and without (-0.002785, $p<0.001$). Although most of these communities do not have appropriate bike share service or even distribution of rail stations, but the low ridership in the few rail station with bike share system supports the fact that bike share system does not serve as a first and last mile solution for rail transit for the South Side, Far South West Side and Far South East side.

The south side community has some accessibly to bike share facility and an even distribution of bus service and some limited access to rail transit. Bus ridership in most of the stops are large. The Far South West side does not have access to any Bike share service or rail transit but has evenly distributed bus service. However, the bus average weekday stop level ridership is mostly low. The Far South East side has limited access to bike close to border of the South side community but does not have bike share in the rest of the neighborhoods. However, the Far south east community has some access to rail transit and there is some even distribution of Bus service. Majority portion of the South Side, Far South West Side and Far South East side are dominated by the low income, Black, Senior and population with disability. The rail accessibility is relatively low with low or almost no access to bike share. Thus, bike share as a first and last mile option is not yet feasible in this community until the overall transit service and bike share system is improved to meet the population needs.

# CHAPTER 4

# MEASURE OF BIKESHARE’S CONTRIBUTION TOWARDS TRANSIT RIDERSHIP CHANGES

The results from Chapter 3 showed that transit ridership is impacted by various social, demographic and economic factor. The chapter also identified that different ethnic minorities have different travel behavior which may be either their own choice, financial condition or access to transit or bike share. black, asian, white origin population; zero auto mobile owner population; population with disability, younger age group (15 to 34 years), population with income below $40,000 and income over $150,000 have been found to have a significant effect on bus ridership with bike share in proximity. On the other hand, population of hispanic , asian and white origin; population with zero and one car ownership; park and ride locations; age group 35 to 64 years and age group over 64 years; population with income below $40,000 and income over $150,000 have been found to have a significant effect on rail ridership with bike share in proximity.

In this chapter, the influence of these contributing factor on the increase or decrease of rail or bus transit in proximity to bike station will be estimated. This will allow comparison between the influence factors contributing towards rail or bus ridership (with bike share) to determine with which transit mode, bike share has a greater acceptability as a first and last mile option. Propensity Scoring Method will be used to determine the increase or decrease in station/stop level transit ridership associated with bike share.

# 1. Methodology

## 1.1. Propensity score matching

Propensity score matching is a method which is defined as the conditional probability designated to a specific treatment with a given set of observed covariates [69].It is an unconventional strategy

which is capable of estimating the effect of receiving treatment and is applicable to observational studies where random assignments cannot me made. The process pairs treatment and control data with very comparable numeric evaluations of propensity scores and nullifies all other unmatched samples. The method allows addressing sample selection bias resulting observable differences between treatment and control groups [70]. This method has been used extensively in social sciences, economics and transportation and land use policies. Application of propensity analysis is common in evaluating self-selection effect in travel behavior differences(effect in travel behavior differences of those living in high- versus low-density areas, effect of built environment on vehicle miles traveled  and exploring contributory effects of neighborhood type on walking behavior [71]–[73] and many other research associated with effects of living near transit oriented areas.

## 1.2. Model selection and application

The propensity score calculated for this research is the probability of a transit (bus or rail) to have bike share facility given their observed social, economic and demographic characteristics. This can be performed by either using a discrete choice model rather than linear probability models. Both multinomial and probit models provide similar results but if the number of alternatives is greater than two, multinomial probit model is preferred. This is because the 'independence from irrelevant alternatives' assumption (IIA) states that the odds ratio between two alternatives are independent of other alternatives and is convenient [74].

The two steps in the observational study consists of assigning treatment group to station with bike share and control group to stations without bike share. A value of 1 is assigned to D when the

transit station has a bike share system within 400 m proximity or 0 otherwise. $Y_i(0)$ and $Y_i(1)$ are the potential outcomes for individual observation, the outcome under the control treatment (without bike share) and the active treatment (with bike share) and hence each observation will be assigned a single treatment ( active or inactive( control)) and can be articulated as follows:

$$Y_i \ (Yi=D_i,\ Y_i\,(1) + (1\text{-}D_i)\ Yi\ (0)).$$

The probit model is designated as D and the independent variables are represented by x; Based on the independent variables chosen ( population , number of house of each ethnicity , population in different income, population in different age group, number of house hold with zero cars) the probit model generates propensity score which estimated the conditional probability of a station being located in the 400m proximity to a bike station and can be expressed as :

$$p(x) = P_r(D{=}1|x) = E\ (D \mid x).$$

Where P(x)= Propensity score; $P_r$ (D = 1|x): probability station to be located near a bike station; x = independent variables; D = treatment effect (located close to bike station).

## 1.3. Matching technique

Once the propensity score has been calculated using the probit model and the related variables, a process of matching can be performed to find a data sample from the stations without bike share facility (control group) which is presumed to have very similar characteristics to that of the station which has bike share. Hence this will roughly set a stage of a treatment group (with bike share system) and a control group (without a bike share system) and allow estimating the effect of bike share on a station with bike share, as a result of bike share access within a 400m proximity. Any

difference between the samples in the treatment and control group will be addressed during the matching process and the propensity score will hold the characteristics of all the factors considered [75]. For instance, the propensity score in this case will summarize factors considered in the model such as number of zero car members, population in different age group, park and ride location, number of bike docks, number of households (white, black, hispanic and asian) and population with income below $40,000 or over $150,000. If the sample falls in the treatment group, it will be assigned a value of 1 and if it falls in the control group it will be assigned 0. It is assumed that when an observed sample been matched, the matched sample from the control group has very similar characteristics with the sample from the treatment group with respect to the independent variables considered while estimating the propensity score. This means that between the treatment sample considered and the sample matched with it, the propensity to be located close to a bike share facility is similar. Thus, resulting matched group is a subsample of the initial group, where treated and control have the similar probability of being treated and the same covariate distribution [76]. However, the two groups only represent the characteristics of the same observation under different condition, that is with and without introducing a bike share facility. The matching method can be performed by using standard statistical techniques may be applied on the matched cohort to generate approximations of the treatment effect [76]. A wide range of matching methods are proposed by past literatures, but nearest neighbor matching is the most common method used. Nearest Neighborhood Matching has been found to be the mostly used method due to its simplicity, best performance and lowest mean square error. In the case nearest neighbor matching each treated observation to be matched with its nearest control sample within specified caliper value and each matched control value is again replaced (for the with replacement case) to be included in multiple matched sample. As a result, when the variance of covariate is matched with control

sample, the order of selection of the treated subject does not influence the formation of matched pairs. Due to same sample being included multiple times, the variability of the baseline covariate with matched sample is reduced and a less biased approximation attributable to caliper width imposing maximum difference in propensity score between the treatment and control sample. Hence it is proposed that matching with replacement is more favored [77].

## 1.4. Average Treatment Effect on the Treated

Once the matching process has been completed the average treatment effect on the treated will be calculated [78] as the most preferred method used in PSM. The average treatment effect on the treated will be calculated once the station with bike share system will be assigned appropriate match from the control group in order to interpret the true effect of implementing bike share in the station. While implementing propensity scoring technique to find the associated effect, two methods can be addressed: 1. Average Treatment Effect 2. Average Treatment Effect on the Treated. It is only possible for one outcome to receive a treatment and can result into only one outcome as a result of the treatment (Bike share). The average treatment effect or the effect of treatment (transit station having bike share) will be represented as follows [79]:

$$E\,[Y\,(1)–Y\,(0)]$$

The Average Treatment Effect is calculation which is the difference between the outcomes if treated and the outcome if they had not been treated:

$$ATT = E\left(\frac{\Delta}{p(x)}, D = 1\right)$$
$$= E\left(\frac{y_1}{p(x)}, D = 1\right) - E\left(\frac{y_0}{p(x)}, D = 0\right)$$

Average treatment effect of bike share would then show the average difference in outcome between circumstances where all stations in the population are assigned to an active treatment or are assigned a bike share system as well as a control system (without bike share). However, computing the average treatment effect may not be the right approach in terms of policy standpoint as it also shows the effect of treatment on the stations for which treatment was not intended [80]. Rather a more relevant estimate could be made by finding the Average Treatment Effect on the Treated. Average treatment on the treated represent the effect of treatment (bike share system) on those samples (transit stations) which has received a bike share. The Average Treatment Effect on the Treated is a more preferred method for policy making and is mostly used for the case for Propensity Score technique. ATT can be  can be represented as [79]:

$$E\,[Y(1) – Y(0) \mid D=1]$$

Nearest neighborhood matching technique has been used in which first a treated subject is chosen, and then its matching subject from the controlled group with closest propensity score to treated subject based on the variables considered is found.  The propensity scores are based on the socio economic and demographic variables considered (Auto ownership, age, income, ethnicity) and the station with the closest socio demographic and economic features are matched. Nearest neighborhood method is used as it gives minimal bias and best performance with the lowest mean square error. [77]. The Average Treatment Effect on the Treated can be expressed as follows [70], [81]:

$$E\,(Y_1 – Y_0 | D=1) = E_x\,(E\,(Y_1 – Y_0 \mid X, D = 1)$$

$$= E_{x\,|D=1}\,(E\,(Y \mid D = 1, x) – E\,(Y \mid D = 0, x)$$

In the equation above, P(x) is the propensity score; D represents the binary treatment variable; Y is the outcome variable. x represents the independent variables. The second part of the equation is counterfactual and is not observable and will be estimated based on matching.

## 2. Variable selection and Data processing

The following section will set focus on the data sources, the variables included in the regression analysis and the method of data sorting and extractions. For the case of Chicago transit bus only average weekday ridership for the month of October (2018) was used. Daily total ridership for the month of October 2018 was used to calculate the percent change in average weekday ridership associated with bike share was used for rail transit. Followed by that daily total ridership for each month (January to December) in 2018 was used to observe the monthly variation in the influence by contributing factors on rail ridership.

Past study on propensity scoring model argued that variable should only be excluded from analysis if there is consensus that the variable is either unrelated to the outcome or not a proper covariate. If there are doubts about these two points, they explicitly advise to include the relevant variables in the propensity score estimation [82]. Thus, all the variables found to be a significant contributing factor in Chapter 3 has been used in estimating the propensity scoring. The dependent variables are average weekday bus station level ridership and average weekday rail total rides. All the independent and dependent variables considered for this study are as listed in Table 12.

Table 12: Variables and their definitions.

| Variable | Definition | Source |
|---|---|---|
| Dependent: | | |
| Bus stop level ridership | Boarding data for October 2018, weekday average | Chicago Transit Agency |
| Rail Station level Ridership Daily Total | Daily total rides for the month of October 2018 (excludes Saturdays and Sundays) | Chicago Data Portal |
| Rail Station level Ridership Weekday Average per Month | Weekday average for all the months throughout the year | Chicago Data portal |
| Independent Variables | | |
| Households Hispanic | Households with a householder who is Hispanic or Latino | NHGIS (National Historical Geographic Information System); 2017 American Community Survey: 5-Year Data [2013-2017, Block Groups & Larger Areas] |
| Household Black | Households with a householder who is Black or African American alone | |
| Household Asian | Households with a householder who is Asian alone | |
| <$40,000 | Population with income over $40,000 (Low income) | |
| >$150,000 | Population with income over $150,000 (High income) | |
| Households with zero Auto ownership | Number of households in CBG that own zero automobiles, 2010 | ACS, 2010 decennial Census, Smart Location Database |
| Households with one Auto ownership | Number of households in CBG that own zero automobiles, 2010 | |
| Population between Ages15 to 35years | | Derived from NHGIS (National Historical Geographic Information System) ;2017 American Community Survey: 5-Year Data [2013-2017, Block Groups & Larger Areas] |
| Population between Ages 35 to 64years | | |
| Population over 64 | | |
| Population with disability | | |
| Park and ride | Park and Ride locations and count within 400m of rail stations | Chicago Data Portal |

All data have been combined, processed and extracted using ArcGIS Pro and independent variables have been extracted as data within a proximity of 400m from the transit stop using the ArcGIS buffer and spatial join feature. Once extracted the data had been combined with location of bike station. Each transit station (bus stop or rail station) which had a bike share facility within 400m proximity was assigned a value of 1 (treatment) and the transit stations without a bike share system had been assigned a value of 0.

# 3. Results and analysis

## 3.1. Propensity scoring

### 3.1.1. Bus

The data available for Chicago Transit Agency bus data was stop level weekday average for October 2018. The sample size consisted of 9756 observations for bus stop level data, out of which 4473 consisted of treated samples and 5283 controlled observations.

The first step was to use the propensity score model to estimate the probability of each bus station to be located close to a bike share system and is represented by the propensity scores based on the independent variables considered for the model. The results of the propensity of the bus stop to be located close to the bike station has been shown in the Table 13 below. Table 13 indicates that bus stops with more household with zero auto ownership, greater number of white population house hold, black population household, Asian household, zero auto owner house hold , population with income below $40,000, income above $150,000 and greater population within the age group of 15 to 34years has a greater propensity to have a bike station located within a proximity of 400m. On the other hand, bus stops with greater population with disability has a lesser propensity to be located near a bike facility.

Table 13: Propensity Score of bus stop being locates close to a bike station.

| | *Coefficients* | *Est. Std Error* | *Z value* | $P_r(>\|z\|)$ |
|---|---|---|---|---|
| Intercept | -1.256 | 4.666e-02 | -26.913 | < 2e-16 *** |
| HH White | 8.936e-04 | 7.573e-05 | 11.800 | < 2e-16 *** |
| Household Black | 6.507e-04 | 9.420e-05 | 6.908 | 4.93e-12 *** |
| Household Asian | 3.025e-03 | 2.427e-04 | 12.466 | < 2e-16 *** |
| Auto Ownership zero | 4.369e-03 | 1.428e-04 | 30.601 | < 2e-16 *** |
| Income below$40,000 | 2.487e-04 | 1.002e-04 | 2.482 | 0.013077 * |
| *Income over $150,000* | 3.790e-04 | 1.147e-04 | 3.304 | 0.000953 *** |
| Population disability | -4.147e-04 | 2.361e-04 | -1.757 | 0.078989. |
| Population 15 to 34year | 1.193e-04 | 4.029e-05 | 2.960 | 0.003075 ** |

*** p<0.001; **p<0.01; *p<0.05

The objective of this research is to determine the extent to which the factors affecting bus ridership has affected the increase or decrease in bus ridership as a result of association with bike share. Calculating the average treatment effect will extent to which the contributing factors affect the change in ridership assuming that all the bus stop had been treated with a bike share facility, which is not the case. As a result, using the average treatment effect on the treated will allow estimating the extent to which the contributing factors affect the change in bus ridership considering the bus stops which has been treated with a bike share system. The matching process will match each treated bus stop with a control stop (without bike share) allowing to find a control sample (without bike share) with very similar characteristics with treatment sample (with bike share).

### 3.1.2. Rail

The Chicago transit rail data has been extracted at a station level from the Chicago data portal. The data is available in form of daily total of station level rides and only weekday average was used. The first step was to use the propensity score model to estimate the probability of each rail station to be located close to a bike share system or bike station and is represented by the propensity scores based on the independent variables considered for the model. The results of the propensity of the rail station to be located close to the bike station has been shown in the Table 14 below. Table 14 indicates that rail stations with greater household with hispanic population, population with income below $40,000 and greater population with zero auto ownership has a greater propensity to have a bike station located within a proximity of 400m. On the other hand, rail station with greater white population household has a lesser propensity to be located near a bike facility.

The purpose of this study is to ascertain the influence of contributing factor on the shift in rail ridership resulting the association with bike share facility. Determining the average treatment effect will provide an evaluation which will assess the change in ridership presuming that all the rail station had been associated with a bike share facility, however it is not the scenario. Estimating the average treatment effect on the treated will permit assessing the shift in rail ridership contemplating the rail stations which essentially has been associated with a bike share system. The matching process will match each treated rail station with a control station (without bike share) allowing to find a control sample (without bike share) with very similar characteristics with treatment sample (with bike share).

Table 14: Propensity of a rail station to be located close to a bike share facility.

| | *Coefficients* | *Est. Std Error* | *Z value* | $P_r(>\|z\|)$ |
|---|---|---|---|---|
| Intercept | 0.71339 | 0.09999 | 7.134 | 9.73e-13*** |
| HH White | -0.0008590 | 0.0002124 | -4.044 | 0.0000526*** |
| Household Hispanic | 0.0021858 | 0.0003776 | 9.383 | <2e-16*** |
| Household Asian | 0.0010392 | 0.0005006 | 2.076 | 0.0379* |
| Auto Ownership zero | 0.0084851 | 0.0005249 | 16.165 | <2e-16*** |
| *Auto Ownership 1* | -0.0009608 | 0.0002421 | -3.969 | 0.0000722*** |
| Income below$40,000 | 0.0035434 | 0.0003776 | 9.383 | <2e-16*** |
| *Income over $150,000* | 0.0057431 | 0.0005102 | 11.257 | <2e-16*** |
| Population 35 to 64 | -0.0024001 | 0.0002521 | -9.520 | <2e-16*** |
| Population over 64 | -0.0023941 | 0.0003692 | -6.485 | 8.87e-11*** |
| Park and Ride | -1.0229775 | 0.0904988 | -11.304 | <2e-16*** |

*** p<0.001; **p<0.01; *p<0.05

## 3.2. Treatment Effects

Figure 43 shows a summary of the findings of the treatment effect in comparison to the observed effect. The average treatment effect on the treated for Bus stop level ridership for weekdays for October 2018 has been estimated to be 36.58 rides per day. This means that a randomly chosen bus stop on receiving the treatment of bike share can have an increase in ridership of 36.58 rides per day. This value is the difference between ridership of treated bus stops and the control matched considering condition as if it had not been treated. The observed difference has been calculated by finding the difference between the mean of average weekday transit ridership in stations/stops without bike share and the ridership in transit station/stop with bike share. The ratio of the Average Treatment Effect on the Treated to the Observed difference permits estimating the influence of the contributing factors on the increase or decrease in transit ridership of stations associated with bike

share. The observed difference has been calculated by finding the difference between the mean of bus ridership in stops without bike share and the ridership in bus stops with bike share (20.87).

The Average treatment effect on the treated for average weekday rail ridership is 1290 rides per day. This means that for a randomly selected rail station, the average daily ridership will increase by 1290 rides. The observed difference in average weekday ridership between matched ridership of rail station with bike share and ridership of bus stop without bike share is 761.156 per day.

While performing analysis of observed difference, it is important to consider the effect of the presence of non-random selection into the treatment in comparison to the control group. For the case of cross-sectional study individual can either be in the treatment or control group. The average treatment effect on the treated represents the difference between ridership with and without addition of bike share. The propensity score matching technique works if all the confounding factors have been included in the analysis [83] . This study includes the factor which have been found to have had a significant effect on the station or stop level ridership of stations or stops with bike share. The observed effect representing travel behavior is a combination of relation between built in environment , socio demographic factor ( observed effect) and unobserved effects [84].

The attitudinal information of the factors considered have not been included in this study. This means that the value of average treatment effect on the treated consists of the effect of bike share, attitudinal effect of the confounding factors and any other unobserved factors.  The ratio of Average Treatment Effect on the Treated to the Observed Difference allows estimation of the influence of the factor on the increase or decrease in ridership. The average treatment on the treated calculated includes the impact of association of transit station with bike share as well as the influence of the behavior of the other factors considered. Average Treatment on the Treated consists of effect of bike share and the effect of the confounding factors considered (attitudinal).

Past studies have found that observed influence of built in environment on travel behavior is comprised of effect of the built in environment and self-selection [71]. Thus in this research the observed influence will consist of effect of bike share as well as effect of self-selection which is a lot of times resulting attitudinal factors [84]. Self-selection has been an emerging theoretical argument in many researches with regards to effect on travel behavior. However a lack of consensus on the magnitude of the effect of self-selection on travel behavior still exists [85]. The observed difference in this case is the difference between the average control and treatment ridership. Now because the observed difference is an average difference between control and treatment and these two stations may be characteristically different, there would be some unobserved effect of the control stations on this observed value which can show a slight reduced positive difference between the treatment and control ridership. The average treatment effect on the treated only represents effect of the treatment so the impact of the stations having bike share is expressed. The ratio of Average Treatment Effect on the Treated to observed difference has been found to be 1.75 for average weekday ridership for bus transit. This means that the contributing factors has 1.75 times effect on the increase in average weekday bus ridership of the bus stop located within 400m proximity of bike share. The effect on bus weekday stop level ridership of being located within 400m proximity accounts for approximately 175% of observed influence. The ratio of Average Treatment Effect on the Treated to the observed difference for rail transit have been found to be 1.69 for October 2018. The effect on rail weekday stop level ridership of being located within 400m proximity accounts for approximately 169% of observed influence.

As observed in the Chapter 3, the low access to transit is prevalent in areas where there is low income, more ethnic minority and more disadvantaged population whereas high access is prevalent in areas where there is high population with young, higher income, white population group. It has

also been observed that there is zero auto ownership for both treatment and control group in certain areas, however, their reason for transit dependency is different. Zero auto owners in low income areas are transit dependent because of their financial instability whereas in high income areas zero auto ownership represents satisfaction with the present transit system. Further, when making residential choices, the control group are more likely to value length of commute and access to transit than the latter, whereas the latter are more likely to consider neighborhood amenities. These findings suggests that there is a likely hood that attitudinal or self-selection behavior may have a greater impact on transit ridership and propensity score will allow separation of the self-selection effect [86].

The ATT value shows the overall effect of bike share in comparison to observed difference which shows the effect of ridership increase between with and without bike share. The point estimate of ATT to the observed effect is 175% for bus ridership and 169% for rail. This means that bike share contributes to majority of the observed difference of bike share on ridership. This value includes the value of the attitudinal factor of factors which have been found to be significant contributors to bike or rail ridership in Chicago [86] . The results indicate that high ridership observed is more as a result of association of transit stops/stations with bike share rather than as a result of self-selection behavior from the contributing factors. The effect of self-selection ( attitudinal factors) has been found by subtracting the ATT value from the observed difference [86]. This value expressed as a percent of observed difference is 75% for the case of bus stop level ridership with bike share and 69% for the station level ridership for rail. Out of the 175% of the observed influence of bike share, 75% has been as a result of self-selection by the contributing factors. Similarly, for the case of rail, out of 169% of the observed influence, 69% has been contributed by the significant factors which affect rail ridership. The bus has a higher percent (75%) of influence

of contributing factor on treatment effects in comparison to rail (69%), this means that residents attitudinal effect is more prominent towards supporting the use of bus transit in combination with bike share than it is for rail transit [86]. The positive value of the influence on the observed influence refers to the fact that bike share has an overall positive effect on the observed impact. Because the ATT value consists of effect of change in ridership as a result of association of transit station/stop with bike share and other factor, the ratio shows a positive effect as a result of both.

## 3.3. Increase from bike share

Travel behavior is considered to be a function of the effect of built in environment, attitudinal factors , observed factors and unobserved explanatory variables [84]. It has been found that attitudes explain travel behavior better than do neighborhood characteristics [71]. For the case of this research, increase or decrease in transit ridership represents the travel behavior while access to bike share service represents built-in factor. In this study treatment is the accessibility of transit to bike share service. Considering the treatment effect , the Average Treatment Effect on the Treated is expected to be greater than Average Treatment Effect [84] and which is the case for both bus and rail transit. If the effect of unobserved factors on transit ridership is independent of unobserved explanatory variables for a given set of observed variables, then Average Treatment Effect on the Treated is supposed to be equal to the Average Treatment Effect. In both the case for bus and rail the average treatment effect on the treated is more than the average treatment effect. This shows that the treatment effect ( associated effect) of bike share some attitudinal factors (due to other factors) included in the value [84].

The effect of bike share access on transit ridership can be assessed at least approximately if controlled for the effect of self-selection (attitudinal factors) by the other factors. From section 3.2, the effect of self-selection on bus has been found to be 75% of the observed influence and for rail to be 69% of the observed influence.

After controlling for the effect of other factors, the change in bus ridership associated with treatment effects (access to bike share) has been found to be 9.15 rides per days for a randomly selected bus stop. The change in rail ridership associated with treatment effects (access to bike share) has been found to be 399 rides per day for a randomly selected rail station location. The effect as result of association with bike access on transit ridership is not very informative unless expressed in form of a desired scale or a relative sense. So, this result has been expressed as percentage of the total mean average weekday ridership (station/ stop level) for both treatment and control cases in combination. This gives an estimation of the increase in comparison with the average of all the station and stop level ridership for rail and bus transit for the city of Chicago. The total average of weekday ridership for all stations for rail is 3734 rides and average stop level ridership for all bus stops in Chicago is 35.21 rides per day. A 25.95 % increase in ridership associated with bike share has been found for bus average weekday stop level ridership. A 10.7% increase in ridership associated with bike share has been found for average weekday rail ridership. This 25.95% and 10.7% increase in the average station level ridership is mainly reflective of the introduction of bike share in those locations which currently have bike share.

Table 15: Treatment effects of Bike share in comparison to observed difference: Bus versus Rail.

| | Bus | Rail | Difference |
|---|---|---|---|
| **Mean Treatment (Average weekday ridership with BSS)** | 46.52 | 3868.84 | N/A |
| **Mean Control (Average weekday ridership without BSS)** | 25.65 | 3107.6 | N/A |
| **Total Mean (Average weekday ridership)** | 35.21 | 3734 | N/A |
| **Observed Difference** | 20.87 | 761.156 | N/A |
| **ATT (Rides/day/stop or station)** | 36.58 | 1290 | N/A |
| **ATT/ Observed difference** (BSS + other factor) | 175% | 169% | 6% |
| **Percent Influence other factors Increase (bike share) Rides/day/station** | 75% | 69.47% | 6.47% |
| **Increase due to bike share (Rides/day/stop)** | 9.15 | 399.9 | N/A |
| **Percent rise ridership from bike share (percent per station)** | 25.95% | 10.7% | 15.25% |

N/A: Values that are not directly comparable to each other. For example, the station level ridership of rail is normally greater in magnitude than bus stop level ridership. BSS= Bike Share System. ATT = Average Treatment on the Treated.

## 3.4. Rail -Monthly variation

The ratio of Average Treatment Effect on the Treated to the Observed difference is the influence of the contributing factor in increasing the rail ridership. The ratio is estimated for each month for the year 2018 for rail transit for the City of Chicago and is plotted in bar chart as shown in Figure 43. The trend for the influence along the year that the influence on rail ridership is not static rather has a fluctuating characteristic from one month to other. Normally the seasonal variation in transit or bike share ridership is assumed to be based on temperature change, especially for the case of Chicago which has warm summer and very cold winters.

A research performed on Chicago Transit Authority ridership behavior as a result of fluctuating weather suggested that the extent to which temperature, rain, snow and wind affect transit ridership may vary depending on the mode, season, and day of week. The general trend found indicated that a good weather can have a positive effect on transit ridership and a bad weather can reduce it. However extremely bad weather can contribute towards increasing transit ridership as some drivers may switch to transit than driving. The study also suggested that the changes in trends could be as a result of weather as well as special events or just due to human perception [87]. This means that the ridership trends reflect the impact of the contributing factors causing the increase or decrease in ridership trend. The trends of influence on rail ridership with bike stations will also be impacted by social, economic and demographic factors identified in Chapter 3. However, a closer look at the trends revealed that the trends in Figure 43 aligns with the institutional (educational or professional) activity scheduled , peak business or holiday period. A study performed on Australian city found that the increasing or decreasing trends in transit ridership is closely aligned with the educational institution semester cycles, other institutional schedules, school year, holidays and weather [88].A similar study performed in Portland Oregon also found

that the transit ridership declined seasonally during periods with increased mean temperatures (especially in the summer) . Decline was also observed by the study for the month ending of March which aligns with the spring break. Similar to this trend in Australia, the study in Portland has also found the transit ridership trends to align with summer vacations, spring break and winter break, and other holidays [89].

The influence of contributing factors has been considered on rail station with bike share within 400m proximity for Chicago. As a result, the seasonal variation of bike ridership will also influence the rail ridership. As Chapter 3 as well as Chapter 1 (Literature review) has identified that bike share can at times have a substitutional effect on rail transit ridership. A study on seasonal variation in Chicago bike share showed that bike share ridership is slightly higher in January, which declines in February and rises in March followed by a decline in April and a rise in May. The month of June till September shows a high bike ridership and then it slowly declined from October to December [90].

The trends for the semester dates of most education institutions as well as holidays for both students and staffs in Illinois aligns with the trends in the graph in Figure 43. Also, a much larger share of rail trips are work trips [87] and most of the middle aged ( 35 to 64years) population which positively influence rail ridership fall within the working group [87], [91], [92]. In Figure 43, the school and university semester breaks have been labelled with brackets. The hatched line depicts any major holidays during which both working group as well as students may take days off. The month of January consists of a list of holidays applicable to all education institutions as well as workplaces (New Year, Winter holiday) and semester in most schools/educational institutions starts around mid-January. The influence on the month of February is significantly high as all schools, workplaces have returned to their normal work scheduled. The cold winter weather

encourages less bike riders hence nullify the effect of substitution effect of bike share on rail. The influence of the contributing factors decreases significantly due to March break in all educational institutions. This may not only be due to students not using transit rather also their parents (ages 35-64 years) reducing school and activity trips because of their children staying home. Many workers (35 to 64 years) also use March break as a holiday time. The decline in positive influence of contributing factors on rail ridership is due to weather getting better as it approaches spring hence increasing the substitutional effect of bike ridership. This is also supported by the fact that high income (>$150,000) has a positive influence on rail ridership with bike share. The spring semester for both schools and university end in May and bike share increases significantly (both ages 35 to 64 years, low income as well as high income) hence showing a substitutional influence on rail ridership. July is normally the month when people of all ages take vacation and hence may refrain from using transit. August, September and October are Fall semester when all educational and workplace are active. November shows a lower influence of contributing factors on rail ridership due to thanksgiving holiday when many workers/ students (young, Ages 35 to 64years, over 64 years, income > $150,000) go to spend time with family out of city. Despite of having Christmas holiday in December, the influence of contributing factors is relatively high as most businesses operate for Christmas shopping and all middle ages (35 to 64years) workers are working till Christmas eve. The decline in level of positive influence as educational institutions and workplaces have partial winter break last week of December.

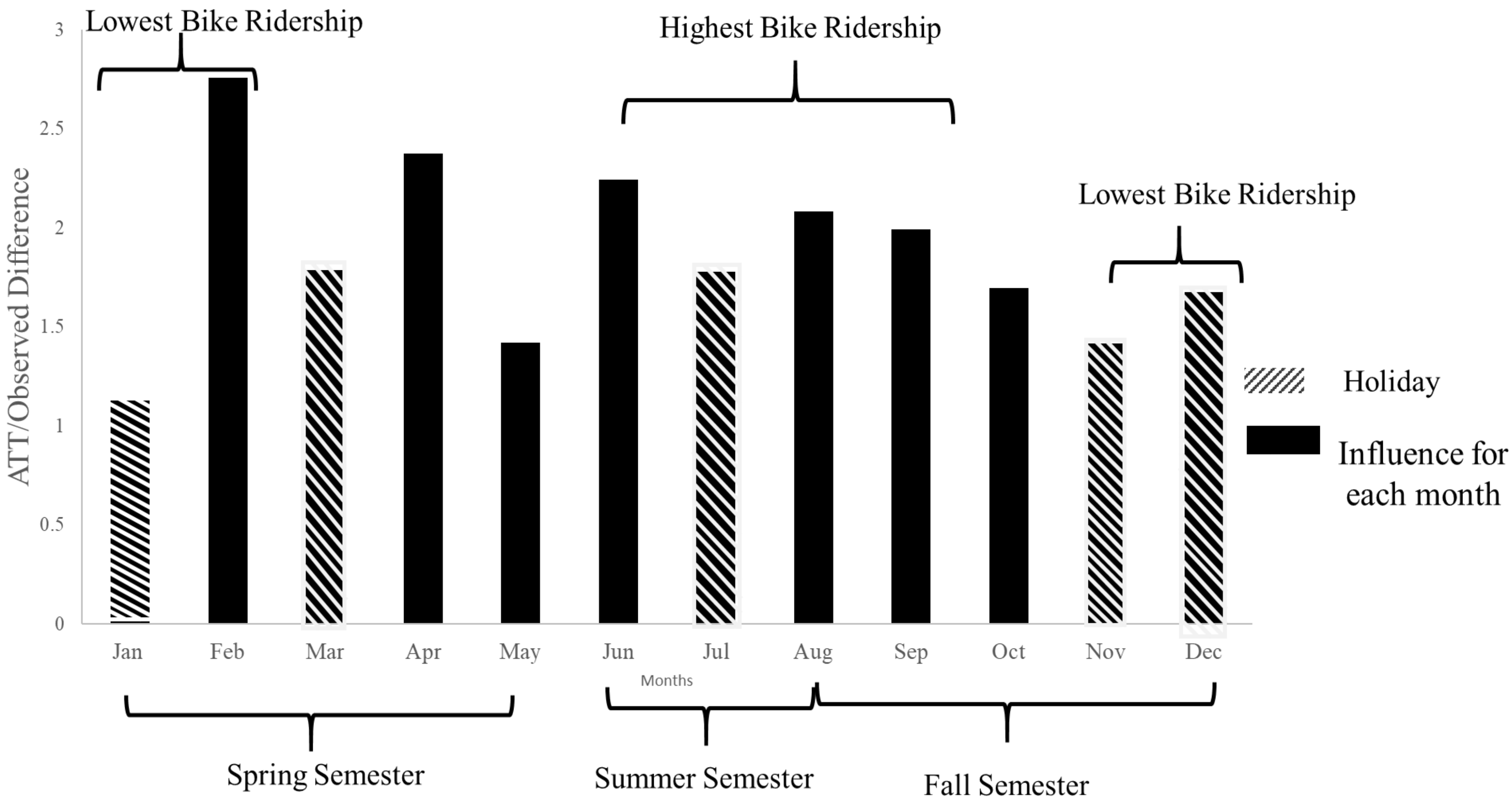


Figure 43: Influence of contributing factor on rail ridership for stations with bike share.

# CHAPTER 5

# CONCLUSION AND FUTURE RECOMMENDATION

This research identified the variations of transit distribution and use across the different communities in Chicago in comparison with the existence of social, economic and ethnic divide. Based on this assessment, the suitability of the different community sides in Chicago, for implementation of micro mobility as a first and last mile options was determined. Certain areas have also been identified to have the right sociodemographic mix suitable for micro mobility which can be successful only if further improvement is made in terms of transit service or bike availability. The factors considered for the analysis are income ranges, different age groups, auto ownership, disability and ethnicity. These variables have been statistically tested on different transit modes (bus or rail) to estimate the impact of these factors on the average weekday transit ridership in terms of whether there is access to bike share or not. The results of the statistical analysis helped determine the variable's behavior towards transit use based on whether the transit station has access to bike share or not. Once impact of the different factors has been determined, the result has been compared to 1) the geographical distribution of different population falling under each category (or factors) across different Chicago community sides (Chapter 3) ; 2) supply or the access to transit and bike share in those areas; 3) The magnitude of station/ stop level ridership for transit. Based on the comparison between the statistical analysis result, population distribution and access to transit and bike share, the 77 communities of Chicago have bene ranked into five different regions. 1) Central, 2) North Side, 3) Far North Side, 4) North west, West and Near west side and South west and 5) South Side, Far South west Side and Far South east side.

# 1. Identifying need of population

Figure 44 identifies the needs of individual population groups and the common expectations they have from public transportation based on findings from past research and regulations in United States. No matter what the major ethnic group is in a community, the population types considered in Figure 44 is what each community will have in different ratio. The ratio of these population groups will affect the attitude towards public transportation of that community as well as their rate of transit or bike share use. Thus, identifying the needs of these population group is desirable to suggest possible implementation measures to improve the transit and bike share system to increase the potential for micro mobility to function as a first and last mile option. The needs for each population group can be divided into common goals towards using public transportation: Connectivity, Physical accessibility, Safety, Affordability, Flexibility, Reliability, and Comfort.

## 1.1. Aging population

Aside from physical accessibility, older population group have a variety of safety, personal security, flexibility, reliability, and comfort concerns about public transit [93]–[95]. The safety and security assurance can be provided by better update about the trip before and during travel. Public transportation can be made more reliable for elderly population by expanding the hours of service and providing additional routes [94], [96]. Comfort and reliability could be facilitated by enhancing driver training to provide a higher level of driver assistance. Flexibility can be allowed by performing route deviation and allowing travelers to disembark more frequently or in a more aging population friendly stop area [93], [94], [97].

Public transit operators can receive federal grant under the 1990 Americans with Disabilities Act (ADA) to provide special demand-responsive services to people with serious disabilities to counterpart bus services. Although ADA complementary service was designed as an alternative for most people with disabilities, until all buses were fully accessible [98], about roughly 58 percent of older people simply do not qualify for ADA complementary paratransit services as they do not have serious physical or mental impairments [27]. Improving transit vehicles, transit stop and associated facilitated to meet the needs of aging population can substantially decrease the amount of special services even with emerging number of aging populations [27]. However, in order to meet the needs of aging population the transit services have to be significantly improved [93], [94], [97], [99].

## 1.2. Disability

The main need for the traveler with disability has been physical accessibility, safety, reliability, flexibility and comfort. Most of the barriers faced by traveler with disability is physical and attitudinal in nature [24]. Issues with physical accessibility as well as comfort issues has been reported by travelers with disability when they had children or had any heavy item to carry (grocery). Other accessibility issues reported includes inadequate accessibility of lifts or bus stops [100] .They have also facing reliability issues due to inadequate announcement of bus stop location or failure to stop at the designated stop location or issues associated with trip booking, trip-booking, and pick-up problems [100]. Other issues related to comfort and security encompasses of poor design of the physical environment, lack of information, negative attitudes. These obstacles

are more severe for travelers with sensory, physical, mental and cognitive disabilities and hence can severely impact their quality of life and mental stability [101].

### 1.3. Low Income

The main trip purpose for low income population is for work purpose trips [18]. This population group has budget constraint as the main barrier to using public transportation. As a results, the low income population bears most of the burden of fare increase because transit fares represent a larger fraction of their disposable income than is the case for higher-income riders [25]. However, transit is their only choice for transportation mode as they mostly do not own vehicle.  This issue could be resolved by subsidizing transit or bike share use and a good example is Philadelphia. In order to encourage more bike share usage amongst low income population, the city of Philadelphia identifies docking stations in low income neighborhoods and allow cash payment and discounts to individuals receiving food stamps [18]. This will provide low income population flexibility by allowing transit use whenever they need and facilitate affordability and reliability by relieving the cost burden.  The low-income group needs better access to both transit and bike share hence better connectivity. They would need stability in terms of cost structure as well as timeliness in transit schedule as most of this income group uses transit for commute purposes [18].

### 1.4. Young population

The major driving force for younger population to use public transit is better connectivity, affordability, flexibility and reliability. Younger age population considers transit to be an

affordable option along with its societal benefits such as digital socializing, connecting with their communities, working on route hence providing them with flexibility [29]. Intersection density and proximity to docking station within 250 m of their workplace were found to be statistically significant predictors of bike share membership [33] [32]. This provides the base that younger population group prefers urban environment for their resident location and are more inclined towards connectivity making transit a reliable choice. The travel choices of millennials have also been found to be influenced by economic factors such as income, employment etc. rather than a shift in values and preferences and may be a reason for the preference of transit [31] over other modes. Therefore, they would prefer a frequent transit service with better accessibility to both transit and bike share system to improve connectivity. They would look for reliability which is associated with frequency of service as well as timeliness. Finally, they desire a stable and affordable fare structure retaining the cost-effectiveness on the consumers' side.

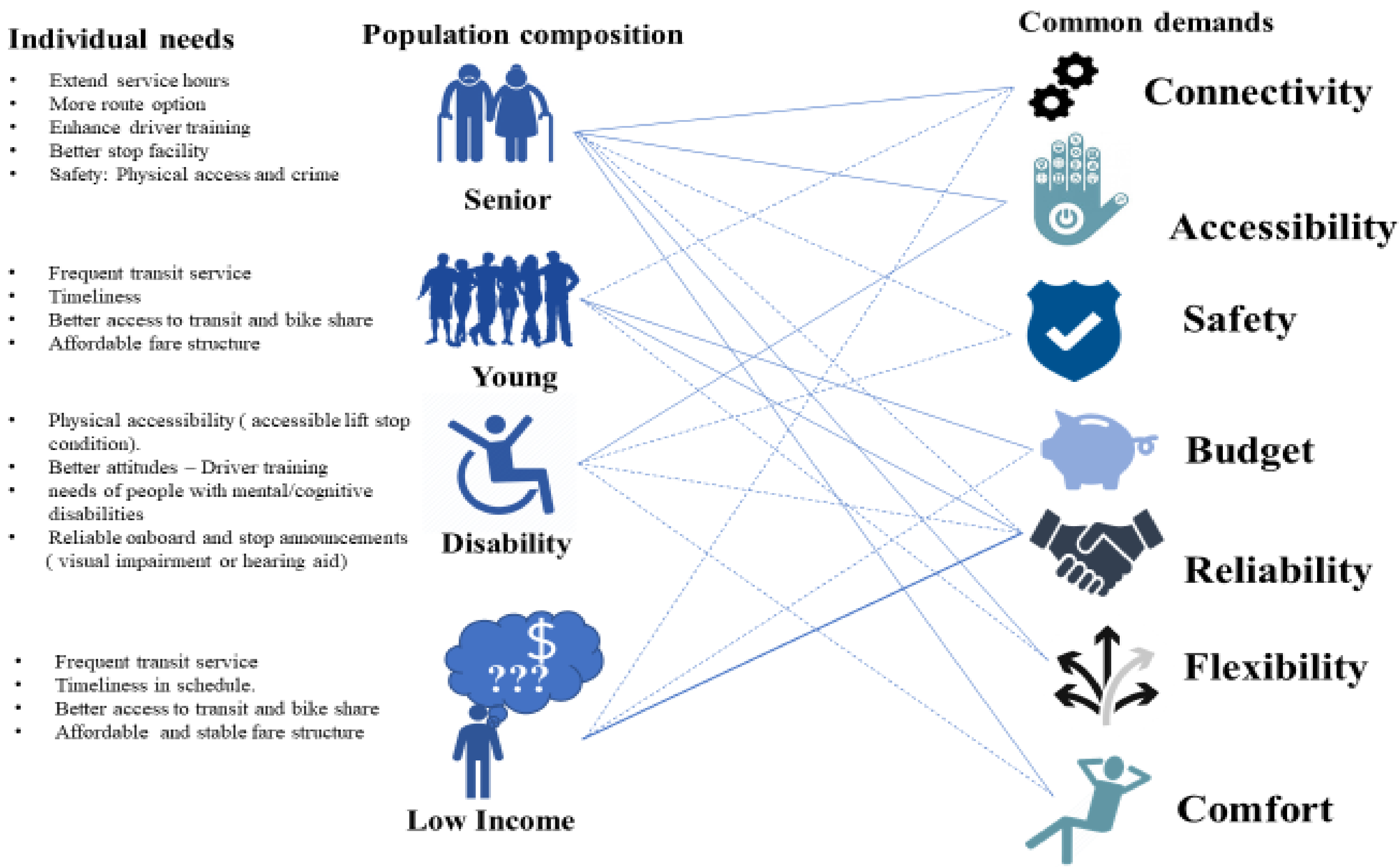


Figure 44: Common Demands and individual needs for different population groups within the community [93], [94], [97],[98], [100], [101].

## 2. Community Level Mobility Goals

Each of the community sides in Chicago has a mix of the population groups identified in different ratio. The results of Chapter 3 helped classify the communities in Chicago into five groups based on their population mix from each of the above identified groups (Figure 44), transit and bike share access and magnitude of station/stop level ridership. The following section now summarizes the gaps or current condition of each of this population group. Figure 45 also suggest possible implementation measures to improve accessibility of bike share service to enable better first and last mile activity in some of the ranked groups. However, in underprivileged communities, the transit and bike share service needs improvement before being assessed for the functionality of micro mobility as a first and last mile option (Figure 45).

***Central (Rank 1)***

The central community has been found to be well connected in terms of accessibility of bus, rail and bike share services. Majority of the population have zero car ownership, and some have one car but there are not many populations with two or more cars. The population has a lower percentage of senior and higher percentage of younger generation who have been found to have a greater acceptability of bike share with bus. Therefore, the community is highly urbanized and has an excellent accessibility to multimodal public transportation. For majority of the population bike share is already acting as a first and last mile option for both the cases of rail and bus. However, younger population shows an exception to this and only accepts bike share as a first and last mile option for bus and has a substitutional effect on rail ridership. Overall trend reflects the travel behavior of the residents rather than any service gap and transit micro mobility is already serving as a first and last mile option for this group.

### *North Side (Rank 2)*

The North Side communities has overall good access to bus service as well as rail transit. The bike share service is relatively good but there is some room for improvement. The greater share of the population has zero auto ownership and thus the community is transit dependent for mobility. Most of the community is well connected. Some room for improvement has been identified to improve connectivity in certain groups of population. Accessibility to bike share in areas with younger population (15-34 years) could be improved for area within 400m proximity to bus stops more as they have more acceptability to bike share as a first and last mile option for bus. Some more bike share access can be added in area with low income population as they have been likely to use bike share as a first and last mile option. This can be further be improved if bike share is subsidized for low incomes (by allowing cash payment) as cost, access, and outreach as the largest barriers to equity [17].

### *Far North Side (Rank 3)*

The Far North Side communities have good access to bus service; nevertheless, the station level ridership is relatively low in most stops. An uneven trend in the distribution of transit as well has bike has been found. The east end near the lake has very good connectivity for both public transit and bike which fades away moving west. Many areas still have a higher younger population who are zero auto ownership. The low-income population and young population in this community has very low access to bike share. Bike share service can be improved by increasing access, providing discounts to people eligible for food stamps and allowing cash payments. If young and low-income population have better access to bike share, the bus ridership has a greater propensity to increase as these two groups are likely to use bikeshare as a first and last mile option. The community has an average of 13.07 percent senior per neighborhood. Most of the areas where the senior resides

have low income population and may not be able to avail paratransit. Transit can be made more reliable for senior by providing extended hours of operation and flexible route options. The west side of the community has a slightly greater population with two plus auto ownership and these areas have a greater population in the age range 35 to 64 years. The west end of the Far North side community is highly populated with white population. The statistical model results showed that white population have potential to use bus or rail transit service more if available in conjunction with bike share. If bike share can be significantly improved in this area, then bus ridership as well as rail ridership may go up as white population have been found to be likely to use bike share as a first and last mile option. Overall, improving transit and bike share access in the west end of the community can greatly improve the transit ridership in these communities.

***North west, West and Near west side and South west (Rank 4)***

West and near west side and South west side barely has any two plus car ownership. There is some concentration of one car auto owners and mostly zero auto ownership and hence the community is completely transit dependent. Two plus car owners are mainly of White origin and are in North west area. Introducing bike can introduce micro mobility and improve bus ridership, which is currently low, by shifting the white population towards transit use as they are more likely use transit in conjunction with bike share. Rail accessibility for all these areas are very limited especially moving westward in each of these communities. Bus ridership is low in general at station level and improvement to bike share would possibly benefit if made close to bus stops. The white population in the West and Near west community are mainly concentrated towards the central community and therefore already has a good access to transit. There is relatively fair distribution of rail stations where there is high concentration of white population amongst these communities.

Black population in the South west and West and Near west side can benefit from bike share service improvement as they are more likely to bus ridership in presence of bike share which also aligns with the geographical concentration of low-income population. Access to bike share is very low in these areas. Subsidizing bike share system or providing discounts to bike share system in these areas will encourage more low-income population use transit. The two communities have the densest hispanic population with poor bike share access. Past study has found that hispanic residents in Chicago are likely to be more adaptable to bikeshare in comparison to black residents [102]. Although hispanic population shows insignificant effect on bus ridership and negative effect on rail ridership when near bike share, introducing adequate bike share service to hispanic populated area can bring a change to this trend which is possibly occurring due to inadequate access to bike share.

***South Side, Far Southwest Side and Far Southeast side (Rank 5)***

South Side, Far South West Side and Far South East side communities has the highest concentration of low-income population. High disability population can be found as well especially in Far south east and South side communities. The same neighborhoods have high population with low income. A lot of these communities have high senior population which is prevalent in the Far south east neighborhood especially in the South Deering neighborhood which is a home to both the low income, disabled and senior population. Bike share and rail transit is almost nonexistent in these areas. There is an urgent need in these areas to subsidize bike share system (cash payment and incorporate with food stamp) for the low-income and improve bus transit service to suit needs of disabled and senior. The communities necessitate first improvement and affordability to transit before considering micro mobility as an option. Once transit

accessibility and service has been improved in this area along with introducing more bike share system, the effect of bike share as a first and last mile option can then be assessed.

A past study found that ,Divvy trips have a positive correlation with annual bike share trips from stations within 300 meters from transit station (rail) [47]. The study finding shows that the ethnic minority impact is more pronounced in Chicago region when the aggregate bike share demand is framed in terms of its distribution amongst different communities, which suggests the possibility of group resistance to mobility services, construed as promoted by and for “privileged” individual [102]. Improving bike share service amongst different communities may help bridge the ethnic and economic divide in transit in the Chicago city.

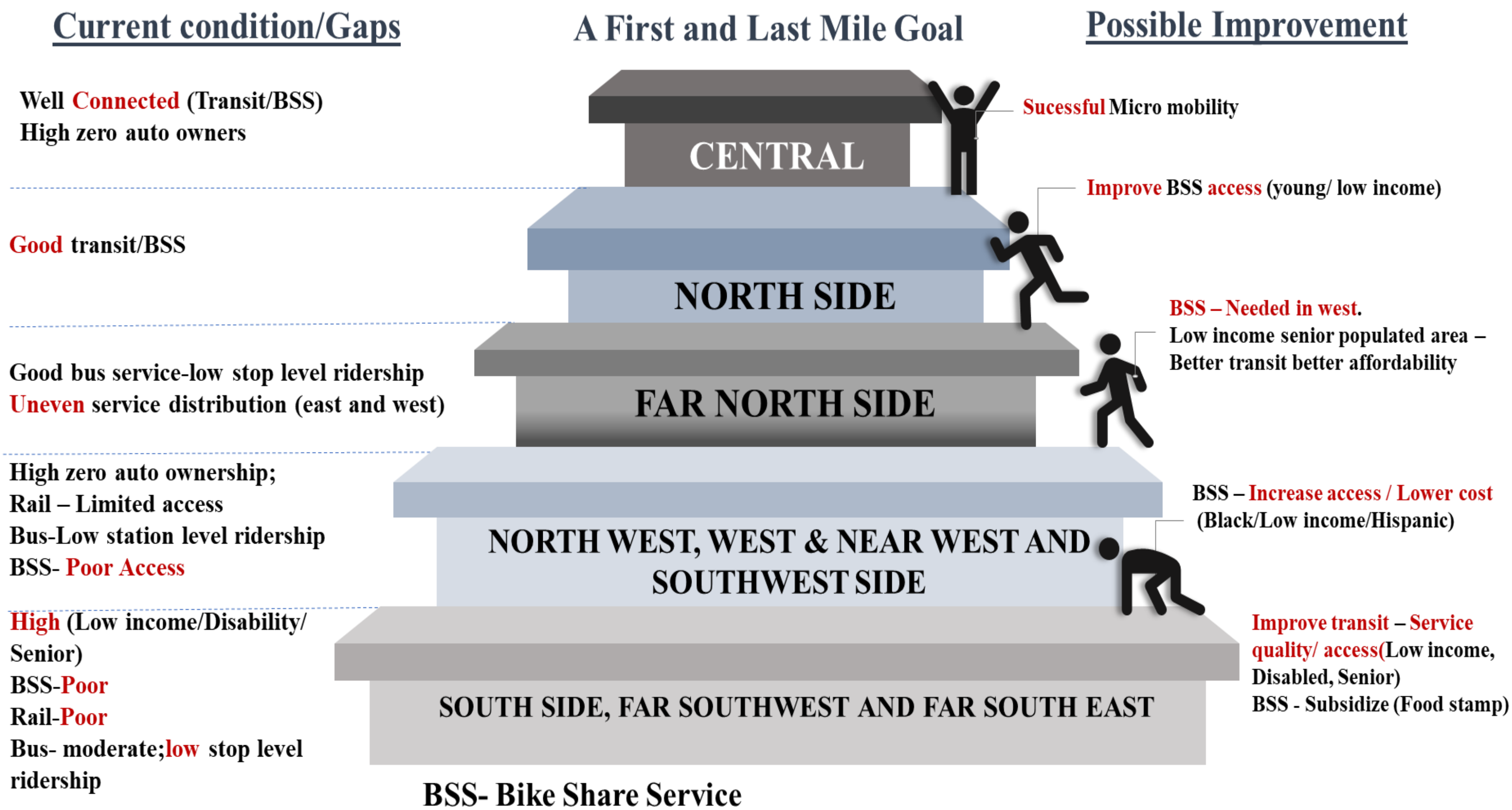


Figure 45: Hierarchy of Chicago community in terms of transit and bike share service and possible improvements.

# 3. Influence of Contributing Factors

After determining the significant factors which contribute towards transit ridership, the second part of the research investigated into the extent of the contribution by bike share towards rail ridership. This was performed by estimating the influence of contributing factors. The influence was the ratio of the associated effect of adding bike share to a location to the observed difference of the mean ridership of stations/stops with/without bike share.

## 3.1. Comparison between bus and rail

The average weekday ridership for October 2018 for stations/stops with bike share was used for both bus and rail transit to determine the influence of the contributing towards the increase or decrease of ridership. Both contributing factors for bus and rail transit has a positive effect increasing the ridership for stations with bike share. This implies that overall bike share is functioning as a first and last mile option in Chicago. The treatment effect on ridership is a combination of the effect as a result of association due to bike share as well as self-selection (attitudinal). The influence of contributing factors was found to be 175% of the observed difference for bus and 169% of the observed difference for rail. Out of these values, 75% of the observed influence for bus and 69% of the observed influence for rail was due to self-selection by the other factors. This shows that attitudinal effect of the contributing factors has a significant effect on the increase or decrease of transit ridership resulting association with bike share. But the influence on bus ridership has been found to be greater than that of on rail ridership by 6% and was due to the self-selection effect of the contributing factor. An overall 25.95 % increase in ridership associated with bike share has been found for bus average weekday stop level ridership. An overall 10.7% increase in ridership associated with bike share has also been found for average weekday rail

ridership. This shows that micro mobility as a first and last mile option has been better accepted for bus transit by its contributing factor than rail. The contributing factors as discussed in Chapter 3 reflects the preference and needs of the population mix in different communities in Chicago.

As this is an observational study, the assignment of treatment and control group is predetermined. For the case of rail transit, the treatment sample (with BSS) and control is about 82% and 17.5% of the total samples, respectively. On the other hand, for bus the treatment sample (with BSS) and control is about 45% and 54% of the total samples respectively This study estimates the average increase of station level ridership associated with bike share. From the results of Chapter 3, it has been observed that station level ridership is significant for areas which have excellent combination of bus and bike share. On the other hand, the rail stations are in majority located in regions close to bike share, while the southern areas in Chicago lack both bike share and rail. The percent increase of ridership has been found in comparison to the total mean sample. For the case of bus, there is a greater number of stations receiving control than treatment. Therefore, the effect of increase in ridership is more significant for the case of bus as the distribution of control and treatment stations are rather even. Contrarily, rail station sample has about 82% treatment station and 17.5% control samples. So, the percentage increase is mainly representative of the increase of ridership in the treatment stations rather than all the communities, as we have observed in chapter 3 that many of the communities do not have access to rail transit.

## 3.2. Monthly variation of influence on rail ridership

The monthly variation in the influence of contributing factor towards rail ridership showed fluctuating trends. The trends were compared with the monthly trends in transit ridership, Divvy monthly ridership, holidays and institutional activity cycles. It was found that the influence of contributing factors on rail ridership is affected by change in weather condition, increasing or decreasing bike ridership along the year, holidays and special occasions. Most of the rail transit trip purpose is for work trips and therefore holidays (March break, Winter Break, Summer holidays, Thanksgiving) shows significant decline in rail ridership during these times. The weather also has an influence on rail ridership as it also affected by bike ridership or driver decision. In warm weather when bike share ridership goes significantly high, then it has been observed to have decreased the influence of the contributing factor on rail ridership showing the impact of substitutional effect of bike share on rail ridership. Consequently, February showed a significantly high positive influence on rail ridership. This synchronizes with the low bike ridership due to extreme cold condition in Chicago. February is also the time when snowstorms or blizzards occur and may cause many vehicle drivers to switch to transit. Finally, February is the time when all educational institutions are running in full capacity and all workers have returned form New year's holiday.

This research sheds light on how mobility needs can vary amongst communities based on their social, economic and demographic differences. The mobility needs assessed not only includes transit but also under what circumstances micro mobility may be relevant. The research also helps identify the gaps which are to be fulfilled in order to be able to efficiently use micro mobility as a first and last mile option. Based on the statistical analysis and geographic distribution of transit and bike share service in each region, the 77 communities in Chicago has been ranked into 5

classes. The central community has been found to be well connected in terms of accessibility of bus, rail and bike share services has been ranked to be on top and is functioning well in terms of micro mobility as a first and last mile goal. The North side community has been ranked second as it has overall good access to bus service as well as access to rail transit. There is some room for improvement to better implement micro mobility as a first and last mile goal to increase transit ridership. This can be done by improving bike share access in areas with high density of young population (15 -34 years) due to their greater acceptability to bike share as a first and last mile option for bus based on statistical results. The Far North Side has been ranked to be third as this community group has very uneven distribution of transit and bike share moving east to west. The west side of the community group has some access to bus transit while rail service is very low. Although west side is populated by white population which are statistically well receptive to bike share and transit in combination, the density of bike share service is very poor. North West, West and Near west and Southwest Side has been ranked as fourth level in terms of improvements required for transit and bike share service. Patches of areas in these community groups have population of ethnic minority with most hispanic population density and low-income group, both with very poor bike share facility. Finally, South Side, Far South west Side and Far South east side has been ranked fifth and the lowest. This group of community has the highest population with senior, disability, low income group and black minority. The areas have very poor bus and rail service while almost no bike share service. Extensive improvement in transit service and bike share system is needed backup by subsidized cost structure. Hence, severe social, ethnic and economic imbalance was identified with respect to access to transit and bike share amongst the 77 communities in the city of Chicago. In this study, the communities have been classified based on their economic distribution as well as transit service quality. Other cities or communities can

consider this example and follow this as a road map towards accomplishing bridging the gap in transit service, understand the trends of transit micro mobility and ways to accomplish the benchmark towards accomplishing the first and last mile goals. The study also takes an insight into superposition of age and geographical growth to see their combined effects on transit ridership or what heterogeneity exists between the two, if any. An analysis on other demographic factors including ethnicity, income levels, household composition, and auto ownership assisted determining the actual impact of micro mobility as was suggested by past research [1].

The analysis of contribution by bike share uncovered the fact that the rise or fall of transit ridership is not only due to presence of bike share, rather the personal preferences (attitudinal factor, self-selection) of the major factors contributing to the increase or decrease contributes to a large percent of the ridership change. Therefore, while considering whether micro mobility will function efficiently in a community will depend largely on the social and demographic population mix of that area and their personal preferences. The analysis of the seasonal variation of the influence of contributing factors towards transit ridership can help transit agencies identify the true ridership trends and thus avoid misinterpretation of the data. Of course, the timetable or basic service cannot be changed based on weather related factors. But by estimating the influence of these contributing factor on transit for these different conditions (Weather, Institutional activity peak, Holidays), transit agency can either increase or decrease the resources it allocates in route frequency, staff, hours of operation etc. For larger cities, this estimation can also be implemented in a community level.

This research identified accessibility to a major reason for low transit ridership amongst ethnic minority and low income. However, the bike share stations could possibly have been expanded in areas which have high transit station level ridership. If this is the case then instead of bike share

being a driving force towards transit ridership, transit would be a driving force towards bike share ridership. This could possibly be the case specifically for bus stops and BSS location as the difference between stop level ridership for stops with and without bike share is very significant in comparison to rail. Hence, this could also be the reason for such a large estimation of increase in bus stop level ridership associated with bike share in comparison to rail. This makes the process of distribution of bike stations to be a major limitation of the research outcome. If this is the case, then a possible recommendation is to still impose equity in the distribution of transit and bike share access for the betterment of ethnic minority and low-income population. Bus stops are more reachable in comparison to rail as the distance between bus stops are lesser in comparison to rail. This may be the reason for bus to be functioning better as a first and last mile option with bike share in comparison to rail and therefore can be another limitation of the findings of this research.

# 4. Future Recommendation

Most larger cities have ethnic or economic divisions within their communities and in Chicago the difference is just profound. Transit agencies normally establish policies common to all community boundaries. As identified by this research, each population type will have a different need. Consequently, sometimes the reason for ridership decline may not be users not being willing to use public transportation but rather unwanted challenges like safety, cost or social acceptance. Instead, a detail analysis of the transit usage behavior amongst the population mix as well as their accessibility to transit may paint a better picture of the service gap. This may shed light on gaps in transit or bike services in different areas which if improved may improve the overall ridership trends.

Most transit agency tends to decrease service in response to declining transit ridership. The findings from this research implies that the distribution of transit and bike share accessibility has an impact on the trends of ridership of transit. Rather than reducing service as a reaction to decreasing ridership, some agencies might consider tailoring portions of their service toward addressing older cohorts' needs and preferences. One such trait might be immediate accessibility for those elderly not willing or able to walk nearly as far as those in younger age groups. Adding services that older age cohorts find useful could potentially induce higher trip rates for those groups by increasing mobility options [1]. Accordingly, transit agencies should aim to develop transit systems that account for the mobility needs and preferences of seniors, a situation that requires an increased understanding of the nuances of aging and generational differences in the transportation behavior and mode choice of seniors [34]. Significant benefit can be achieved by improving safety in transit. Safe walking environment and stations areas on the origin and the high accessibility in the destination are key elements of transit trip and last mile problem [103].

Governments often makes substantial financial commitments to expanding public transit service in recent years; As a result, both service levels and, especially, public expenditures have grown dramatically. Instinctively investing in areas where there is no need for further investment in transit as the use has reached it optimum level will not result into any rise in ridership. On the other hand, investing in an advanced phase of public transportation development (Such as evaluating the first and last mile behavior) whereas there is basic gap in the transit system will not provide a rise in public transportation use. For example, the study result showed that the Far South East and Far South West area has large population of low-income group, disability and senior who has very low access to bike share and transit. In such areas transit and bike service should firstly be improved to suit the needs of its residents before being evaluated for suitability of first and last mile option.

Targeted transit investments can be made to increase transit reliability and accessibility which could make transit more adaptable to a wide variety of travelers and trips and, thus, be more amenable to life cycle changes [104].

This research showed a positive effect of rail transit station level ridership and most of the rail routes are synchronized with park and ride facility. On the other hand, park and ride locations are not aligned with bus stops. A few bus stops with nearby by park and ride facility showed some significant effect on bus stop level ridership. Therefore, transit agencies can plan to align the park and ride facilities together and make bike share accessible to those stations. This will encourage many people living in the suburbs of Chicago to use bus rather than using personal vehicle. Future research can analyze the effect of fare increase in different community groups in Chicago and observe how bike share may impact transit use in different communities.

The scope of this research for estimating the influence of contributing factor was limited to rail transit with bike share within 400m proximity. Past research on Chicago transit bus ridership has found that bus ridership is more sensitive to weather than is rail, and weekend ridership is more sensitive to weather than is weekday ridership. The study has identified that bus routes parallel to rail lines are more sensitive to weather because of the substitution effect by rail transit on bus [87]. Further research can be continued in area to: 1. Estimate the variation of influence of contributing factor on bus ridership;2. The influence of rail and bus running parallelly can be compared to identify whether the influence of contributing factor also has a substitutional effect ( rail substitutes bus) resulting the special conditions ( Holidays, Institutional activity cycles, Weather) in presence of bike share in proximity. This will assist in developing a comprehensive framework for effect of bike share as a first and last mile option for both bus and rail transit hence allowing a deeper insight into its feasibility.

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