Socio-Economic and Built Environment Analysis of NYC Citi Bike Electric Bike Share Origin and Destinations

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ABSTRACT

Station based electric bike share system (E-BSS) require less physical exertion to bike and allow for faster and longer distance travel, which has the potential to replace shorter car trips and fill the gaps of transit deserts. Despite the benefits of E-BSS, research shows that bike share systems are disproportionately used by white middle income populations. This thesis uses Geographic Information System (GIS) analysis to understand the travel patterns of E-BSS, the impact of race, income, built environment, and pricing characteristics on trip duration, and origin and destination (OD) patterns. The results show that E-BSS was used for slightly longer distances and duration than classic bikes. Moreover, the four built environment characteristics had statistically significant impact on trip duration. While race and income were not statistically significant to trip duration, spatial segregation of socioeconomics and disparity of E-BSS use point to the lack of E-BSS accessibility for low-income Black groups.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

Station based electric bike share system (E-BSS) can become a key environmentally friendly transportation option. With the Inflation Reduction Act, there is momentum at the federal level to address climate issues through sustainable transportation modes and infrastructure (Banayan, 2022). Moreover, with efforts to decarbonize through policies such as low emissions areas and sustainable transportation modes (Yanocha et al., 2022), E-BSS can help reduce carbon emission through mode shift from driving to e-biking. E-bikes can also replace shorter car trips, complement, or substitute public transportation, and be used for longer travel and commuting modes (Reck et. al, 2022). Due to the pedal assist and/or throttle function, e-bikes allow riders to travel longer distances in shorter time frames and with less effort than classic bikes. These functions can potentially reduce barriers for people concerned about hilly terrains and the physical exertion required to bike. As a more affordable and environmentally friendly option compared to driving, e-bikes can fill in the transportation gaps where public transit service is limited (Glusac, 2021).

When an e-bike share system is equitably planned, it can become a key transportation option to access destinations especially for those who do not own vehicles, live in transportation deserts in the outskirts of the city, and are low-income people of color. For example, for those who tradeoff transit accessibility, lower transportation cost, density, and mixed-use in the city core for cheaper housing options in the outskirts of the city, e-bikes can play an important role. Even for the local government, adding e-bike share stations can be a less expensive investment and quicker process than adding additional bus routes or subway stations. Moreover, for those who have not been on an e-bike, the e-bike share system provides low-barrier opportunities for people to test it out as another viable mode of transportation – whether for recreational use, utilitarian purposes, or commuting (Handy & Fitch, 2020). Due to these benefits, E-BSS has the potential to increase access to various opportunity areas with different destinations and a diversity of socio-economic and land uses.

Despite the benefits of e-bikes, there are multiple barriers that make it challenging for people, especially marginalized groups to consider cycling and use e-bikes as a viable transportation option. Lack of equitable bike infrastructure can be a barrier to increasing accessibility and usage of e-bikes. The availability and distribution of shared e-bikes and their docking stations limit travel options and accessibility. Especially for marginalized groups, these barriers can be accentuated. E-bike stations and safe bike infrastructures may be disproportionately distributed to higher income groups with a majority white population, making e-biking less accessible and more dangerous for marginalized groups. Price can also be a major barrier in accessing e-bikes. While private e-bikes are less expensive than car ownership, they are still more expensive than traditional bikes. Depending on its pricing scheme, shared e-bike trip costs can add up quickly and even be comparable to the price of public transportation trips. Without discounts and reduced fares for those who qualify, e-bike trip costs can still be a burden to those who just fall short of meeting the qualifications.

This thesis specifically examines the New York City Citi Bike System. In New York City, e-bikes were first introduced into the Citi Bike System in 2018. However, due to problems with the brakes, e-bikes were removed from the system in 2019, but soon returned in 2020. Most recently in May of 2022, Lyft deployed newer upgraded e-bikes to its existing fleet of 4000 older e-bikes (Colon 2020, Citi Bike 2022). These upgraded e-bikes were equipped with batteries that last 60 miles and motor speed that reaches 18 mph, which allows for faster trips. Citi Bike members, Reduced Fare Bikeshare members, and Lyft Pink members had early access to these newer e-bikes and new members received a 15-day free membership trial (Citi Bike, 2022). The cost of an e-bike trip is more expensive than a classic bike trip. In 2022, for non-members, an e-bike trip cost $0.23/min. For annual members, in addition to the base pay of $15.42/month, e-bike trip cost $0.15/min capped at $3 for 45 min ride. However, reduced fare bike share members received additional benefits. Recipients of SNAP and New York Housing Authority residents paid a monthly membership of $5 and e-bike trips cost only an addition of $0.05/min (Citi Bike, 2022). However, in January of 2023, Lyft increased prices of bikeshare across the board, making bikeshare more expensive for all riders (Citi Bike, 2023).

In this thesis, I studied the Citi E-bike Share System in NYC to answer these three research questions regarding E-BSS travel behavior and socio-economic and built environment characteristics of origin and destination (OD) trips:

a. Are E-BSS being used for further distance trips compared to classic E-BSS?
    i. How does the travel behavior of NYC Citi E-BSS differ from classic BSS over space and time regarding ridership, travel distance, and travel duration?
b. How do the socio-economic and built environment characteristics and pricing scheme affect E-BSS trip duration?
    i. What are the socio-economic characteristics (race and income) around E-BSS at the census block group level?

    ii. What are the built environment characteristics (race and income) around E-BSS at the census block group level?
    iii. What are the pricing schemes of E-BSS?
c. To what extent are E-BSS being used to increase accessibility to areas with different socio-economic characteristics?
    i. What percentage of trips are being made to block groups with the same race and income characteristics and to different race and income characteristics?

This thesis begins with an overview of electric bike share systems within the larger conversation of bike share systems. Chapter 2: Literature Review walks through research done on the topic of bike share ridership and factors impacting bike share usage, specifically socioeconomics, built environment, and costs. Chapter 3: Methodology introduces the data that was used for analysis and walks through the methods used to answer the three research question starting with travel behavior, regression analysis using socio-economic, built environment, and price data, and the OD pairs. Chapter 4: Results presents the product of the analysis with maps, charts, and graphs. Finally, Chapter 5: Conclusion and Policy Implications and Chapter 6: Limitations and Recommendation for Future Research wrap up this thesis by summarizing and highlighting key findings and suggesting action steps for implementation and future research. These sections offer a synthesis of findings and ideas for cities, non-profit organizations, operators, and the public to consider.

CHAPTER 2: LITERATURE REVIEW

The literature review provides a brief overview of the existing studies and knowledge on the electric bike share system and its travel behavior, socio-demographic profiles such as racial and economic factors and built environment factors. The literature review situates this study within the wider conversation of shared micromobility and its findings. This paper examines studies with diverse uses of methods in analyzing E-BSS and BSS and pulls methods that fit best with the goals of this paper. Since there are limited studies on E-BSS travel behavior and demographic studies of E-BSS riders, this literature review will also touch on studies of traditional BSS travel behaviors and their demographic profile to transfer some analysis methods that can be implemented for E-BSS. As equity and accessibility is weaved throughout this paper, the literature review lays out foundational and key concepts of transportation equity and accessibility particularly for shared mobility, biking, and marginalized groups defined as those who are transit dependent, living in transit deserts, and low income people of color.

Bike Share Ridership

Station-Based Electric Bike Share System

The temporal and spatial ridership trends of station-based E-BSS shed light on how they are being used across various cities. Shared e-bikes have been booming over the years with 14.5 million station-based e-bike trips made in 2021 and two-thirds of the station-based bike share systems deploying e-bikes (NACTO, 2022). E-bikes are being used for various purposes such as commuting, recreation, and for utilitarian purposes like grocery shopping. Their usages differ also in time frame, trip duration, and trip distances. In a tourist city like Park City, Utah, 85% of the shared e-bike trips were made by non-regular users (casual riders) and a large portion of the trips generated by both user types were loop trips, suggesting that E-BSS were used more for recreational purposes such as sightseeing or tourism. Moreover, they were used for longer distances, averaging about 4.65 miles and 4.90 miles for both casual users and members. Considering the context of Park City, these longer distance trips were most likely used for leisurely purposes (He et. al, 2019). In Philadelphia, another study found that the trips starting from non-disadvantaged areas significantly increased during morning and evening peak commuting hours, indicating that they were mostly used for commuting purposes. The average trip duration in Philadelphia was 24.49 min and average trip distance was 1.3 miles for both user types (Caspi, 2022).

Dockless Electric Bike Share System

Dockless electric bike share system ridership shares some similarities and differences from that of station-based E-BSS. Depending on the context of the city, they are also used for varying purposes, time frames, trip durations, and distances. In Teng Zhou City, China, dockless E-BSS rides were on average less than 10 minutes and less than 3 miles. Temporally, there were ridership peaks during morning and evening rush hours with a steeper peak during evening rush hours and a smoother peak during noon lunch hours. When examining the ridership trends spatially, the study found that trips concentrated toward the city center during the morning rush hours and trips diffused in various directions during the evening rush hours (Li et. al, 2019). Another study in Zurich, Switzerland concluded that a large portion of the trips were for commuting purposes. The mean trip duration was 10.3 minutes and mean trip distance was 1.55 miles and the distance range of these trips overlapped with traditional public transportation and taxi services, suggesting that the dockless e-bikes cater to the same market (Guidon et. al, 2019).

Beyond Ridership

While researching shared micromobility travel behaviors provide insight on how they are being used, there are limitations to studying travel behavior to compare its usage within the study area, across cities, and the different modes of shared micromobility. Where comparing usage within the study area, there is variability in the route taken, trip taken, and purposes for each trip. Using GPS would most accurately depict the trip route, distance, and time frame. But when using the distance measured by shortest route, it reduces the variability of routes and distances taken from the same origin and destination pair. When comparing usage across cities, the travel behaviors, trip duration, and trip distance are specific to the context of the city. The built environment, land use, socio-demographic composition, and shared micromobility operation that are specific to the city influence the usage of BSS. Moreover, the operation, design, and functions of the different shared micromobilities change rider's choices and behaviors, adding another layer of complexity in understanding ridership patterns of shared micromobility across cities.

Factors Influencing Bike Share Usage

Various factors influence the usage of a bike share system. Raky and Andres (2022) pointed out six main factors that impact the usage of bikes and BSS. Factors influencing the use of bicycles are the built environment, socio-demographics, psychological factors, natural environment, and costs. While these factors are general to bicycles, factors such as time savings, financial savings, further travel, convenience, bus inconvenience, speed, ease of use, and age specifically impact the use of electric bicycles (Kazemzadeh and Ronchi, 2021). The main components influencing bike share use specifically are the BSS characteristics such as the bike design, ease of registration and bike availability. BSS fares and the network features influence both the bicycle and BSS use (Raky and Andres, 2022). As illustrated in Figure 1, a user's decision to take a shared e-bike trip can be multi-faceted, with some decisions general to bikes and some specific to BSS.

Inequity and injustice in transportation add another layer of complexity to the elements influencing bike share usage, especially for lower income groups and people of color. Lee, Sener, and Jones (2017) grouped active transportation equity into four categories – social equity, spatial equity, procedural equity, and distribution of benfits and costs. Social equity is analyzed along socio-demographic lines and the disparate impact policy has had on accessibility to different groups. Social inequity shows up in the disparity of bike share usage between income groups and race groups. Spatial equity refers to access in terms of distributional effect. An example of spatial inequity is the lack of BSS stations or bike infrastructure in areas with a larger non-White population. Procedural equity is fairness in decision making. Inequitable procedure can be the lack of engagement, consideration, and representation of disadvantaged groups in the design and implementation of BSS or even planning in general. Finally, distribution of benefits and costs refers to how the costs and the benefit of active transportation are fairly distributed. An example can be the differing quality of bike infrastructure or the accessibility to key destinations (Lee, Sener, and Jones, 2017). Dill and McNeil (2021) noted that shared mobility services have the potential to increase accessibility and provide more modal options. However, they recognized that physical proximity and the use of shared vehicles may differ by various socio-economic groups depending on the capability of people achieving goals or functions with the resources that are available.

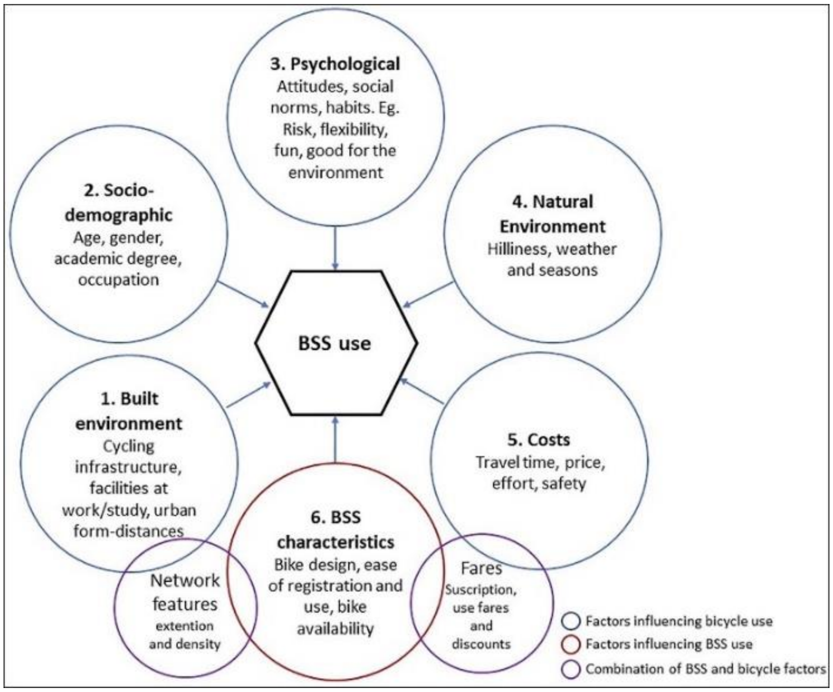


Figure 1: Diagram depicting the factors that affect BSS use (Raky and Andres, 2022).

Built Environment and Land Use Factors

Different land use categories have varying relationship to BSS ridership. Residential uses generally increase the demand of BSS use in the morning during commuting peak hours and attract trips during the evening peak hours for members (Caspi, 2022; Caspi and Noland, 2019). Density of employment and commercial uses are also positively associated with BSS use as destinations in the morning (Caspi, 2022; Wang et al., 2018). Social activities also have a positive impact on ridership (Wang and Chen, 2020; Guidon et al., 2019). One study found that out of all the land use factors, density of food services such as cafes and restaurants had the biggest role in impacting the BSS use (Wang and Chen, 2020). Another study found similar results, with restaurants and bars generating demand mostly in the evenings and weekends. Interestingly, sports facilities, cinemas, and event halls did not have a significant effect on ridership (Guidon et al., 2019). There is a general consensus in the literature that population density, mixed land use, and commercial land use is positively associated with BSS use (Noland et al., 2016; Wang et al., 2018). However, Wang and Chen (2020) pointed out that these land use types may not automatically increase BSS use, but the allocation and availability of bikes play a more important role in attracting use. Depending on the context of area, the impact of built environment will have varying impacts on E-BSS use by space and time.

The presence of bike infrastructure also has a positive association with BSS ridership (Noland et al., 2016; Caspi and Noland, 2016; Bielinski et al., 2021; He et al., 2019). According to a study done by NACTO, as cities build more bike lanes, the more people ride bicycles and the less severe the bike crashes (NACTO, 2016). One study found that a safe bike infrastructure for biking encouraged BSS use for non-riders. However, they also note that the presence of safe bike infrastructure was not significantly related to the frequency of BSS use, suggesting that lack of safe bike infrastructure may not impact frequency of rides for those who already regularly use BSS (Bielinski et al., 2021). Nonetheless, safe, protected bike lanes allow varying levels of bikers to bike more comfortably and use BSS.

Multiple studies agree that the transit access or the presence of transit is positively related to BSS usage (Noland et al., 2016; Noland et al., 2019, He et al., 2019, Guidon et al., 2019, Younes & Baiocchi, 2022). One study highlighted the nuanced impact of public transit on BSS use. The authors noted that the origin stations in the morning were negatively associated with BSS use while destination stations in the morning were positively associated with BSS. On the other hand, origin stations in the evening were positively associated with BSS and negatively associated with destination stations. (Noland et al., 2019). Noland et al. (2019) suggested that BSS was used to complement public transit as a solution for first and last mile trips. However, this may also suggest that BSS was used as a substitute for transit. The negative relationship to transit in the morning may be the result of residential land use with low accessibility to transit. The positive relationship to transit may be the result of dense mixed uses at the downtown center where transit accessibility is high. Another study done in Tricity, Poland, showed that while shared e-bikes acted as a first and last mile transport to and from public transportation stops, residents who used public transportation were more associated with renting e-bikes, indicating substitution (Bielinski et al, 2021).

Socio-Economic Factors

Shared micromobility and station-based electric bike shares have the potential to fill the gap of transit deserts, especially in areas with low access to transit for those who do not own personal vehicles. However, there is disparity in the use of BSS. Research have shown that people of color and lower income groups are underrepresented as members in the BSS system (Grasso et al., 2020; Dill and McNeil, 2020). Other studies have also found that areas with more White population and higher income groups generated more ridership (Caspi, 2022; Caspi & Noland, 2019; Guidon et al., 2019). Caspi and Noland (2019) examined the distribution of trips and found that stations in high-income areas generated 2.5 times more trips than in low-income areas. Capsi (2022) compared classic bike share and e-bike share usage in Philadelphia and found that proportions of the Black population and households under poverty decreased the demand of both classic bikes and e-bikes. When examining race and income separately, the White population had a stronger relationship to ridership than median household income (Caspi, 2022).

While there is a general consensus that BSS users are predominantly White and higher income groups, there are nuanced results. A study done in Philadelphia showed that low-income areas surrounded by universities with large student populations had a significant positive influence on ridership (Caspi and Noland, 2019). In this study, student population most likely generated ridership in the low-income areas. Students may contribute to the overall lower median household income because they may not be making much money as an individual during their time at school. However, they may have educational financial support, scholarships, loans, family support, and future employment opportunities. These characteristics make the student population unique from low-income households and families and need to be distinguished.

Consistent with other studies, Caspi (2022) found that E-BSS ridership was higher in non-disadvantaged areas and lower in disadvantaged areas. In Philadelphia, disadvantaged areas were generally in the periphery of the city and further away from the median center of stations. The lower rates of ridership among disadvantaged groups can partially be explained by the limited stations at the periphery of the city. Studies have found that the distance from the median center of stations has a negative association with ridership and ridership increases with the density of stations (Caspi and Noland, 2019; NACTO, 2015). The higher the density of stations, the more trips generated. This indicates that stations in the periphery tend to get less ridership, because destinations are restricted by where stations are available which limits travel options. Despite this barrier, Caspi (2022) found that e-bike trips increased the overall ridership in disadvantaged areas. E-bikes were also used for longer duration and distance trips than those of non-disadvantaged areas. This result suggests that lower-income minority groups used E-BSS as a viable mode of transportation from the periphery of the city into other areas of the city.

Disparity in access contributes to the lack of not only ridership, but also membership among low-income minority groups. Lack of access to safe bike lanes hinders marginalized groups from using BSS. Although there are many studies indicating a positive relationship between safe bike infrastructure and BSS use, safe bike infrastructure is not readily accessible, especially in lower-income areas. One study found that bike infrastructures were two times more accessible near high income areas than in low-income areas (Tucker and Manaugh, 2017). Moreover, lack of physical proximity to bike share stations is also an issue. Even with physical access to BSS, people of color are less likely to be members or use BSS as frequently as the White population (Dill and McNeil, 2020). One study found when Citi Bike launched in 2013, they were used overwhelmingly by White male. Even after two years of its launch and physically availability of stations in Bedford Stuyvesant, a neighborhood with high minority low-income groups, only 18% of the residents had used shared bikes even though 84% of its residents knew it existed (Palutz, 2021; *Bringing Equitable Bike Share to Bed-Stuy,* 2017). Another study found that people living in disadvantaged areas use the BSS if the stations are available in their neighborhoods and they have used it progressively over time. However, the authors emphasize that usage is conditional to price and its affordability in relation to other transportation modes (Goodman and Cheshire, 2014). These research results suggest that there are multiple barriers discouraging disadvantaged groups from using BSS and E-BSS. Some of those barriers that are specific to lower-income groups include factors such as cost, time limit, liability concerns, credit card payment methods, computer access, and lack of knowledge (Dill and McNeil, 2020). Putting a bike share station near disadvantaged areas is not sufficient to improve equitable access. Instead, Qian and Jaller (2021) stressed that the coupling of access to the bike share service with access to desirable destinations or opportunities is essential in improving equitable transportation access for disadvantaged groups.

Cities such as Philadelphia, Washington D.C., Boston, and New York have incorporated low-income pricing, equity zones, and bike availability requirements for low-income areas. However, a study pointed out that even with these equity programs, minority areas still had lower ridership. In response, the authors suggested that these programs were not sufficient (Younes and Baiocchi, 2022). The issue is not the lack of willingness, but lack of information. A study found that an overwhelming number of low income, minority residents had a favorable view of BSS (Schneider, 2017). However, studies suggest that lack of information about equity programs, access to safe streets, access to protective gear, and reassurance about hidden fees play a role in the underrepresentation of low-income minority groups in BSS (Schneider, 2017;

Younes and Baiocchi, 2022). On a positive note, one study found that members who have accessed the equity programs use BSS as frequently as other regular members. The study concluded that when physical access and other barriers are addressed, BSS has the potential to provide increased accessibility and travel options for low-income people (Dill and McNeil, 2020). Another report highlighted that with active partnership and community engagement around BSS use in Bedford Stuyvesant, a neighborhood with many low-income households and people of color, they saw a 225% increase in trips and a 56% increase in new membership. Therefore, to close the racial and wealth gap in BSS usage, holistic strategies such as group rides, education classes, community partnership, and redesigning of ads are needed (Palutz, 2021).

Costs - Pricing

The prices of E-BSS rides are different depending on the city. In Park City, the price of a shared e-bike trip was a fixed price instead of a price accrued by time. A single trip was $2 for the first 45 minutes and an additional $2 for the next 30 minutes. Moreover, there were discounted membership plans - $18 weekly, $30 monthly, and $90 yearly – which covered all shared e-bike trips that were within 45 minutes (He et al., 2019). While this study did not examine the impact of pricing schemes on ridership, the fixed pricing scheme may explain the longer trip distances of 4.65 miles and 4.90 miles compared to that of other E-BSS systems. The Smide E-BSS in Zurich was priced pro rata on a per minute basis with a base price of 5 CHF ($5.60 USD) for rides within 20 minutes (Guidon et al., 2019). Since the price of Smide trips was relatively higher than that of public transportation, this may partially explain why higher income groups drove demand for dockless E-BSS. Philadelphia's Indego's pass cost $17 a month or $156 a year for regular users and $5 a month or $48 a year for food-stamp holders. In addition to Indego's membership fee, e-bike usage cost 15¢ per minute and 5¢ per minute for food-stamp holders (Caspi, 2022). While the overall e-bike ridership was still lower in disadvantaged areas, the findings show that e-bike trips increased the overall ridership in disadvantaged areas. The reduced price for food stamp holders, or disadvantaged groups, may have helped partially lower some barriers to encourage e-bike use.

The pricing scheme of BSS and E-BSS impact user's travel decisions. The pricing structure of BSS can influence whether someone uses BSS or not, what type pricing option to choose, and duration of trips. One study found that more than 90% of BSS trips in Washington DC and Brisbane, Australia was within 30 minutes, the time threshold before additional costs is charged. They also noted, however, that the mean trip duration was 11 minutes in DC and 12 minutes in Brisbane and hypothesized that the users were either unaffected by pricing or chose other transportation modes for longer distanced trips (Ahillen et al., 2013). Surveys done in the Bay Area highlighted that the most frequent write-in responses were regarding how the 30-minute limit was not enough for a trip (Shaheen et all, 2015). Another study found that users from disadvantaged areas were more sensitive to the extra charges after the free 30-minute ride. The willingness to pay for additional trip time for trips made between disadvantaged areas declined after a certain trip time variability compared to other trips made between non-disadvantaged areas (Qian and Jaller, 2021). One study found that with the expansion of BSS to low-income areas, membership for the marginalized groups doubled along with an increase in casual rides in the 'highly-deprived' stations. However, with a twofold increase in BSS price, trips made by casual riders decreased while trips made by members stayed stable. The authors concluded that the decline in casual user trips may have disproportionately impacted low-income areas (Goodman and Cheshire, 2014), as some studies found that low-income people more likely to use a casual ride and use BSS for shorter-term than members (Goodman and Cheshire, 2014; Kaviti et al., 2019).

CHAPTER 3: METHODOLOGY

This chapter begins with an introduction to the three main data used for analysis – NYC Citi Bike data, Smart Location Database, and US Census ACS data. The chapter then walks through in detail the steps and decisions made for method of analysis. First it explains analysis methods for travel behavior, then for regression analysis, and lastly for OD pairs. As for regression analysis, it dives into the process of cleaning and analyzing socio-economic data, built environment data, and price for descriptive maps and statistics and spatial regression analysis. Then it ends with a section on OD pairs which explains how race and median household income data was categorized for descriptive statistics and visualization.

Data

The bike share trip data was obtained from the NYC Citi Bike website and downloaded for the summer months of June, July, and August of 2022. Starting in 2022, Citi Bike changed their data sharing information and started to clearly identify whether a trip was taken by a classic bike or an e-bike. However, they discontinued sharing any demographic information such as gender and age. Since NYC Citi Bike share docks are available only in four boroughs of NYC – Bronx, Manhattan, Queens, and Brooklyn – Staten Island was excluded in the analysis. This thesis selects and analyzes trips taken by e-bikes. Classic bike data was used in the travel behavior analysis for general comparative analysis. Trip information such as start time, end time, origin location, destination location, and membership types were used for analysis.

Demographics data was taken from the 2017-2021 American Community Survey 5-year data at the census block group level. This time frame was chosen because the 5-year data is collected from a larger sample and is more reliable. Moreover, this was the most recent data available that was closest to 2022. Race and income information, specifically “White Alone”, “Black or African American Alone” and “Median Household Income (In 2021 Inflation Adjusted Dollars)” were the three socio-economic factors considered in this study.

As for built environment factors, this analysis used data from the 2021 version 3.0 Smart Location Database. The Smart Location Database measures location efficiency at the census block group level using 90+ attributes to summarize characteristics such as demographics, built environment, land use, transit, and employment. These attributes are calculated by the U.S. Environmental Protection Agency from data collected in 2017-2019 from multiple reputable sources. The built environment factors analyzed in this study examine residential, population, and employment density, mix of employment and housing, auto-oriented and pedestrian-oriented network links, transit, and walkability, similar to that of the study done by Younes & Baiocchi (2021). Appendix 1 provides more description of the variables used in the analysis. In addition, the Smart Location Database metadata explains all the calculated variables in detail.

This analysis was also influenced by informal initial conversations with practitioners such as transportation planners in the City of Boston and City of Cambridge, a staff member at Institute of Transportation and Development Policy, and a staff member at Lyft. While these informal conversations were not formally included in the data analysis, these conversations helped spur ideas for this thesis.

Travel Behavior

The NYC Citi Bike data was analyzed for the three summer months of June, July, and August 2022. Python packages such as pandas, geopandas, numpy, osmnx, and networkx, and seaborn was used to clean the Citi bike trip data and analyze the travel patterns. All trips in June, July, and August were first combined, which had a total of 10,611,582 trips. Then, any trips with duration lower than 1 minute was removed to reduce trips that may have been a mistake. The data contained a rideable type of “docked_bike”, a separate type from “electric_bike” and “classic_bike”. This category is unclear how they were different from “electric_bike” and “classic_bike” and was therefore removed from the study. The resulting total number of electric and classic bike trips for the summer of 2022 was 10,208,021 trips.

Each trip contained unique start and end latitude and longtitude to indicate where the trips started and ended. Since each station contains multiple bike docks, one set of start and end longtitude and latitude was designated for each station docks. There was a total of 1,591 stations used in the summer of 2022 after dropping stations ending in New Jersey. Then each of the trips were grouped by the origin and destination pairs which resulted in 744,307 unique OD pairs. The shortest distance between each unique origin and destination pair was calculated using the OSMnx on the Open Streets Road network. Finally, the distances in miles for OD pairs were joined back to all the trips.

In order to analyze and visualize ridership in python, the time data was transformed to a datetime data type. Then, each trip was grouped by time of the day and day of the week to find the total number of trips by time and average trips per week. These datasets were used to visualize the ridership patterns. Moreover, data frames were created to compare ridership by classic bikes vs. e-bikes and casual riders vs. members.

Regression: Impact of Socio-Economic, Built Environment Characteristics, and Price on E-BSS Trip Duration

Socio-Economic Data

Since there was no demographic data at the trip level, ACS data was used to understand the characteristics of race and income at the census block group containing stations. Black population, White population, and median household income were downloaded at the census block group. Then each station point was spatially joined with the NYC block groups. Using a common GEOID, race and income data were merged to the corresponding station dock. This resulted in a dataset of stations with race and income data for the corresponding census block group. This method was used to understand the socio-economic component of the census block groups that contain an E-BSS station. Out of the 1,591 stations used to analyze ridership patterns, only 1288 stations were analyzed for the regression because the rest of the stations either did not have race, income, or trip data. As for race, most of the stations that were dropped were in census block groups that are parks or industrial areas where people do not live. As for the median household income, there were no observed clear patterns or reasons as to why they did not contain income information.

Built Environment and Land Use Data

In conjunction with understanding the socio-economic characteristics at the census block group level with E-BSS station, this paper also examined the built environment and land use surrounding the E-BSS stations at the census block group level. Twelve Smart Location Database variables were chosen for the built environment and land use characteristics. Since some of the variables had multicollinearity, this study used R Studio to conduct Principal Component Analysis (PCA) to remove redundancy and high correlation between the twelve variables. After running PCA, new variables, the principal components, were constructed. The first four principal components were chosen and their values were merged with the corresponding stations.

Census Block Group vs. Service Area

Census block group was the geographic scale at which this study was conducted. Creating a service area around each bike station was considered but calculating an area weighted means or the population weighted means of the service area would assume that the variables are uniformly distributed. Since both the ACS 17-21 five-year data and the Smart Location Database were all originally calculated at the census block group level, using this geographic scale preserves the data as close to its original and reduces the chance of losing accuracy of the data.

One of the limitations of analyzing at the census block group level is that the stations are characterized by just one census block group. Stations that are on the border of census block groups may be used by residents of neighboring census block groups and the built environment surrounding the stations impact E-BSS usage.

Price

The mean price of E-BSS trips was assigned for each station. The table summarizes the different pricing schemes for members, reduced fare riders, and casual riders for both classic bikes and electric bikes. Since casual riders have a base fee of $3.99 per trip, base membership costs were calculated for both members and reduced fare riders to account for the membership price. The base membership cost per trip was calculated using this formula: (Base Monthly Membership Price / (Average membership trips per month/Average Active Annual Members per month). Then the average trip duration was calculated for each station, which was then used to find the average price for electric bike share trips per E-BSS stations.

Four E-BSS pricing categories were created: 1. Members with cap of $3.00 during the 45-minute period, 2. Members without a cap, 3. Reduced Fare Riders, and 4. Casual riders. E-bike trips for members were capped at $3 for 45 minutes or less that started or ended outside of Manhattan. Before October 31, 2022, there was a glitch in the Citi Bike system which allowed all member e-bike trips to be capped at $3, allowing trips between Queens and Brooklyn to be capped at $3 as well (Colon, 2022). Since this restriction was not set in place during the period of this study, members without a cap were excluded in the pricing category for the regression analysis.

These pricing categories and schemes were used to calculate the price per trip by different price structures. Moreover, the price for each pricing structure was averaged out to the stations level and used for regression analysis.

	Annual Members	**Reduced Fare Members**
Base Per Trip Cost	$1.26	$0.41
Base Monthly Cost	15.42	$5
Base Annually Membership	$185	$60
Classic Bikes (45 min max)	No additional fee	No additional fee
Electric Bikes	$0.15/min	$0.05/min
Extra Time Fees (after 45 min)	$0.15/min	$0.15/min

Table 1: Pricing scheme of Citi Bike membership and trips

	Casual Riders
Single Ride (30 min max)	$3.99
Day Pass	$15
Electric Bikes	$0.23/min
Extra Time Fees (after 30 min)	$0.23/min

Table 2: Pricing scheme of Citi Bike causal rides

Spatial Regression Analysis

I used R Studio to run a regression analysis for member mean e-bike trip duration and causal rider mean e-bike trip duration. The independent or explanatory variables used in the model were Black, Median Household Income, the four principal components derived from the PCA, member pricing cap, reduced pricing, and casual pricing. Since the data was aggregated at the station level, which is a point, distance-based neighbors' method was used to define neighbors and determine the weight matrix. The weight matrix was calculated so that all stations had at least one neighbor. Before running the regression, Global Moran's I and correlation matrix was calculated to see if there were spatial autocorrelation in the dependent and independent variables and any correlation between the independent variables.

First, I ran an Ordinary Least Square (OLS) regression model along with OLS diagnostics for multicollinearity to check for dependency among the independent variables. Then, I ran the Global Moran's I test for the OLS residuals to check for spatial autocorrelation. A different weight matrix was used for LOCAL Moran's I for OLS residuals. For additional diagnostics test, lagged value for the dependent variable was used to run a regression to see if the coefficient on the lag was significant and if there was significant spatial dependency. After running through these tests, Lagrange Multiplier Test for Residuals was used to determine whether to use a Spatial Error Regression model or the Spatial Lag Regression Model to account for spatial autocorrelation between neighbors. Based on the tests, a Spatial Lag Regression model were chosen as the best fit for this study. Finally Global Moran's I was run again to make sure that spatial autocorrelation was accounted for the residuals in this model.

Socio-Economic Characteristics with the Trip Origin and Destination (OD) Pairs

ACS race data was categorized into two: dominant White block group or dominant Black block group using the Index of Concentration at the Extremes (ICE) index.

The ICE formula is: $\mathrm{ICE_i} = \frac{(\mathrm{A_i} - \mathrm{P_i})}{\mathrm{T_i}}$ "Where A is the number of persons in the advantaged group in community i, Pi is the number of persons in the deprived group and T_i is the total. The result is bounded by -1 and +1. An ICE value of -1 indicates concentration of the deprived condition, and an ICE value of +1 indicates concentration of the advantaged position" (De Maio & Sengupta, 2016).

This formula was used to calculate whether each census block group was dominantly White or Black. Then these race categories were merged to the corresponding station docks. While this race categorization is not perfectly accurate, since NYC is spatially segregated, these designations of race at the block group will still provide general insights about the race characteristics at each station.

Median household income was divided into three categories: low income, middle income, and high income. They were evenly split into terciles with low-income households ranging from \$2499-\$85000, middle-income households ranging from \$85001-\$167500, and high-income households ranging from \$167501-\$250001. Most low-income households qualify for SNAP and NYCHA public housing, two measurements used by Citi bike to provide reduced fare membership. Some middle-income households may qualify for the reduced fare, but many may fall short of qualifying and may pay regular membership price. Each station was assigned a median household income bracket - low, middle, or high – with the corresponding block group GEOID.

The race categories and three income categories were merged to all E-BSS start and end station docks to shed light on whether trips started and ended at areas with similar or different socio-economic characteristics and to what extent E-BSS were used to improve accessibility to areas with different socio-economic characteristics.

CHAPTER 4: RESULTS

This chapter begins with E-BSS travel behavior analysis, specifically the average daily trips, average weekly trips, trip distance, and trip duration. This chapter then examines the spatial distribution and clusters of race, income, and built environment at the census block group level in the four boroughs of NYC. The price schemes of E-BSS are shown in relation to the travel duration of E-BSS and other transportation modes. These three factors are then incorporated into the spatial regression analysis results. Finally, this chapter ends with a visualization of the OD trips made between and across different race and income characteristics.

Travel Behavior Analysis

Understanding the basic travel patterns of E-BSS is essential in providing further insight into the interplay of race, income, built environment, and price to E-BSS. Figure 1 below visualizes the 1,591 stations that were active and used at least once, during the months of June to August of 2022.

Figure 2: Locations of 1,591 Active Stations in Jun-Aug 2022

Average Daily Trip:

Similar to classic bike ridership pattern, e-bike average daily trips have AM and PM peaks, but they are not as prominent as the classic bike AM and PM peaks. This indicates that e-bikes are being used as a commuting mode during the AM and PM peak hours, but they are also being utilized for non-commuting purposes during off peak hours. Figure 3 conveys how Citi Bike members who own monthly, annual, or discounted passes are more likely to use the e-bike for commute modes than the Citi Bike casual riders who buy single ride passes. Figure 4 on the right shows that about 20-30% of the trips are being taken by e-bikes and the rest by classic bikes. E-bikes are generally used more often than classic bikes when considering the number and the types of bikes available, as e-bikes constitute 20% of the bike share fleet. It is interesting to note that percentage of e-bike ridership compared to classic bike ridership decreases to about 20% during AM and PM peaks and increases during non-peak hours, especially in the early afternoon and during the dawn. This is another indicator suggesting that while e-bikes are used for commuting purposes, they may be used as much for recreational or utilitarian purposes during non-AM and PM peak hours.

Figure 3: Average Daily trip by rideable type (left) & Average daily e-bike trips by membership type (right)

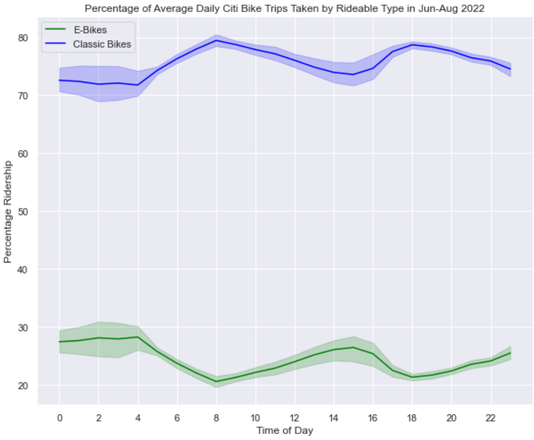


Figure 4: Percentage of trips taken by rideable type

Average Weekly Trips:

Average weekly trips for e-bike trips also have a similar pattern to that of classic bike trips. They both follow the AM and PM peak patterns throughout the weekday. The PM peak is consistently higher than AM peaks. Trips taken during the AM peaks are most likely used for commuting purposes while the trips taken during the PM peaks may be more varied. They may be taken not just to commute back home, but also to visit restaurants, stop by third spaces, and run other errands, which will result in more travel and use. However, ridership pattern changes during the weekend. E-bike trips used by members also follow a very similar AM and PM peak patterns, but the e-bike trips used by casual riders peak only during the PM times during the weekdays. While the average trip count for members steadily drops at its lowest during the weekend, average trip count for casual riders stays consistent even during the weekend, which indicates that casual riders may be using bike share for more leisurely or utilitarian trips than the members. Figure 5 conveys how a larger share of e-bikes are used during non-AM and PM peak hours. When examining the weekly patterns, the usage of e-bikes ranges from about 18-34%, slightly higher than that of daily e-bike usage range.

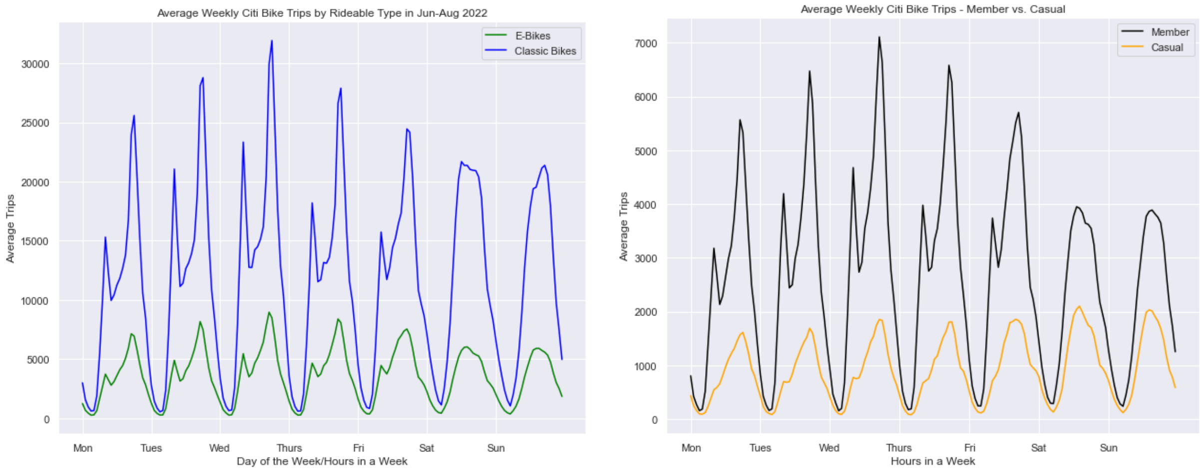


Figure 5: Average weekly trips by rideable type (left) & Average weekly trips of e-bike trips by membership type (right)

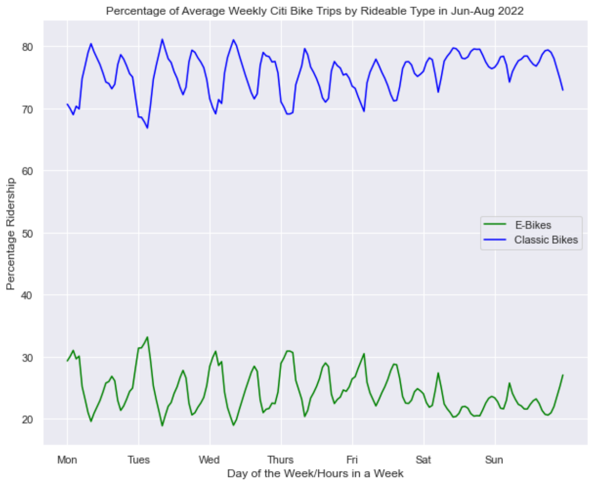


Figure 6: Percentage of average weekly trips by rideable type

Trip Distance and Duration:

When comparing e-bikes with classic bikes, the mean trip distance for e-bike trips is 2.72 miles and classic bike trips is 2.21 miles. Moreover, the mean duration of e-bike trips is 16.88 minutes and classic bike trips is 16.31 minutes. While the difference in trip duration between e-bikes and classic bikes is small with 57 seconds, the difference in trip distance is notable with

0.51 mile. This indicates that e-bikes on average are being used for slightly longer trips. Since e-bikes travel at higher speeds within the same distance, this difference of about half a mile saves a few minutes of travel time for e-bike riders as opposed to taking a classic bike to travel the same distance.

While e-bikes on average were used for 0.51 mile longer trips, the difference in trip distance between e-bike trips and classic bike trips is notable, but quite small. This suggests that e-bikes may not be utilized as much as its potential to travel much longer distances in shorter amount of time to cross boroughs and bridge boundaries. However, this may be due to the pricing scheme of E-BSS. Since e-bike trips are charged marginally per minute with increased per minute charge after 30 minutes for casual riders and 45 minutes for members, riders may be conscious of how long they are taking the trip and the total cost of the trip, which affects the trip distance and duration of rides. Especially for low-income or lower middle-income riders who do not qualify or do not know about the reduced fare membership may be more conscious about their total trip duration and cost.

As for the e-bike trips, members mean trip duration is 2.69 miles and casual riders mean trip duration is 2.79 miles, indicating that members on average travel 0.10 miles less distance than that of casual riders. Members mean trip duration is 14.93 minutes and casual riders mean trip duration is 23.03 minutes, which is quite large, about an 8-minute difference. The larger difference in trip duration compared to trip distance suggests that more casual riders may use e-bikes for recreational purposes and take more time as opposed to commuting purposes, which is a time sensitive trip.

Figure 9 further supports the assumption made regarding member and casual riders e-bike trips. Clusters of stations with higher member mean trip duration are generally on the outer edges of the boroughs. As for casual riders mean trip duration, these are a cluster of stations with higher mean trip duration near central park and other locations, suggesting that casual riders may take e-bikes for longer trips for recreational purposes.

	Membership Type	**Mean Trip Distance**	**Mean Trip Duration**
Classic Bikes	**All**	2.21 miles	16.31 minutes
Electric Bikes	**All**	2.72 miles	16.88 minutes
	Members	2.69 miles	14.73 minutes
	Casual Riders	2.79 miles	23.03 minutes

Table 3: Summary table showing the mean trip distance and mean trip duration of classic and electric bikes

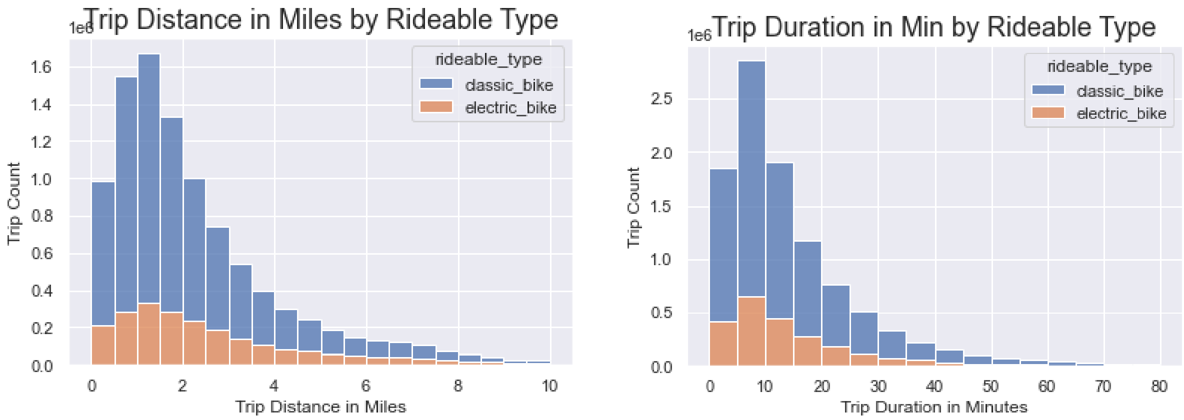


Figure 7: Trip distance in miles by rideable type (left) & Trip duration in minutes by rideable type (right)

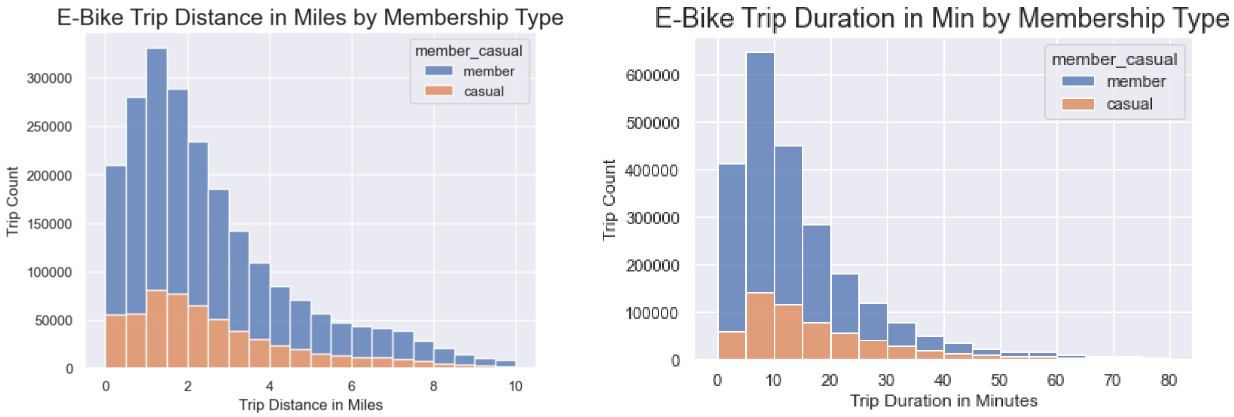


Figure 8: E-bike trip distance in miles by membership type (left) & E-bike trip duration in minutes by membership type (right)

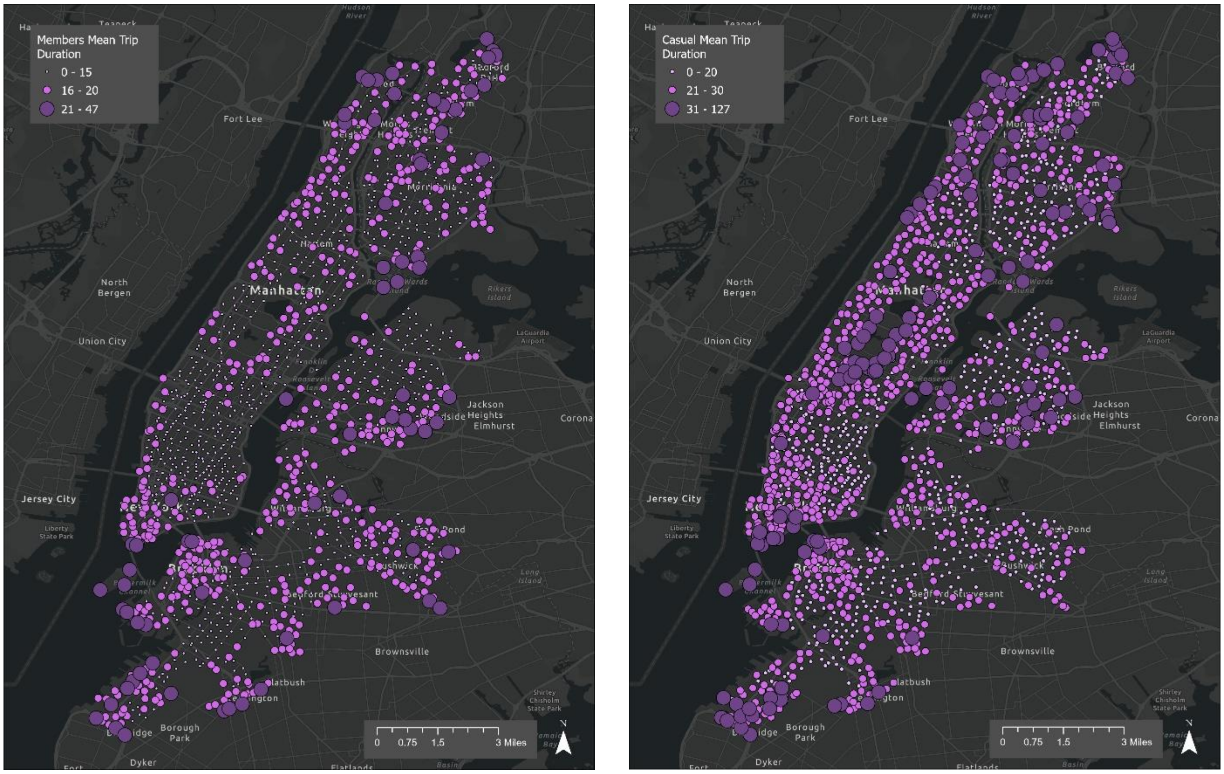


Figure 9. Mean Trip Duration of Members (left) & Mean Trip Duration of Casual Riders (right)

Spatial Regression Examining the Impact of Socio-Economic, Built Environment Characteristics, and Price on E-BSS Trip Duration

Socio-Economic Characteristics by Census Block Groups

Identifying the spatial clusters and segregation of race and median household income in NYC is important in understanding e-bike usage. Figure 10 below shows the spatial distribution of race in the four boroughs of NYC for White and Black population. NYC is highly spatially segregated as there are distinct clusters with either majority White or Black population. While mid and southern Manhattan have a high concentration of White population, northern Manhattan, Bronx, parts of Brooklyn have a high concentration of Black population.

Figure 11 shows the average household income. The highest income households are concentrated in mid and lower parts of Manhattan and parts of Brooklyn that are closer to Manhattan. The lowest income households are concentrated in northern Manhattan and Bronx which also has a concentration of Black population. The Citi Bike Share stations are located mostly in areas with high- and middle-income households expect in Bronx, where there are clusters of low-income groups.

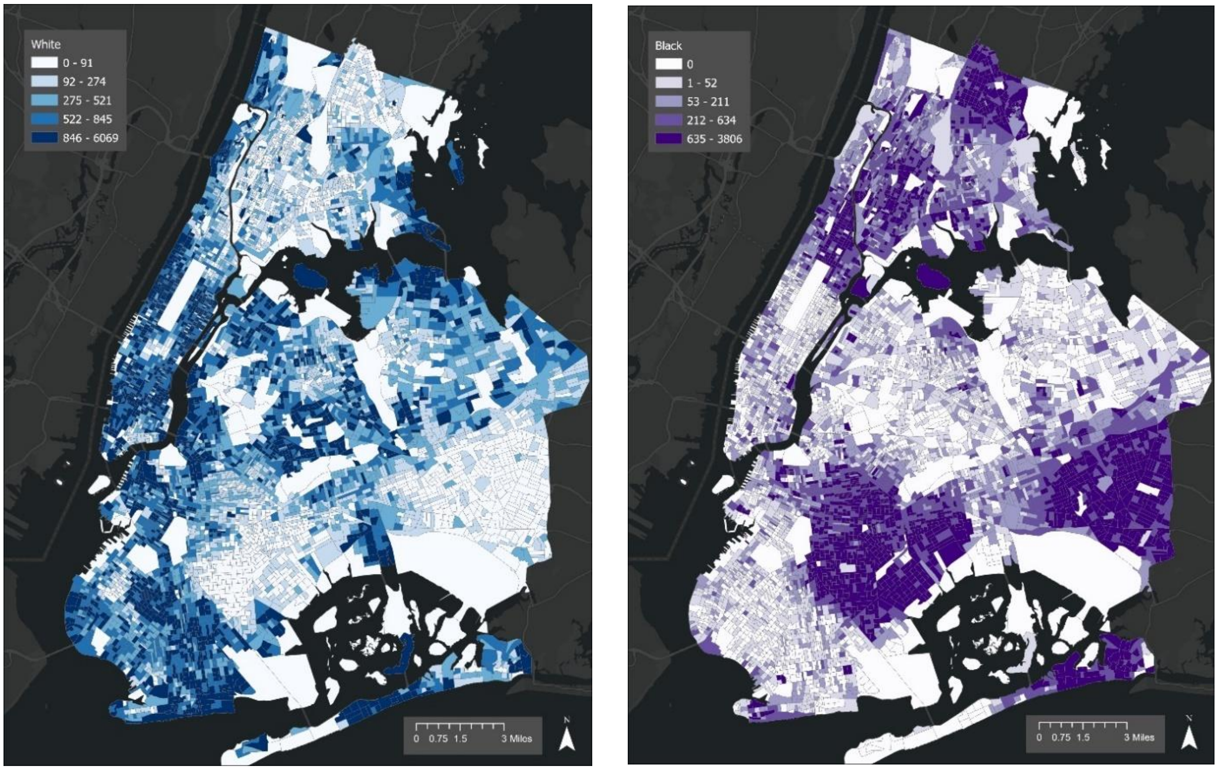


Figure 10: Race by census block group from ACS 2016-2021 Data

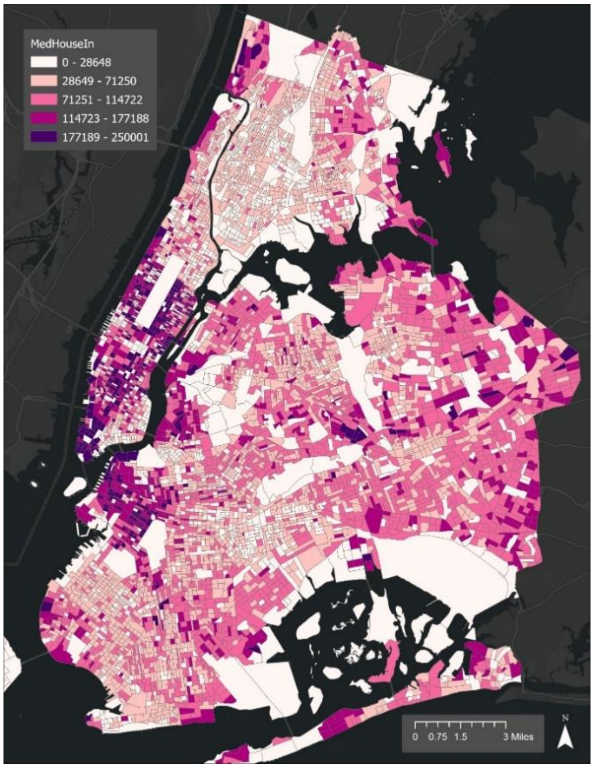


Figure 11: Median household income by census block group from ACS 2016-2021 Data

Smart Location Database: Built Environment

The principal component analysis produced a total of twelve principal components (PC). Out of the twelve, only the first four principal components were selected as they explained most of the variance. The first four components had eigenvalues of more than 0.99 and explained a total 73.79% of the variances. The highest variable loadings were then examined to categorize and interpret each principal component. These four PCs were defined as such as below and the detailed PCA results are included in appendix 2.

PC1 – High Access to Jobs

PC2 – Walkable Suburbs

PC3 - High employment and park density

PC4 – Auto-oriented

Principal component 1 (PC1), categorized as high access to jobs, represents areas with high accessibility to jobs, transit, and residences as shown in Figure 12 on the top left. Most of Manhattan has a higher presence and value of PC1, along with other areas such as the Bronx, and western parts of Queens and Brooklyn. Since PC1 includes frequency of transit service in its higher variable loading, the map shows higher values of PC1 around the MTA transit lines. Generally, Citi Bike stations are placed in areas with higher values of PC1.

Principal component 2 (PC2), categorized as walkable suburbs, represents areas that are walkable with high pedestrian-oriented links and has a balance of employment and households with moderate population and residential density. Manhattan scores very low in PC2 but other boroughs score relatively higher in PC2. Most of Queens scores higher in PC2 and some parts of Brooklyn and Bronx score moderately high.

Principal component 3 (PC3), categorized as high employment density and park density, represents areas density of employment of park but with low population density where people generally do not live and simply visit for work or for recreation as shown in Figure 12 on the bottom left. PC3 seems to generally cover manufacturing districts, commercial districts, and parks. A few clusters of major manufacturing districts with high PC3 values are shown in southern edges of Bronx, southwestern edges of Manhattan, western edges of Brooklyn and the east of Roosevelt Island in Queens. Some of the commercial districts included in PC3 may be southern parts of Manhattan. The low population density loading may indicate park areas such as the Central Park, Bronx Park, Van Cortlandt Park, Inwood Hill Park, Randall Island Park, and the Cemeteries.

Principal component 4 (PC4), categorized as auto-oriented, represents areas with high network density in terms of auto-oriented links as shown in Figure 12 on the bottom right. Areas with MTA access have a very low PC4 value, which generally has higher pedestrian-oriented links and transit frequencies. Generally, areas with highways, expressways, and parkways near the edges of each borough, bridges, and major manufacturing districts have higher score of PC4.

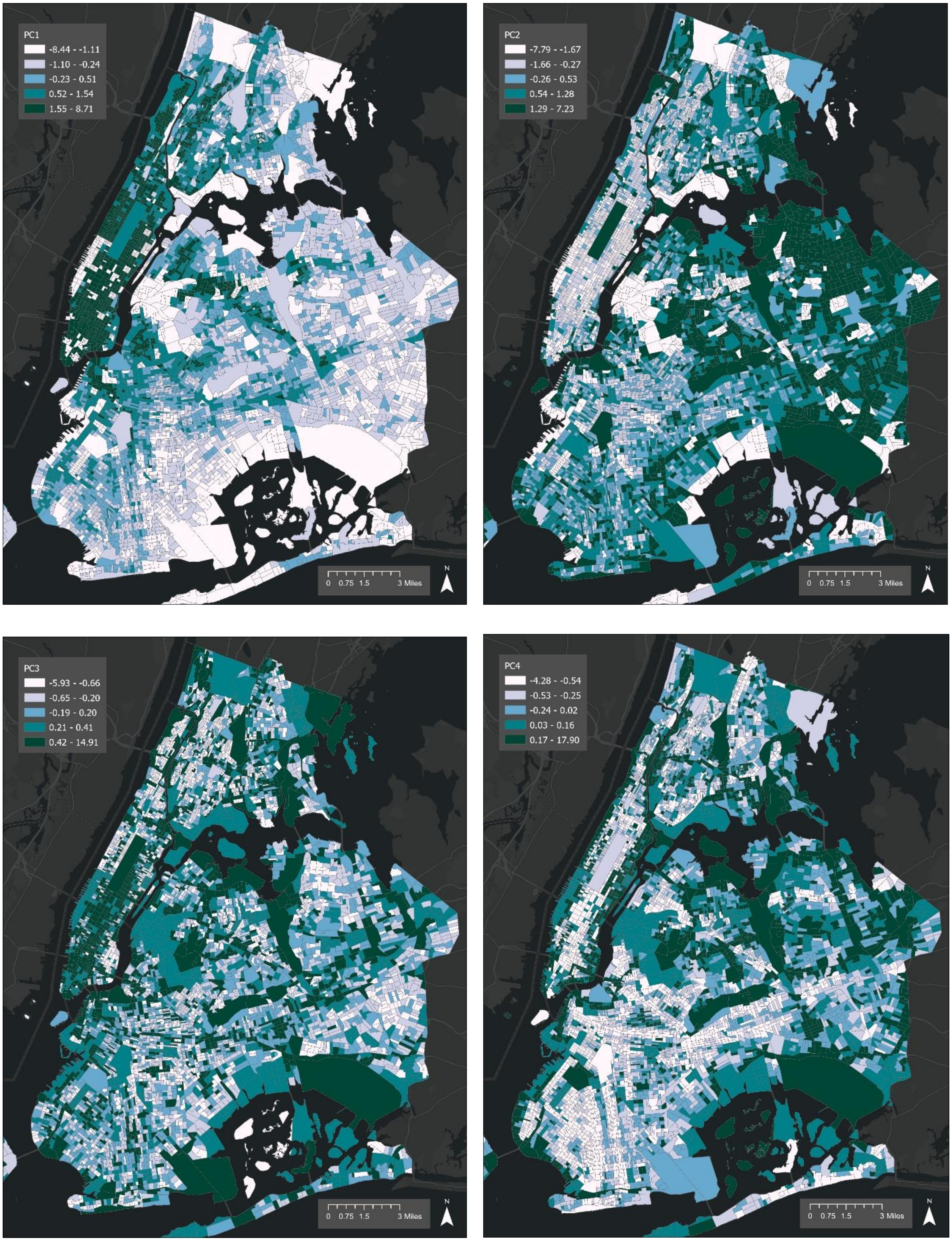


Figure 12: Maps picturing principal components 1, 2, 3, and 4 in quantiles.

Average ridership by stations by 1000 population for all our PCs conveys the usage of E-BSS by different built environment characteristics. The average ridership by stations by 1000 population for all four boroughs was calculated using this method: ((member trip + casual trip)/total population) * 1000. Then, the fifth quantiles were selected to find the average ridership by stations by 1000 population for each PCs. Table 4 shows how the 5th quantile for "Walkable Suburbs" had the least number of stations and ridership when considering population size. Auto-oriented areas came next with the lowest number of stations and ridership. Areas with "High Access to Jobs" and "High Employment and Park Density" generated more than two times the ridership compared to the other two built environment characteristics.

The mean trip duration was compared for each of the four principal components. Table 5 on the top shows the differences in mean trip duration by each PCs. For each PCs, the highest 5th quantile was selected to calculate the mean trip duration. As for members mean trip duration, high values of "Walkable Suburbs" had the longest mean trip duration with high values of "Auto-Oriented" areas coming next. Clusters of high Walkable Suburbs and Auto-Oriented areas are generally concentrated in Bronx, Queens, or Brooklyn or at the periphery of the boroughs and the e-bike share system. This coincides with lower number of stations and ridership in these two built environment characteristics. These results help explain the longer trip durations. However, these differences are very small with only a 1 min and 20 second difference between the longest and the shortest mean trip duration.

Membership Type	**Total Trips (1,591 stations)**	**Average Ridership by Station (1,591 stations)**	***Average Ridership by Stations by population (1000) (1,471 stations)**	***PC1 High Access to Jobs (631 stations)**	***PC2 Walkable Suburbs (210 stations)**	***PC3 High employment and park density (531 stations)**	***PC4 Auto Oriented (340 stations)**
All	2,375,476	1,414	2,110	2,970	1,245	3,316	1,308
Members	1,760,225	1,048	1,569	2,235	877	2478	980
Casual Riders	615,251	366	540	735	368	838	328

Table 4: Average Ridership by Station for all four PC's

Membership Type	**Mean Trip Duration (1,591 stations)**	***Mean Trip Duration by Station (1,591 stations)**	***PC1 High Access to Jobs (631 stations)**	***PC2 Walkable Suburbs (210 stations)**	***PC3 High employment and park density (531 stations)**	***PC4 Auto Oriented (340 stations)**
Members	14.73 min	15.4 min	14.9 min	16.1 min	15.2 min	15.5 min
Casual Riders	23.03 min	22.5 min	22.6 min	23 min	23 min	23.2 min

Table 5: Mean trip duration for all four PC's

Price

Due to the pricing scheme of shared e-bike use, e-bike trip cost varies depending on the membership type, discount eligibility, and types of trips. Since e-bike prices accumulate every additional minute of the ride, the cost of the total trip can accrue quite quickly. It is the most expensive for casual riders to take an e-bike. Their rate increases by $0.23 every minute, resulting in $6.90 by 30 minutes. When the base single-fee is taken into account, the total cost of a 30-minute ride is $10.89. As for members, there are three different pricing schemes. E-bike trips made outside of Manhattan are not subject to a $3 price cap within a 45-minute ride. All trips that do not start or end in Manhattan continue to accrue price, resulting in $4.5 by 30 minutes and $5.76 with base fee. Trips that start or end in Manhattan are subject to the cap, resulting in $3 by 30 minutes and $4.26 with base fee. However, these trips start accruing price again at 45 minutes. Reduced fare members have the cheapest price. Their trips accrue by $0.05 minutes, resulting in $1.5 by 30 minutes and $1.91 with base fee included.

Interestingly, the price difference between reduced fare members and members with cap decreases to about $0.80 after 45 minutes as reduced fare trips start accruing at $0.15 at 45 minutes and trips starting and ending at Manhattan stops accruing price from 20 minutes into the ride to 45 minutes. This indicates that for longer e-bike trips made to and from Manhattan, membership discount does not provide as many benefits. It is important to emphasize that these costs are incurred for every e-bike trip.

If they are used regularly for commuting purposes, 5 times a week, 2 times a day, the costs can add up a significant amount over time. Depending on the e-bike trip duration and frequency of those trips, the price can be comparable or even more expensive than MTA trips and membership. MTA pay-per-price fare for most riders on subways and local, limited, and select bus services is $2.75 per ride with varying membership prices and reduced fare prices (*Everything you need to know about fares and tolls in New York*, n.d.). One of the benefits of bike share use is the low cost of membership with unlimited trips, but with the e-bike share pricing scheme, it loses that low-cost characteristic. While it has the potential to be used in transit deserts, e-bike trips may cost more than transit depending on the distance. As for the municipality, it may be more cost effective to install a bike station instead of another transit route and stop. This pricing scheme reduces access, especially for low to middle income people who just fall short of qualifying for the reduced fare and for low-income people who are not aware of the reduced fare.

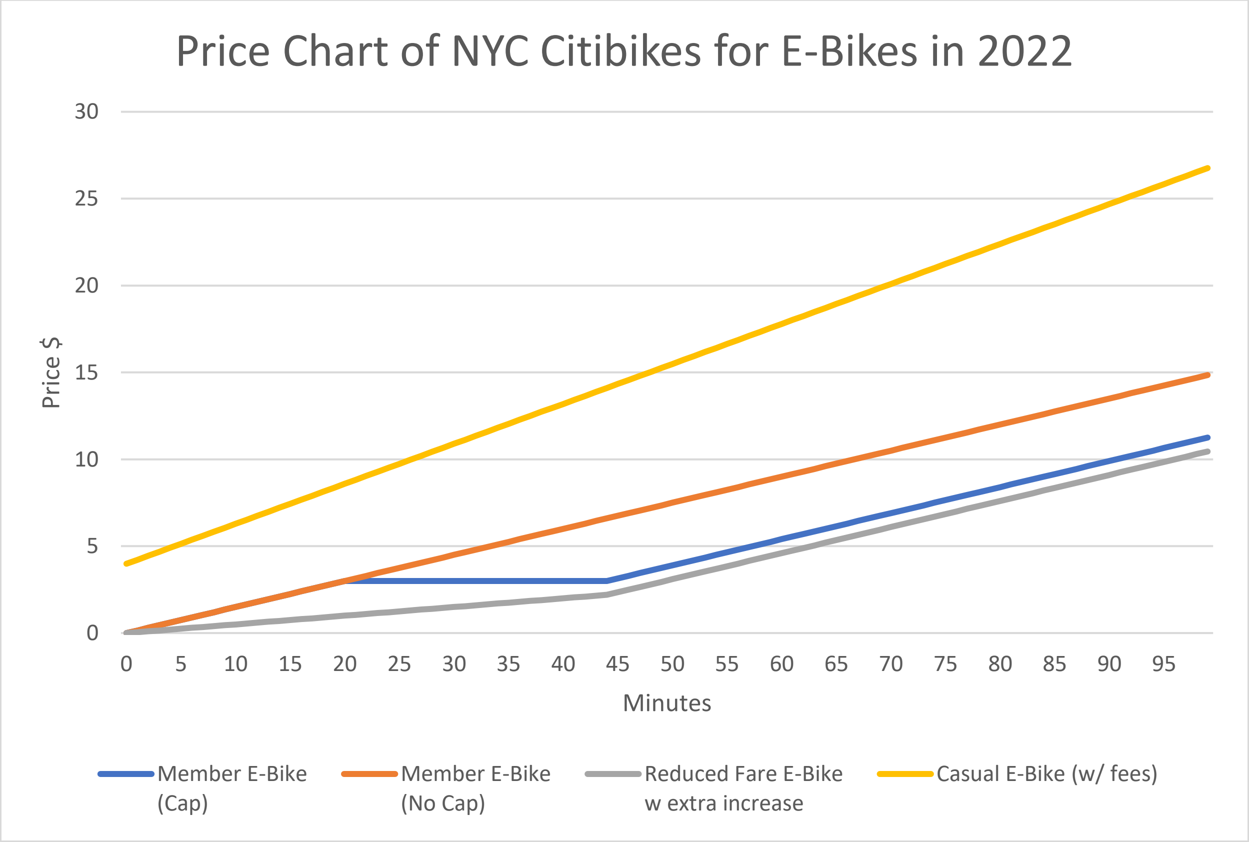


Figure 13: Four different pricing schemes of shared electric bike use over time.

	Member (No Cap)	Members (Cap)	Reduced Fare	Casual	MTA
Base Fee per trip	$1.26	$1.26	$0.41	$3.99	$2.75
Mean Trip Duration w/o fees	$2.10	$2.10	$0.7	$5.29	-
30 minutes w/o fees	$4.50	$3.00	$1.5	$6.90	-
45 minutes w/o fees	$6.75	$3.15	$2.35	$10.35	-
Mean Trip Duration 10 times a week (w/ fees)	$33.60	$33.60	$11.1	$92.80	$27.50
30 minutes 10 times a week (w/ fees)	$57.60	$42.60	$19.10	$108.90	$27.50

Table 6: Different costs of e-bikes rides by membership type, trip duration, and frequency of ride compared to the cost of MTA

Spatial Regression Analysis

Global Moran’s I

The Global Moran’s results on the dependent and independent variables showed that they were all spatially autocorrelated and statistically significant. As for the member mean trip duration, Global Moran’s I was 0.29 and significant at the $p<0.01$ level. Global Moran for the casual mean trip duration was 0.23 and significant at the $p<0.01$ level. This indicates that stations that are close to each other are similar to their neighbors when comparing mean trip duration of trips that begin at that station. Appendix 3 shows the randomized and non-randomized Global Moran’s I results for the two dependent variables- member mean trip duration and causal mean trip duration.

Correlation

Correlation scatter plot matrix between the different dependent variables – member mean trip duration and casual mean trip duration with race and built environment variables are shown in Figure 14 and Figure 15. Trip duration was significantly correlated, with both White and Black populations. Median Household Income were also highly correlated with both Black and White population and statistically significant. To avoid multicollinearity between the White, Black, and Median Household Income, the White population was dropped, and only the Black population and Median Household Income were included but separately (since percentage black population and income were also correlated with each other) for the regression models.

Members mean trip duration is very highly correlated with its two pricing structures - member capped price and reduced price - and are statistically significant. Casual mean trip duration, it is also very highly correlated with its pricing structure. There was a very high and significant multicollinearity between the trip duration and pricing structures. This result is reasonable because the three price categories were calculated using the average trip duration per station and they are dependent on the time utilization of e-bikes. Moreover, since the original data did not specify the individual trip cost and did not identify whether a rider had regular annual membership or reduced fare membership, this study was not able to examine the impact of varying membership type or costs of trips in determining the trip duration of shared e-bike trips. Therefore, pricing structures were dropped for the regression model analysis.

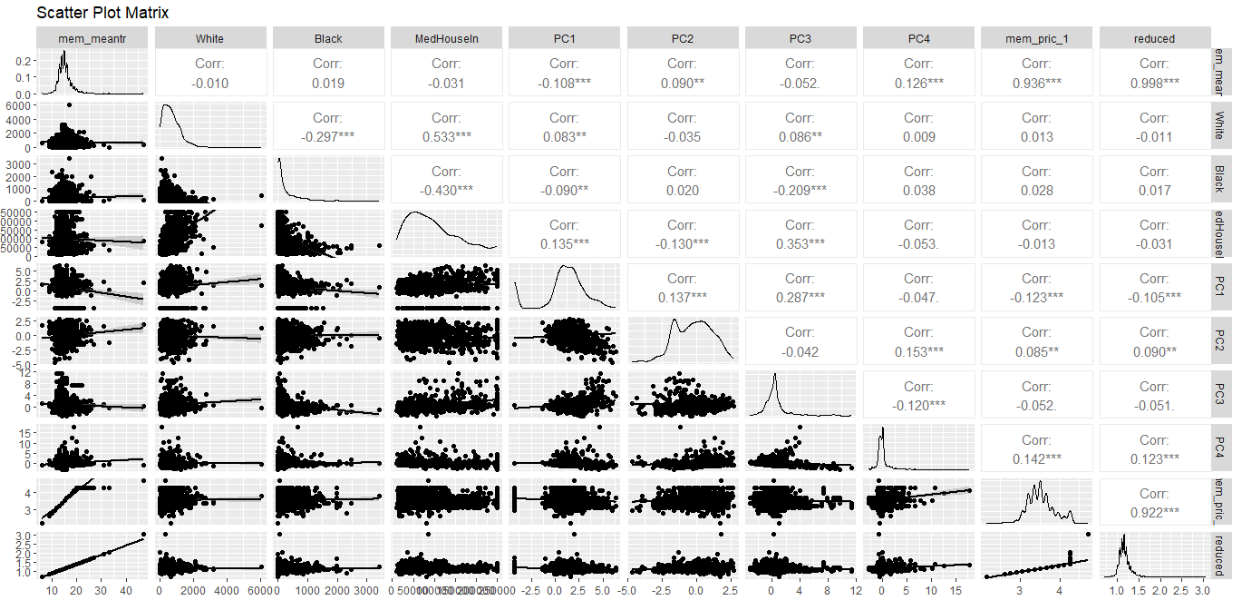


Figure 14: Scatter plot matrix showing the correlation between the member mean trip duration with other independent variables.

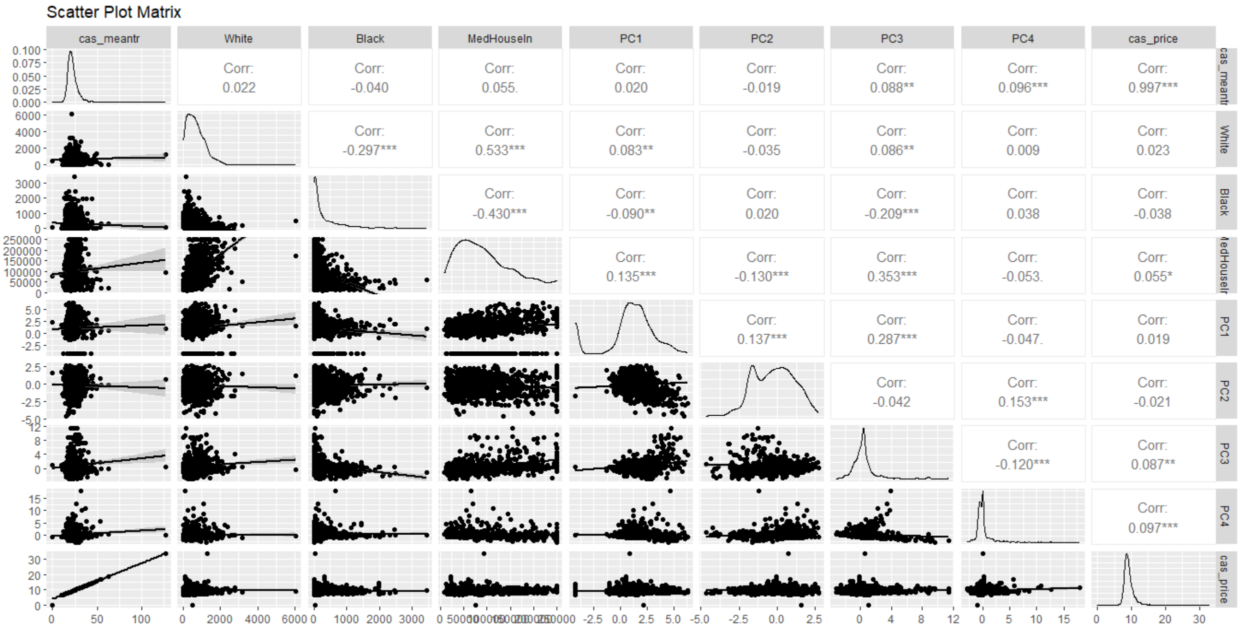


Figure 15: Scatter plot matrix showing the correlation between the casual mean trip duration with other independent variables.

Ordinary Least Square (OLS) Model

The OLS model was run two separate times for member mean trip duration – once including median household income and another including percentage Black population. The OLS result showed that median household income and Black population were not statistically significant in predicting member mean trip duration. However, PC1 and PC4 were statistically significant in influencing mean trip duration at the 0.001 level and PC2 were statistically significant at the 0.01 level.

The OLS model was run two separate times also for casual mean trip duration – again once including median household income and another including Black population. The OLS result showed that median household income and Black population were not statistically significant in predicting casual mean trip duration. Instead, PC4 was statistically significant at the 0.001 level and PC3 was statistically significant at the 0.01 level in influencing the casual mean trip duration.

The Global Moran's I test for the OLS residuals (Appendix 3) indicated that there was statistically significant spatial autocorrelation. Lagrange multiplier tests were found to suggest that a Spatial Lag Regression Model would need to be estimated.

Spatial Lag Regression Model

The Lagrange Multiplier Test results for all four OLS residuals showed that LMerr, LMlag, RLMlag, SARMA were statistically significant except for RLMerr. Since RLMerr was not statistically significant, the Spatial Lag Regression Model was used to account for spatial autocorrelation.

The spatial lag regression model showed that PC1, PC2, and PC4 were statistically significant in predicting member mean trip duration. While the coefficient estimates were slightly different from the OLS model, the same variables were statistically significant after accounting for spatial autocorrelation of the residuals. PC1, high accessibility to jobs, had a negative relationship to member mean trip duration, indicating that the more accessible a location is to jobs, transit, and residences, the less time a person will spend on the e-bike and the less money they will spend on e-bike trips. PC2, walkable suburbs, had a positive relationship with member mean trip duration, suggesting that people living in areas in walkable but moderate density of population and residences would spend more time and money on a e-bike trip to get to workplaces or other areas of interest. PC4, auto-oriented areas, also had a positive relationship with member mean trip duration, pointing to the fact that e-bike trips made from stations with auto-oriented characteristics would have longer trip duration. As there is less access to transit services or walkable areas, users may use e-bikes for longer distances and duration to get to destinations, which would also increase the price of the trip.

As for casual mean trip duration, PC3 and PC4 had a statistically significant relationship with the dependent variable. PC3, high employment and park density, had a positive relationship with casual mean trip duration, suggesting that casual riders taking an e-bike from stations near parks, commercial districts, or manufacturing districts take longer trips and pay more for trips. Casual riders generally take e-bikes more for recreational purposes and the results back the assumption that casual users would take an e-bike to tour Manhattan or visit parks. PC4, auto-oriented areas, also had a positive relationship with casual mean trip duration. This suggests that causal riders also take longer and more expensive e-bike trips from stations that are in auto-oriented areas.

For both member and casual mean trip duration, race and income variables were not statistically significant. The lack of statistical significance may be due to the fact that there are larger White population living in census block groups with stations. Trips starting from White dominant group were 1,781,239 trips while trips starting from dominant Black groups were 318,079 trips. This is partially a result of a disproportionately high number of stations located in high White dominant block groups, which results in more trips generated from station with high White dominant block groups. Moreover, race and income were calculated at the census block group and does not accurately represent the socio-economic characteristics of the riders and each individual trip.

	Dependent variable:			
	Member Mean Trip Duration			
	OLS 1	OLS 2	SLR 1	SLR 2
Income	0.00000	-	0.00000	-
	0.00000	-	0.00000	-
Black	-	0.00001	-	0.00002
	-	-0.0002	-	0.0002
PC1	-0.132***	-0.132***	-0.076**	-0.079**
	-0.033	-0.033	0.03	0.03
PC2	0.183***	0.183***	0.118**	0.119**
	-0.058	-0.058	0.052	0.052
PC3	-0.005	-0.003	0.029	0.028
	-0.041	-0.04	0.037	0.035
PC4	0.204***	0.204***	0.142***	0.142***
	-0.053	-0.053	0.048	0.048
Constant	15.402***	15.409***	6.689	6.669
	-0.143	-0.101	0.557	0.548
Rho	-	-	0.5699	0.5698
Observations	1,288	1,288	1,288	1,288
R2	0.034	0.034	-	-
Adjusted R2	0.03	0.03	-	-
Residual Std. Error (df = 1282)	2.671	2.671	-	-
F Statistic (df = 5; 1282)	9.037***	9.036***	-	-
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 7: OLS and Spatial Lag Regression results for member mean trip duration

	Dependent variable:			
	Casual Trip Duration			
	OLS 1	OLS 2	SLR 1	SLR 2
Income	0	-	0	-
	0	-	0	-
Black	-	-0.0004	-	-0.0003
	-	-0.0004	-	0.0004
PC1	0.0005	0.002	-0.003	-0.002
	-0.078	-0.078	0.072	0.072
PC2	-0.139	-0.152	0.02	0.01
	-0.137	-0.136	0.125	0.124
PC3	0.287***	0.298***	0.187**	0.195**
	-0.096	-0.093	0.089	0.085
PC4	0.501***	0.503***	0.326***	0.328**
	-0.125	-0.125	0.115	0.115
Constant	21.910***	22.248***	0.104***	10.681***
	-0.334	-0.237	0.881	0.874
Rho	-	-	0.524***	0.524***
Observations	1,288	1,288	1,288	1,288
R2	0.021	0.021	-	-
Adjusted R2	0.017	0.017	-	-
Residual Std. Error (df = 1282)	6.249	6.249	-	-
F Statistic (df = 5; 1282)	5.461***	5.469***		
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 8: OLS and Spatial Lag Regression results for casual mean trip duration

Socio-Economic Characteristics with Trip Origin and Destination (OD) Pairs

Along with spatial segregation of race, there is also segregation of E-BSS usage. Figure 16 visualizes the dominant race characteristics of census block groups containing at least one station. Dominant White groups are mostly in the mid and lower parts of Manhattan and most of Queens and Brooklyn. Dominant Black groups are mostly in upper Manhattan, Bronx, and edges of the Brooklyn. In terms of White and Black racial components, more stations are in dominant White areas. The E-BSS OD trips also point to this phenomenon with 85% of all E-BSS trips starting from a dominant White census block group. Out of all the E-BSS trips starting from White dominant block groups, most of the trips are made to other White dominant block groups, again emphasizing the segregation of E-BSS usage. As for e-bike trips that start from Black dominant groups, about half of the trips are made to other Black dominant groups and the rest to other White dominant groups. While there are some trips made across socio-demographic differences, those trips are very few.

There is segregation of E-BSS usage by median household income block group characteristics. E-BSS trips start most equally among low-, middle-, and high-income block groups. However, there are the least number of e-bike trips that are made to and from low-income block groups. More than half of the trips starting from low-income block groups stay within other low-income areas. While e-bikes are being used to increase accessibility of trips between low-income groups to middle- and high- income areas, they are a smaller percentage trips compared to the rest of the e-bike trips. In addition, out of trips starting from middle- and high-income groups, only a small portion, 14% and 20%, are trips made to low-income groups.

Figure 16: Census block groups with E-BSS stations and spatial visualization of the dominant race categories (left) and percentage of e-bike start trips by dominant race (right).

Figure 17: Census block groups with E-BSS stations and spatial visualization of the median household income categories (left) and percentage of e-bike start trips by income groups (right).

Spatial visualization of the OD pair by specific combination of race and income areas shed light on where trips are being made and to what degree. Figure 18 on the left conveys OD pairs made from Black Low-Income areas to other Black Low-Income areas. A large portion of these trips are being made within Bronx and upper Manhattan. Another cluster of these trips are made in Northern Brooklyn, bordering Queens. There are some trips that are made from Bronx to Queens and Brooklyn. Figure 18 in the middle shows OD pairs made from Black Low-Income areas to White high-income areas. These trips cover a large area of Manhattan Brooklyn. Within Manhattan, there are more trips from lower income areas and minority dominant areas to higher income and White dominant areas. There are a few OD trips starting from the Bronx area going into Manhattan, but these trips are far fewer than trips made within Manhattan and Brooklyn-Queens. Figure 18 on the right pictures OD trips made between Black low-income areas to White high-income areas. These trips are concentrated in mid and lower Manhattan with trips also being made between Queens and Brooklyn.

These spatial visualizations highlight the spatial segregation of Black low-income areas from White high-income areas. It is evident most Black low-income areas are in the Bronx and some parts of Brooklyn. Most White high-income areas are concentrated in Manhattan and parts of Brooklyn. Trips made to and from Queens are not as significant in these maps as a large portion of the area is middle income. This also suggests that E-BSS stations are more accessible in dominant White and high-income areas. Especially in Queens and Brooklyn, E-BSS stations are lacking in areas that are lower income and dominantly Black. As NYC and Lyft continue to grow the E-BSS system, they can consider expanding to areas that have less accessibility and have a higher concentration of marginalized groups.

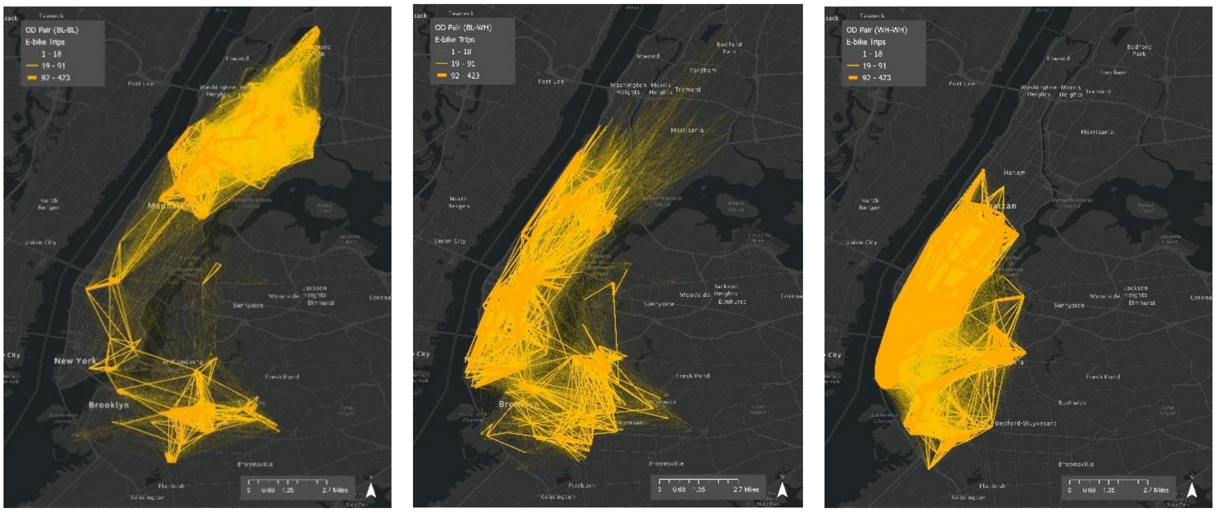


Figure 18. Spatial Visualization of OD pair specific to Black Low Income areas to Black Low Income areas (left), Black Low Income to White High Income areas (middle), and White High Income to White High Income (right).

CHAPTER 5: CONCLUSION & POLICY IMPLICATIONS

Conclusion

This thesis examined the travel behavior, trip distance, and trip duration of NYC Citi Bike Electric Bike Share program for the summer months of 2022 and compared it to classic bike share. The travel behavior analysis showed that e-bikes member trips followed the morning and evening peak patterns while casual trips followed a more even curve. In addition, E-BSS casual trips were longer than member trips, indicating that member trips were more likely used for commuting than for casual trips. In comparison to classic bikes, E-bikes were used for slightly longer distances and duration. The longer trips were generally in the periphery of the station systems for member trips, and near parks for casual riders.

Along with descriptive statistics of E-BSS ridership patterns, this thesis aimed to answer how socio-economic, built environment, and price factors impacted mean trip duration of E-BSS member and casual rider trips. Spatial Lag Regression Models were estimated to account for autocorrelation in variables and pricing was removed from the analysis, since there was high correlation between price and trip duration as trip duration determined price. The spatial lag regression results pointed out that race and income were not statistically significant in predicting member or casual mean trip durations. Since race and income data were collected at the census block group level and not at the trip level and more stations were in majority White census block groups, this lack of statistical significance is not surprising. As for the built environment, walkable suburbs and auto-oriented areas were associated with longer member mean trip duration and accessible areas were associated with shorter member mean trip duration. In addition, high employment and park density and auto-oriented areas were associated with longer casual mean trip duration. These results can also be transferable to trip cost as trip duration determines the price of trips.

Lastly, this thesis examined the extent to which E-BSS increase accessibility to areas with different socio-economic characteristics. Findings showed that there was spatial segregation of Black and White population as Black dominant groups were clustered in the northern and western parts of NYC. There was also spatial segregation of median household income as the lowest median household income groups clustered in the northern parts of NYC. More importantly, the origin and destination of E-BSS trip highlighted the segregation of E-BSS use. Most of the trips started from White dominant areas and only a small percentage of trips either ended at Black dominant areas or started from Black dominant areas. As for income, the least percentage of trips were made to low-income areas. Moreover, the OD pair spatial visualization further highlighted the spatial segregation of trips made within specific parts of Manhattan depending on the racial and income component of the start and end trips.

Policy Implications

Expanding E-BSS to other eastern parts of Queens and Brooklyn can increase the accessibility of E-BSS to other low-income and non-White areas and fill the public transportation gaps. A large portion of the stations that are on the periphery of the electric bike share system are located in lower income, Black dominant census block groups. These stations have less options for travel via e-bike because there are less stations surrounding them, which limits destinations. Moreover, clusters of majority Black and minority communities live in the eastern parts of Brooklyn and Queens. These areas are generally lower in “High Access to Jobs” and higher in “Walkable Suburbs” and “Auto-oriented” characteristics. They have less transit accessibility, less sustainable and affordable options for travel, and may require a car to access jobs and essential destinations, which also results in higher transportation costs. Therefore, adding more stations to these “auto-oriented walkable suburbs” with higher low-income and non-White groups will increase coverage and physical accessibility to E-BSS, provide more options for travel, increase accessibility to destinations, and reduce the dependence on driving.

Adjusting the pricing scheme of electric bike share trips can further unlock its potential to be used for longer distance rides and to replace shorter car trips. Instead of a price scheme that incurs cost with time, an affordable fixed pricing scheme may encourage more riders to consider E-BSS for longer distance trips and use it to replace shorter car trips. For example, an E-BSS regular member ride can cost a fixed amount of $2 for rides under 45 minutes, $1 for reduced fare members, and $2.5 for casual riders. Such pricing scheme would reduce the cost burden especially for riders taking e-bikes from walkable suburbs, auto-oriented areas, and transit deserts. Moreover, this cost would then be comparable to public transportation and much more affordable than driving. If NYC DOT and Lyft were to keep the per minute pricing scheme, I suggest that NYC DOT and Lyft reduce the per minute cost through outside funding sources. Another suggestion is to cap the price at $3 for all e-bike rides within 45 minutes for all users and keep the $0.05 per minute cost even after 45 minutes for reduced fare riders.

Land use planning can also result in equitable usage of E-BSS. Census block groups with characteristics of PC1, high accessibility to a mix of jobs and transit, a good mix of employment and households, and higher population density creates a good environment for not only biking and traveling, but also for accessing various uses and purposes. Therefore, equitably planning to incorporate these built environment characteristics can increase accessibility to key opportunities. Rather than having to travel longer distances to reach places with uses such as a mix of jobs, commercial use, and residential and walkable transit-oriented infrastructures, these amenities and opportunities can be distributed more equitably. I suggest the New York City Department of City Planning consider changing zoning to allow for the more mixed use commercial and low-high density residential districts across the city.

To reduce the racial and income segregation of E-BSS use, community partnerships with local advocacy groups and organizations can help promote E-BSS usage amongst more marginalized groups. Since lower income minority groups face more barriers to E-BSS usage, holistic efforts need to be made not for, but with, those impacted. There are already local organizations that have built trust with the marginalized groups and actively engage them on a regular basis. I encourage NYC DOT and Lyft to partner with those organizations to build partnerships. One great case study is the partnership built between the Bedford Stuyvesant Restoration, Motivate, NYC DOT, NYC Department of Health and Mental Hygiene to improve health and mobility via Citi Bike for residents of Bedford Stuyvesant (*Bringing Equitable Bike Share to Bed-Stuy*, 2017). Some community engagement activities can include bike education programs, community bike rides, block parties with free bike safety equipment giveaways, and information sessions about E-BSS. I suggest that NYC DOT and Lyft target neighborhoods with high low-income households and people of color and especially in areas that are auto oriented with less public transportation options.

CHAPTER 6: LIMITATIONS & RECOMMENDATIONS FOR FUTURE RESEARCH

Limitations

One of the most significant limitations of this study is the unit of analysis. Each part of the study analysis was done at different units. The ridership analysis is done at the trip level, which is the smallest and the most detailed unit of analysis. Doing analysis at the trip level preserves the original data and allows for the most accurate analysis. Since there were no socio-economic and built environment factors at the individual trip level, this analysis examined these datasets at the census block group and attached the results to the stations within each census block group. The race, income, and built environment data are representative of these characteristics at the census block group and they do not specifically indicate who used the E-BSS. An assumption is made as to who may have used E-BSS depending on who lives in and what land uses are in the census block group that contains the stations. It is important to highlight that the census block group race and income does not accurately represent the demographics of E-BSS riders. Regression analysis was done at the station level with individual trip data aggregated at the station level and race, income, and built environment data assigned to the corresponding stations. By aggregating the trip level to the station, it loses the accuracy and granularity of data. Moreover, stations are not in the center of the census block groups and many times are at the edges of census block group boundaries. Characteristics of immediate neighboring census blocks also impact usage of E-BSS, but they are not accounted for.

Another limitation is that this thesis studies only three months of e-bike data. This study examines e-bike data only for the summer months of June, July, and August 2022. It does not include a whole year of data, which reduces the comprehensiveness of the analysis. Moreover, this thesis focuses on quantitative analysis and does not include qualitative analysis. Qualitative analysis such as interviews and surveys can provide a more holistic analysis and fill in gaps regarding the purposes of trips and reduce the assumptions made in quantitative analysis. However, due to lack of time and resources, qualitative analysis was not included in this thesis.

Recommendations for Future Research

For future research, I recommend doing a full analysis comparing shared e-bikes to shared classic bikes. To better understand how shared e-bike usage is unique or similar to shared classic bikes, further analysis needs to compare the spatial patterns and regression analysis for classic bike mean trip duration as well. It would be interesting to observe whether there are spatial differences in where there is higher ridership and longer trip duration. Moreover, comparison of how race, income, built environment characteristics influence mean trip duration and trip counts for both e-bikes and classic bikes can shed light on what catalyzes e-bike trips as opposed to classic bike trips. Spatial visualization of OD pairs for classic bikes can be insightful to observe where trips are taking place by race and income and note the spatial characteristics of where e-bikes are generally taken compared to classic bikes. Running a T-test between e-bikes and classic bikes will provide additional analysis to show to what degree their usage and trip duration are different by race, income, price, membership type, and built environment.

To improve the accuracy of the regression analysis, I recommend doing an analysis at the trip level instead of at the station dock level. Running an analysis at the trip level reduces the need to aggregate the individual trip data to the station level and provides more granular result.

I also recommend comparing how the increase in shared e-bike price in 2023 impacted trip duration and ridership by race, income, space. This analysis can be used to examine which areas, census block groups, and neighborhoods with certain socio-economic characteristics saw a decrease in trip duration and/or ridership. The results would point to the importance of pricing appropriately to increase ridership, promote e-bikes for longer trips in transit deserts, catalyze mode shift from driving to e-biking, and encourage use for marginalized groups.

An in-depth analysis of the impact of the pricing scheme on ridership and trip duration by race and income could be key for better deployment of e-bikes in locations with transit deserts. However, this will require data on the price per trip as well as more details that distinguish trips made by those who pay reduced price and full membership price. This additional component to the data indicating reduced fare riders can further enhance data analysis on reduced fare rider’s travel patterns. It would be interesting to observe how e-bike ridership and trip duration differ for reduced fare ridership and members and whether lower pricing increases ridership in areas with dominantly low-income and minority groups.

These future studies on E-BSS are essential in increasing equitable access to alternative modes of transportation and advancing decarbonization strategies for cities. Fully understanding E-BSS’s functions, travel patterns, socio-economic characteristics, built environment factors, and pricing will allow policy makers to strategize how to shift people from driving to other sustainable modes, make E-BSS more accessible for everyone, and improve mobility via equitable and environmentally friendly travel mode.

APPENDIX

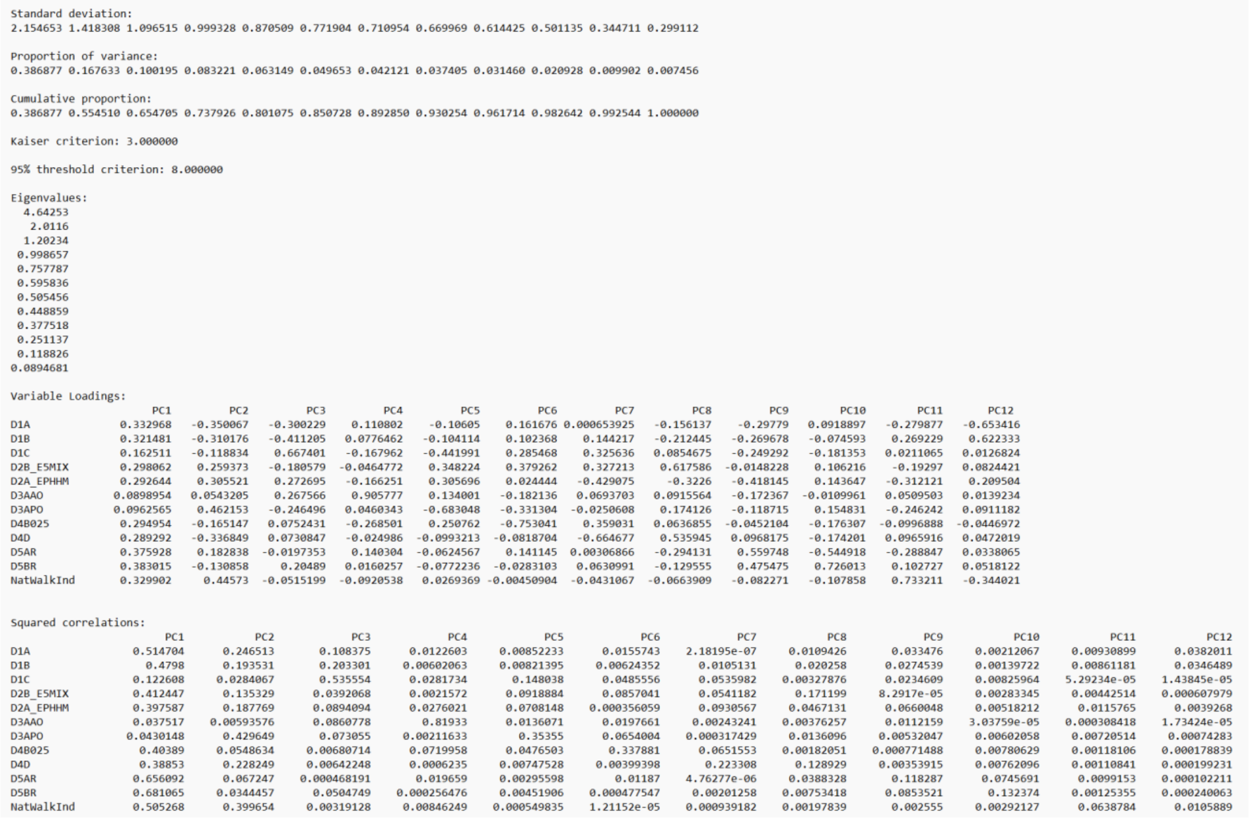
Appendix 1: List of Smart Location Database Built Environment and Land Use Variables Used

Field Name	Description	Notes
D1A	Gross residential density (HU/acre) on unprotected land	
D1B	Gross population density (people/acre) on unprotected land	
D1C	Gross employment density (jobs/acre) on unprotected land	
D2B_E5MIX	5-tier employment entropy (denominator set to observed employment types in the CBG)	This refers to the evenness of distribution or mix of retail, office, industrial, service, and entertainment employment types. This does not consider the aggregate quantity of employment.
D2A_EPHHM	Employment and household entropy	This refers to the evenness of distribution or mix of occupied housing and retail,

		office, industrial, service, and entertainment employment types.
D3AAO	Network density in terms of facility miles of auto-oriented links per square mile	Link with speed limit of 41mph+ Facilities where pedestrians are restricted.
D3APO	Network density in terms of facility miles of pedestrian-oriented links per square mile	Links with a speed limit of maximum 30mph where pedestrians are permitted with maximum 3 lanes going in one direction. Pathways or trails where automobile is not permitted.
D4B025	Proportion of CBG employment within ¼ mile of fixed-guideway transit stop	
D4D	Aggregate frequency of transit service [D4c] per square mile	

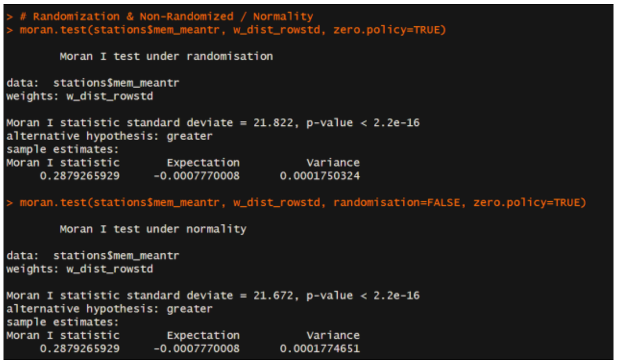
D5AR	Jobs within 45 minutes auto travel time, time-decay (network travel time) weighted	
D5BR	Jobs within 45-minute transit commute, distance decay (walk network travel time, GTFS schedules) weighted	
NatWalkInd	Walkability index comprised of weighted sum of the ranked values of [D2a_EpHHm] (D2A_Ranked), [D2b_E8MixA] (D2B_Ranked), [D3b] (D3B_Ranked) and [D4a] (D4A_Ranked)	

Appendix 2: Detailed Result of Principal Component Analysis

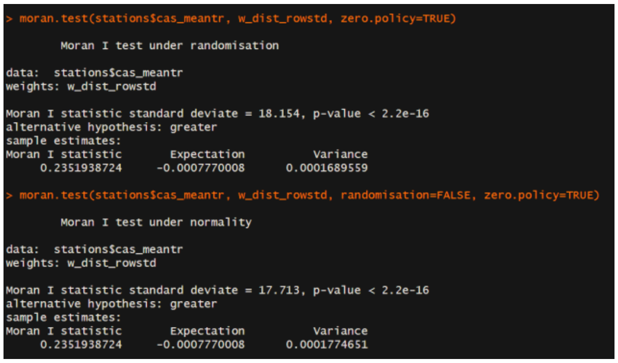


```
Standard deviation:
2.154653 1.418308 1.096515 0.999328 0.870509 0.771904 0.710954 0.669969 0.614425 0.501135 0.344711 0.299112

Proportion of variance:
0.386877 0.167633 0.100195 0.083221 0.063149 0.049653 0.042121 0.037405 0.031460 0.020928 0.009902 0.007456

Cumulative proportion:
0.386877 0.554510 0.654705 0.737926 0.801075 0.850728 0.892850 0.930254 0.961714 0.982642 0.992544 1.000000

Kaiser criterion: 3.000000

95% threshold criterion: 8.000000

Eigenvalues:
  4.64253
   2.0116
  1.20234
 0.998657
 0.757787
 0.595836
 0.505456
 0.448859
 0.377518
 0.251137
 0.118826
0.0894681

Variable Loadings:
                     PC1         PC2         PC3         PC4         PC5         PC6         PC7         PC8         PC9        PC10        PC11        PC12
D1A             0.332968   -0.350067   -0.300229    0.110802    -0.10605    0.161676 0.000653925   -0.156137    -0.29779   0.0918897   -0.279877   -0.653416
D1B             0.321481   -0.310176   -0.411205   0.0776462   -0.104114    0.102368    0.144217   -0.212445   -0.269678   -0.074593    0.269229    0.622333
D1C             0.162511   -0.118834    0.667401   -0.167962   -0.441991    0.285468    0.325636   0.0854675   -0.249292   -0.181353   0.0211065   0.0126824
D2B_E5MIX       0.298062    0.259373   -0.180579  -0.0464772    0.348224    0.379262    0.327213    0.617586  -0.0148228    0.106216    -0.19297   0.0824421
D2A_EPHHM       0.292644    0.305521    0.272695   -0.166251    0.305696    0.024444   -0.429075     -0.3226   -0.418145    0.143647   -0.312121    0.209504
D3AAO          0.0898954   0.0543205    0.267566    0.905777    0.134001   -0.182136   0.0693703   0.0915564   -0.172367  -0.0109961   0.0509503   0.0139234
D3APO          0.0962565    0.462153   -0.246496   0.0460343   -0.683048   -0.331304  -0.0250608    0.174126   -0.118715    0.154831   -0.246242   0.0911182
D4B025          0.294954   -0.165147   0.0752431   -0.268501    0.250762   -0.753041    0.359031   0.0636855  -0.0452104   -0.176307  -0.0996888  -0.0446972
D4D             0.289292   -0.336849   0.0730847   -0.024986  -0.0993213  -0.0818704   -0.664677    0.535945   0.0968175   -0.174201   0.0965916   0.0472019
D5AR            0.375928    0.182838  -0.0197353    0.140304  -0.0624567    0.141145  0.00306866   -0.294131    0.559748   -0.544918   -0.288847   0.0338065
D5BR            0.383015   -0.130858     0.20489   0.0160257  -0.0772236  -0.0283103   0.0630991   -0.129555    0.475475    0.726013    0.102727   0.0518122
NatWalkInd      0.329902     0.44573  -0.0515199  -0.0920538   0.0269369 -0.00450904  -0.0431067  -0.0663909   -0.082271   -0.107858    0.733211   -0.344021


Squared correlations:
                       PC1           PC2           PC3           PC4           PC5           PC6           PC7           PC8           PC9          PC10          PC11          PC12
D1A               0.514704      0.246513      0.108375     0.0122603    0.00852233     0.0155743   2.18195e-07     0.0109426      0.033476    0.00212067    0.00930899     0.0382011
D1B                 0.4798      0.193531      0.203301    0.00602063    0.00821395    0.00624352     0.0105131      0.020258     0.0274539    0.00139722    0.00861181     0.0346489
D1C               0.122608     0.0284067      0.535554     0.0281734      0.148038     0.0485556     0.0535982    0.00327876     0.0234609    0.00825964   5.29234e-05   1.43845e-05
D2B_E5MIX         0.412447      0.135329     0.0392068     0.0021572     0.0918884     0.0857041     0.0541182      0.171199    8.2917e-05    0.00283345    0.00442514   0.000607979
D2A_EPHHM         0.397587      0.187769     0.0894094     0.0276021     0.0708148   0.000356059     0.0930567     0.0467131     0.0660048    0.00518212     0.0115765     0.0039268
D3AAO             0.037517    0.00593576     0.0860778       0.81933     0.0136071     0.0197661    0.00243241    0.00376257     0.0112159   3.03759e-05   0.000308418   1.73424e-05
D3APO            0.0430148      0.429649      0.073055    0.00211633       0.35355     0.0654004   0.000317429     0.0136096    0.00532047    0.00602058    0.00720514    0.00074283
D4B025             0.40389     0.0548634    0.00680714     0.0719958     0.0476503      0.337881     0.0651553    0.00182051   0.000771488    0.00780629    0.00118106   0.000178839
D4D                0.38853      0.228249    0.00642248     0.0006235    0.00747528    0.00399398      0.223308      0.128929    0.00353915    0.00762096    0.00110841   0.000199231
D5AR              0.656092      0.067247   0.000468191      0.019659    0.00295598       0.01187   4.76277e-06     0.0388328      0.118287     0.0745691     0.0099153   0.000102211
D5BR              0.681065     0.0344457     0.0504749   0.000256476    0.00451906   0.000477547    0.00201258    0.00753418     0.0853521      0.132374    0.00125355   0.000240063
NatWalkInd        0.505268      0.399654    0.00319128    0.00846249   0.000549835   1.21152e-05   0.000939182    0.00197839      0.002555    0.00292127     0.0638784     0.0105889
```

Appendix 3: Global Moran's I Results

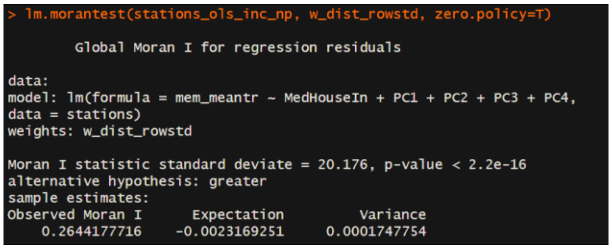


```
> # Randomization & Non-Randomized / Normality
> moran.test(stations$mem_meantr, w_dist_rowstd, zero.policy=TRUE)

        Moran I test under randomisation

data:  stations$mem_meantr
weights: w_dist_rowstd

Moran I statistic standard deviate = 21.822, p-value < 2.2e-16
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
     0.2879265929     -0.0007770008      0.0001750324

> moran.test(stations$mem_meantr, w_dist_rowstd, randomisation=FALSE, zero.policy=TRUE)

        Moran I test under normality

data:  stations$mem_meantr
weights: w_dist_rowstd

Moran I statistic standard deviate = 21.672, p-value < 2.2e-16
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
     0.2879265929     -0.0007770008      0.0001774651
```

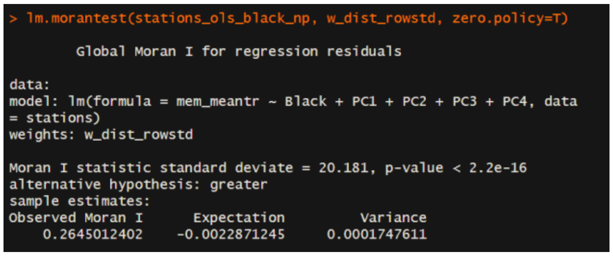


```
> moran.test(stations$cas_meantr, w_dist_rowstd, zero.policy=TRUE)

        Moran I test under randomisation

data:  stations$cas_meantr
weights: w_dist_rowstd

Moran I statistic standard deviate = 18.154, p-value < 2.2e-16
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
     0.2351938724     -0.0007770008      0.0001689559

> moran.test(stations$cas_meantr, w_dist_rowstd, randomisation=FALSE, zero.policy=TRUE)

        Moran I test under normality

data:  stations$cas_meantr
weights: w_dist_rowstd

Moran I statistic standard deviate = 17.713, p-value < 2.2e-16
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
     0.2351938724     -0.0007770008      0.0001774651
```

Global Moran's I result for Dependent Variables – member mean trip duration on the left and for casual mean trip duration on the right

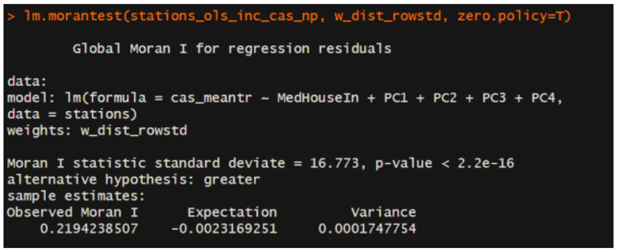


```
> lm.morantest(stations_ols_inc_np, w_dist_rowstd, zero.policy=T)

        Global Moran I for regression residuals

data:
model: lm(formula = mem_meantr ~ MedHouseIn + PC1 + PC2 + PC3 + PC4,
data = stations)
weights: w_dist_rowstd

Moran I statistic standard deviate = 20.176, p-value < 2.2e-16
alternative hypothesis: greater
sample estimates:
Observed Moran I      Expectation         Variance
    0.2644177716    -0.0023169251     0.0001747754
```

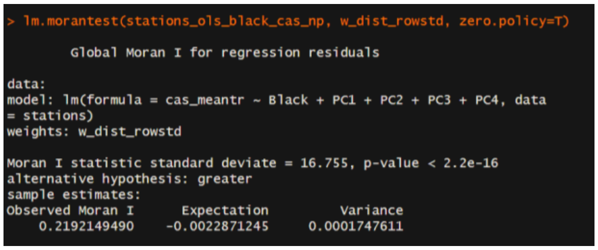


```
> lm.morantest(stations_ols_black_np, w_dist_rowstd, zero.policy=T)

        Global Moran I for regression residuals

data:
model: lm(formula = mem_meantr ~ Black + PC1 + PC2 + PC3 + PC4, data
= stations)
weights: w_dist_rowstd

Moran I statistic standard deviate = 20.181, p-value < 2.2e-16
alternative hypothesis: greater
sample estimates:
Observed Moran I      Expectation         Variance
    0.2645012402    -0.0022871245     0.0001747611
```

Global Moran's I Results for Ordinary Least Squares Residuals – member mean trip duration

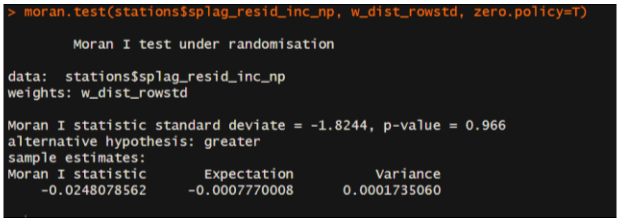


```
> lm.morantest(stations_ols_inc_cas_np, w_dist_rowstd, zero.policy=T)

        Global Moran I for regression residuals

data:
model: lm(formula = cas_meantr ~ MedHouseIn + PC1 + PC2 + PC3 + PC4,
data = stations)
weights: w_dist_rowstd

Moran I statistic standard deviate = 16.773, p-value < 2.2e-16
alternative hypothesis: greater
sample estimates:
Observed Moran I      Expectation         Variance
    0.2194238507    -0.0023169251     0.0001747754
```

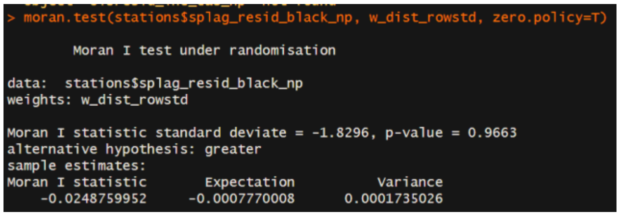


```
> lm.morantest(stations_ols_black_cas_np, w_dist_rowstd, zero.policy=T)

        Global Moran I for regression residuals

data:
model: lm(formula = cas_meantr ~ Black + PC1 + PC2 + PC3 + PC4, data
= stations)
weights: w_dist_rowstd

Moran I statistic standard deviate = 16.755, p-value < 2.2e-16
alternative hypothesis: greater
sample estimates:
Observed Moran I      Expectation         Variance
    0.2192149490    -0.0022871245     0.0001747611
```

Global Moran's I Results for Ordinary Least Squares Residuals – casual mean trip duration

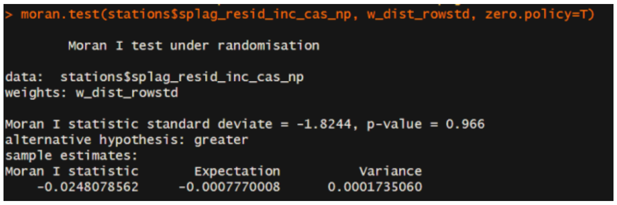


```
> moran.test(stations$splag_resid_inc_np, w_dist_rowstd, zero.policy=T)

        Moran I test under randomisation

data:  stations$splag_resid_inc_np
weights: w_dist_rowstd

Moran I statistic standard deviate = -1.8244, p-value = 0.966
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
    -0.0248078562     -0.0007770008      0.0001735060
```

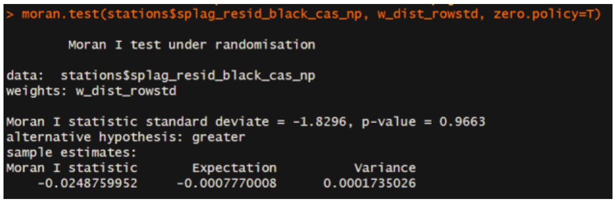


```
> moran.test(stations$splag_resid_black_np, w_dist_rowstd, zero.policy=T)

        Moran I test under randomisation

data:  stations$splag_resid_black_np
weights: w_dist_rowstd

Moran I statistic standard deviate = -1.8296, p-value = 0.9663
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
    -0.0248759952     -0.0007770008      0.0001735026
```

Global Moran’s I Results for Spatial Lag Regression Residuals – Member Mean Trip Duration



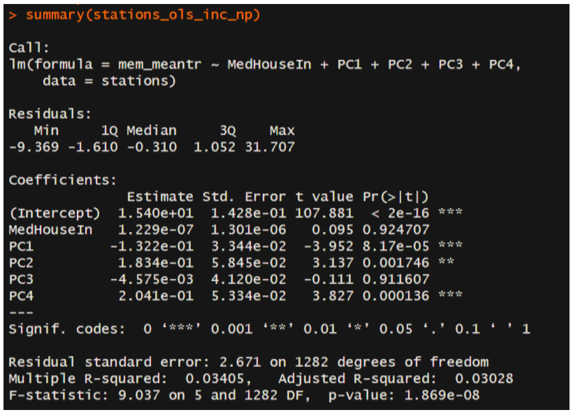
```
> moran.test(stations$splag_resid_inc_cas_np, w_dist_rowstd, zero.policy=T)

        Moran I test under randomisation

data:  stations$splag_resid_inc_cas_np
weights: w_dist_rowstd

Moran I statistic standard deviate = -1.8244, p-value = 0.966
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
    -0.0248078562     -0.0007770008      0.0001735060
```



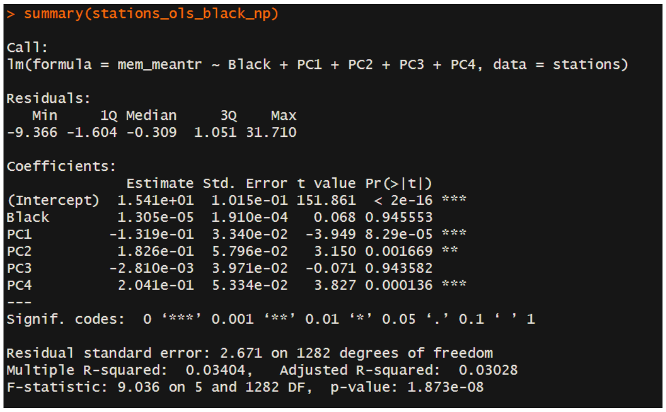
```
> moran.test(stations$splag_resid_black_cas_np, w_dist_rowstd, zero.policy=T)

        Moran I test under randomisation

data:  stations$splag_resid_black_cas_np
weights: w_dist_rowstd

Moran I statistic standard deviate = -1.8296, p-value = 0.9663
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
    -0.0248759952     -0.0007770008      0.0001735026
```

Global Moran’s I Results for Spatial Lag Regression Residuals – Casual Mean Trip Duration

Appendix 4: Detailed OLS Model Results

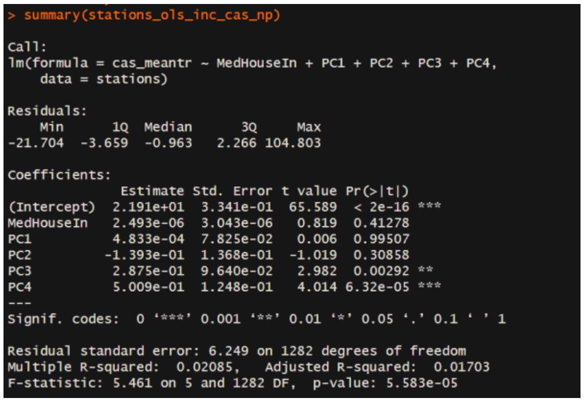


```
> summary(stations_ols_inc_np)

Call:
lm(formula = mem_meantr ~ MedHouseIn + PC1 + PC2 + PC3 + PC4,
    data = stations)

Residuals:
   Min     1Q Median     3Q    Max 
-9.369 -1.610 -0.310  1.052 31.707 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  1.540e+01  1.428e-01 107.881  < 2e-16 ***
MedHouseIn   1.229e-07  1.301e-06   0.095 0.924707    
PC1         -1.322e-01  3.344e-02  -3.952 8.17e-05 ***
PC2          1.834e-01  5.845e-02   3.137 0.001746 ** 
PC3         -4.575e-03  4.120e-02  -0.111 0.911607    
PC4          2.041e-01  5.334e-02   3.827 0.000136 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.671 on 1282 degrees of freedom
Multiple R-squared:  0.03405,	Adjusted R-squared:  0.03028 
F-statistic: 9.037 on 5 and 1282 DF,  p-value: 1.869e-08
```

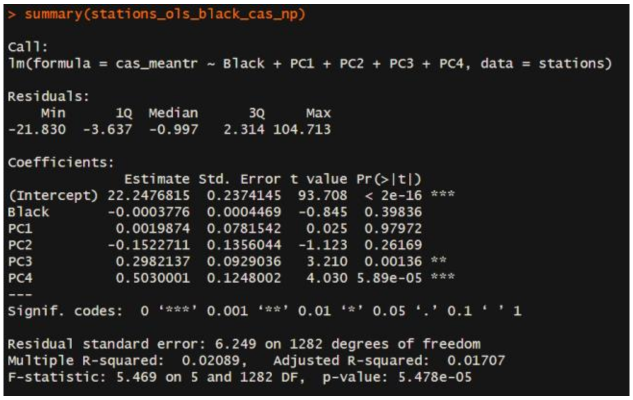


```
> summary(stations_ols_black_np)

Call:
lm(formula = mem_meantr ~ Black + PC1 + PC2 + PC3 + PC4, data = stations)

Residuals:
   Min     1Q Median     3Q    Max 
-9.366 -1.604 -0.309  1.051 31.710 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  1.541e+01  1.015e-01 151.861  < 2e-16 ***
Black        1.305e-05  1.910e-04   0.068 0.945553    
PC1         -1.319e-01  3.340e-02  -3.949 8.29e-05 ***
PC2          1.826e-01  5.796e-02   3.150 0.001669 ** 
PC3         -2.810e-03  3.971e-02  -0.071 0.943582    
PC4          2.041e-01  5.334e-02   3.827 0.000136 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.671 on 1282 degrees of freedom
Multiple R-squared:  0.03404,	Adjusted R-squared:  0.03028 
F-statistic: 9.036 on 5 and 1282 DF,  p-value: 1.873e-08
```

OLS results for the member mean trip duration including only median household income and PCs on the left and OLS results for member mean trip duration including only Black population and PCs on the right.



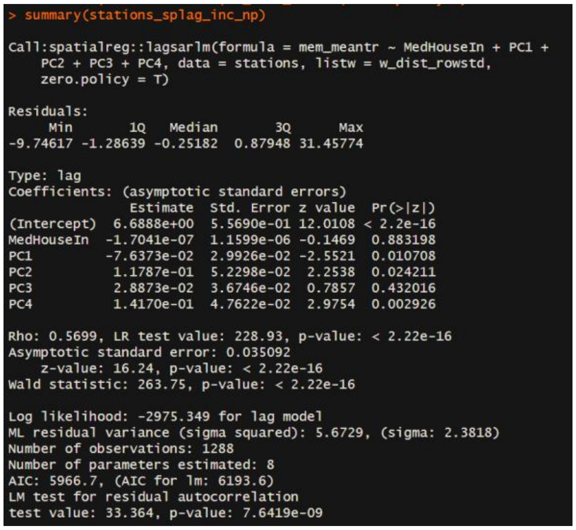
```
> summary(stations_ols_inc_cas_np)

Call:
lm(formula = cas_meantr ~ MedHouseIn + PC1 + PC2 + PC3 + PC4,
    data = stations)

Residuals:
    Min      1Q  Median      3Q     Max 
-21.704  -3.659  -0.963   2.266 104.803 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  2.191e+01  3.341e-01  65.589  < 2e-16 ***
MedHouseIn   2.493e-06  3.043e-06   0.819  0.41278    
PC1          4.833e-04  7.825e-02   0.006  0.99507    
PC2         -1.393e-01  1.368e-01  -1.019  0.30858    
PC3          2.875e-01  9.640e-02   2.982  0.00292 ** 
PC4          5.009e-01  1.248e-01   4.014 6.32e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6.249 on 1282 degrees of freedom
Multiple R-squared:  0.02085,	Adjusted R-squared:  0.01703 
F-statistic: 5.461 on 5 and 1282 DF,  p-value: 5.583e-05
```



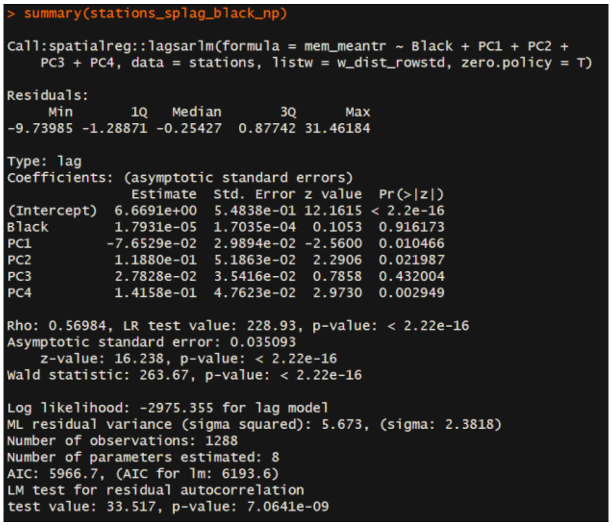
```
> summary(stations_ols_black_cas_np)

Call:
lm(formula = cas_meantr ~ Black + PC1 + PC2 + PC3 + PC4, data = stations)

Residuals:
    Min      1Q  Median      3Q     Max 
-21.830  -3.637  -0.997   2.314 104.713 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) 22.2476815  0.2374145  93.708  < 2e-16 ***
Black       -0.0003776  0.0004469  -0.845  0.39836    
PC1          0.0019874  0.0781542   0.025  0.97972    
PC2         -0.1522711  0.1356044  -1.123  0.26169    
PC3          0.2982137  0.0929036   3.210  0.00136 ** 
PC4          0.5030001  0.1248002   4.030 5.89e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6.249 on 1282 degrees of freedom
Multiple R-squared:  0.02089,	Adjusted R-squared:  0.01707 
F-statistic: 5.469 on 5 and 1282 DF,  p-value: 5.478e-05
```

OLS results for the casual mean trip duration including only median household income and PCs on the left and OLS results for casual mean trip duration including only Black population and PCs on the right.

Appendix 5: Detailed Spatial Lag Model Results

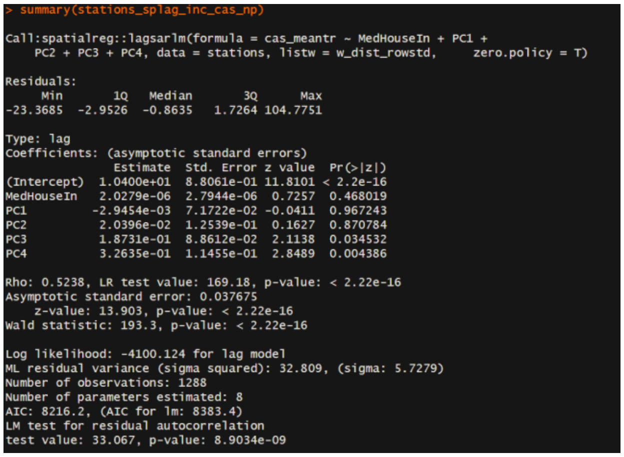


```
> summary(stations_splag_inc_np)

Call:spatialreg::lagsarlm(formula = mem_meantr ~ MedHouseIn + PC1 +
    PC2 + PC3 + PC4, data = stations, listw = w_dist_rowstd,
    zero.policy = T)

Residuals:
     Min       1Q   Median       3Q      Max
-9.74617 -1.28639 -0.25182  0.87948 31.45774

Type: lag
Coefficients: (asymptotic standard errors)
               Estimate  Std. Error z value  Pr(>|z|)
(Intercept)  6.6888e+00  5.5690e-01 12.0108 < 2.2e-16
MedHouseIn  -1.7041e-07  1.1599e-06 -0.1469  0.883198
PC1         -7.6373e-02  2.9926e-02 -2.5521  0.010708
PC2          1.1787e-01  5.2298e-02  2.2538  0.024211
PC3          2.8873e-02  3.6746e-02  0.7857  0.432016
PC4          1.4170e-01  4.7622e-02  2.9754  0.002926

Rho: 0.5699, LR test value: 228.93, p-value: < 2.22e-16
Asymptotic standard error: 0.035092
    z-value: 16.24, p-value: < 2.22e-16
Wald statistic: 263.75, p-value: < 2.22e-16

Log likelihood: -2975.349 for lag model
ML residual variance (sigma squared): 5.6729, (sigma: 2.3818)
Number of observations: 1288
Number of parameters estimated: 8
AIC: 5966.7, (AIC for lm: 6193.6)
LM test for residual autocorrelation
test value: 33.364, p-value: 7.6419e-09
```

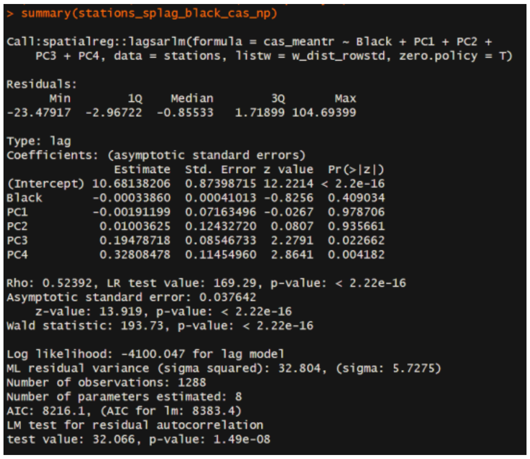


```
> summary(stations_splag_black_np)

Call:spatialreg::lagsarlm(formula = mem_meantr ~ Black + PC1 + PC2 +
    PC3 + PC4, data = stations, listw = w_dist_rowstd, zero.policy = T)

Residuals:
     Min       1Q   Median       3Q      Max
-9.73985 -1.28871 -0.25427  0.87742 31.46184

Type: lag
Coefficients: (asymptotic standard errors)
               Estimate  Std. Error z value  Pr(>|z|)
(Intercept)  6.6691e+00  5.4838e-01 12.1615 < 2.2e-16
Black        1.7931e-05  1.7035e-04  0.1053  0.916173
PC1         -7.6529e-02  2.9894e-02 -2.5600  0.010466
PC2          1.1880e-01  5.1863e-02  2.2906  0.021987
PC3          2.7828e-02  3.5416e-02  0.7858  0.432004
PC4          1.4158e-01  4.7623e-02  2.9730  0.002949

Rho: 0.56984, LR test value: 228.93, p-value: < 2.22e-16
Asymptotic standard error: 0.035093
    z-value: 16.238, p-value: < 2.22e-16
Wald statistic: 263.67, p-value: < 2.22e-16

Log likelihood: -2975.355 for lag model
ML residual variance (sigma squared): 5.673, (sigma: 2.3818)
Number of observations: 1288
Number of parameters estimated: 8
AIC: 5966.7, (AIC for lm: 6193.6)
LM test for residual autocorrelation
test value: 33.517, p-value: 7.0641e-09
```

Spatial Lag Regression results for the member mean trip duration including only median household income and PCs on the left and for member mean trip duration including only Black population and PCs on the right.



```
> summary(stations_splag_inc_cas_np)

Call:spatialreg::lagsarlm(formula = cas_meantr ~ MedHouseIn + PC1 +
    PC2 + PC3 + PC4, data = stations, listw = w_dist_rowstd,     zero.policy = T)

Residuals:
     Min       1Q   Median       3Q      Max
-23.3685  -2.9526  -0.8635   1.7264 104.7751

Type: lag
Coefficients: (asymptotic standard errors)
              Estimate  Std. Error z value  Pr(>|z|)
(Intercept)  1.0400e+01  8.8061e-01 11.8101 < 2.2e-16
MedHouseIn   2.0279e-06  2.7944e-06  0.7257  0.468019
PC1         -2.9454e-03  7.1722e-02 -0.0411  0.967243
PC2          2.0396e-02  1.2539e-01  0.1627  0.870784
PC3          1.8731e-01  8.8612e-02  2.1138  0.034532
PC4          3.2635e-01  1.1455e-01  2.8489  0.004386

Rho: 0.5238, LR test value: 169.18, p-value: < 2.22e-16
Asymptotic standard error: 0.037675
    z-value: 13.903, p-value: < 2.22e-16
Wald statistic: 193.3, p-value: < 2.22e-16

Log likelihood: -4100.124 for lag model
ML residual variance (sigma squared): 32.809, (sigma: 5.7279)
Number of observations: 1288
Number of parameters estimated: 8
AIC: 8216.2, (AIC for lm: 8383.4)
LM test for residual autocorrelation
test value: 33.067, p-value: 8.9034e-09
```



```
> summary(stations_splag_black_cas_np)

Call:spatialreg::lagsarlm(formula = cas_meantr ~ Black + PC1 + PC2 +
    PC3 + PC4, data = stations, listw = w_dist_rowstd, zero.policy = T)

Residuals:
      Min        1Q    Median        3Q       Max
-23.47917  -2.96722  -0.85533   1.71899 104.69399

Type: lag
Coefficients: (asymptotic standard errors)
               Estimate  Std. Error z value  Pr(>|z|)
(Intercept) 10.68138206  0.87398715 12.2214 < 2.2e-16
Black       -0.00033860  0.00041013 -0.8256  0.409034
PC1         -0.00191199  0.07163496 -0.0267  0.978706
PC2          0.01003625  0.12432720  0.0807  0.935661
PC3          0.19478718  0.08546733  2.2791  0.022662
PC4          0.32808478  0.11454960  2.8641  0.004182

Rho: 0.52392, LR test value: 169.29, p-value: < 2.22e-16
Asymptotic standard error: 0.037642
    z-value: 13.919, p-value: < 2.22e-16
Wald statistic: 193.73, p-value: < 2.22e-16

Log likelihood: -4100.047 for lag model
ML residual variance (sigma squared): 32.804, (sigma: 5.7275)
Number of observations: 1288
Number of parameters estimated: 8
AIC: 8216.1, (AIC for lm: 8383.4)
LM test for residual autocorrelation
test value: 32.066, p-value: 1.49e-08
```

Spatial Lag Regression results for the casual mean trip duration including only median household income and PCs on the left and for casual mean trip duration including only Black population and PCs on the right.

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