MAKING BIKE SHARE TRANSIT COMPATIBLE

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MAKING BIKE SHARE TRANSIT COMPATIBLE

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SUMMARY

The motivation of this research is to make better use of bike share when it comes to trip integration between bike share and transit through better placement of bike share stations. In this thesis, the change in bus ridership at the stop level was analyzed to understand if this is a reasonable metric to alter the way bike share stations are sited. Considering the transit ridership at the planning phase of bike share could help to improve the interdependency of the two modes of travel. For this analysis, the existing user cost of the trip and demographic characters of the region were considered to arrive at locations that would be suitable for bike share and bus station coexistence.

This thesis presents a brief background on bike share services in North America and a literature review of the work done in the field to date, followed by various demographics considered. Then the analysis calculates the impact on transit ridership caused by a change in each demographic metric when they come in contact with bike share through an interaction regression. This will show if these two transportation modes are interconnected.

The results indicate that though bike share has a relative impact on transit ridership, it is not significant enough to alter the way bike share stations should be planned. This shows that it is better to consider bike share as a stand-alone mode of transportation at least when it comes to bus networks. Instead, the results can be used as suggestive guidelines to add stations in low-income block groups and block groups where the higher education attainment rate is below average. However, further study is required before overhauling the current method used for bike share station siting.

CHAPTER 1. INTRODUCTION

Bike sharing has the potential to bridge gaps in existing transportation networks as well as encourage people to use multiple transportation modes. (Martin, 2015)

Bike share has been a growing phenomenon. The primary goal of any bike share system has been to improve the connectivity of the region while also supporting the sustainable movement of citizens from point A to point B. Bike share programs also help in promoting tourism and job creation. (St. Louis Bike Share Study, 2014). Though bike share has benefited the cities in which it has been introduced by providing transport flexibility, reduction to vehicle emissions, health benefits, reduced congestion and fuel consumption, and financial savings for individuals (Nikitas, 2016); greater utilization could potentially be achieved through better coordination between modes. To date, bike share networks are mostly integrated with heavy rail and light rail systems, but a very limited number of bike share stations are integrated with intercity bus and rail networks as shown in Table 1. Less than 10% of the bike share stations are within two block distances of either an intercity bus or rail station.

Table 1 Number of Bike share Stations with Connections to Intercity Modes in the USA
Source: Published by U.S. Department of Transportation, Bureau of Transportation Statistics, Intermodal Passenger Connectivity Database (as of Apr. 16, 2016)

Mode	Connections	Near Connections	No Connection
Bus	61	171	3,075
Rail	23	37	3,053
Ferry	0	4	984
Air	1	1	3,309

NOTE: "Connection to another mode" indicates the number of bike share stations in, directly outside, or within one block of another transportation mode. "Near connections" means a connecting mode is within 1-2 blocks of a bike share station. "No connection" means that another scheduled public transportation mode serves the same metropolitan area as the bike share station but not within two blocks, so it is considered to have no connection. "No service" means that no scheduled public transportation mode serves the same metropolitan area as the bike share station. Multiple modes may serve a station; connectivity counted for each mode served at the station.

Multiple studies have been conducted regarding the usage of bike share and its influence on transit ridership such as Shaheen 2012, Fishman 2013, Martin and Shaheen 2014, Rosenthal 2015, Ricci 2015 and Campbell and Brakewood (2017). All these papers have shown that bike share has a varying impact on transit ridership in the region. However, these studies tend to look at whether there is an impact on transit ridership due to the introduction of bike share but do not analyze if the impact on transit ridership should be a part of siting bike share stations. A bike share network could act as a first- and last-mile connectivity to increase the reach of a local public transit network in addition to serving as a stand-alone mode of transportation. Especially in a country where auto-dependency has made first- and last-mile pedestrian connectivity difficult, bike share could prove as the answer to the last-mile connectivity concerns facing transit. Bike share could be used as a feeder network which would improve not only overall transit ridership but also aid in improving the health of the local community. At the same time, bike share can also act as a substitute for transit trips. So, by analyzing the link between the existing bike share systems and existing bus networks, we can better plan future bike share systems to improve the overall connectivity of the city by having it better interact with the local bus network.

The motivation of this thesis is to analyze if the location of the bike share station has an impact on transit ridership and also if the same can be used as a part of bike share station siting process. This added factor can be used in tandem with the current trip origin and trip destination generation model that is used to site bike share stations. Considering the impact on transit ridership during the design phase of bike share should ensure that both the modes act in a cohesive manner rather than one acting as a substitute for other, thus deteriorating total ridership.

1.1 Objectives

The objective of this research is to understand if transit ridership can be used as a viable tool for siting bike share stations during the planning phase. The current trip generation model used for bike share station siting only considers the maximization of total rides (Chapter 2.2, ITDP Bike share planning guide, 2003). This method allows us to ensure financial stability and ridership, but bike share systems can also provide an alternative to automobile users in locations that are not directly linked to transit routes. The existing OD matrix model does not account for any interaction with other transportation modes. The lack of integration of public transportation modes diminishes the equity of the overall system as not all the neighborhoods are benefited based on their needs (Schneider, 2017). The overarching goal of transit has been to improve the region on an equitable basis by providing reliable and cheap transportation options to residents that need it the most along with maintaining financial stability (Way Forward, APTA 2019). To further the equitable benefit of bike share, the research also concentrates on the relationship between ridership and demographics to better understand the dynamics. It also suggests how the growth of bike share can be altered to better suit people who need it the most.

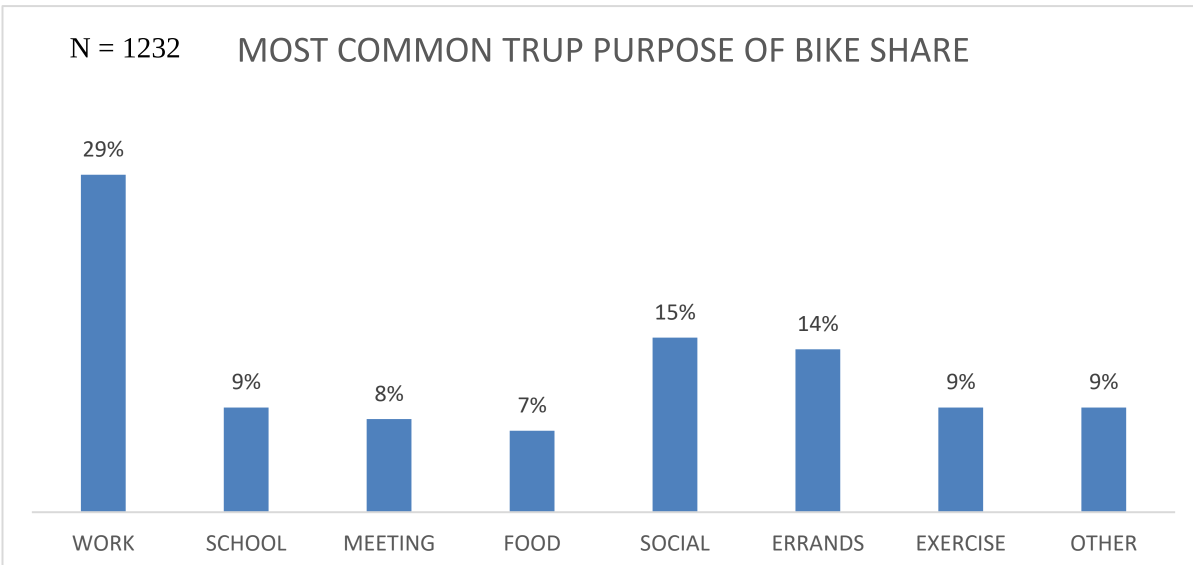

Figure 1 Most common trip purpose of bike share Source: Nice Ride Minnesota, 2011

The lack of bike share in low-income neighborhoods is only part of the problem (Levin, 2017), the other part of it is what do we use it for. A 2011 Minnesota survey showed the primary trip purpose of bike share users to be mostly standalone trips such as errand, and social get-togethers (Nice ride Minnesota, 2011) Only 38% percent of the users used it daily as a part of their regular commute to work or to school, as shown in Figure 1; the rest were stand-alone trips. If bike share were to be better integrated more users who are currently using automobiles would be able to use it as a part of their daily commute.

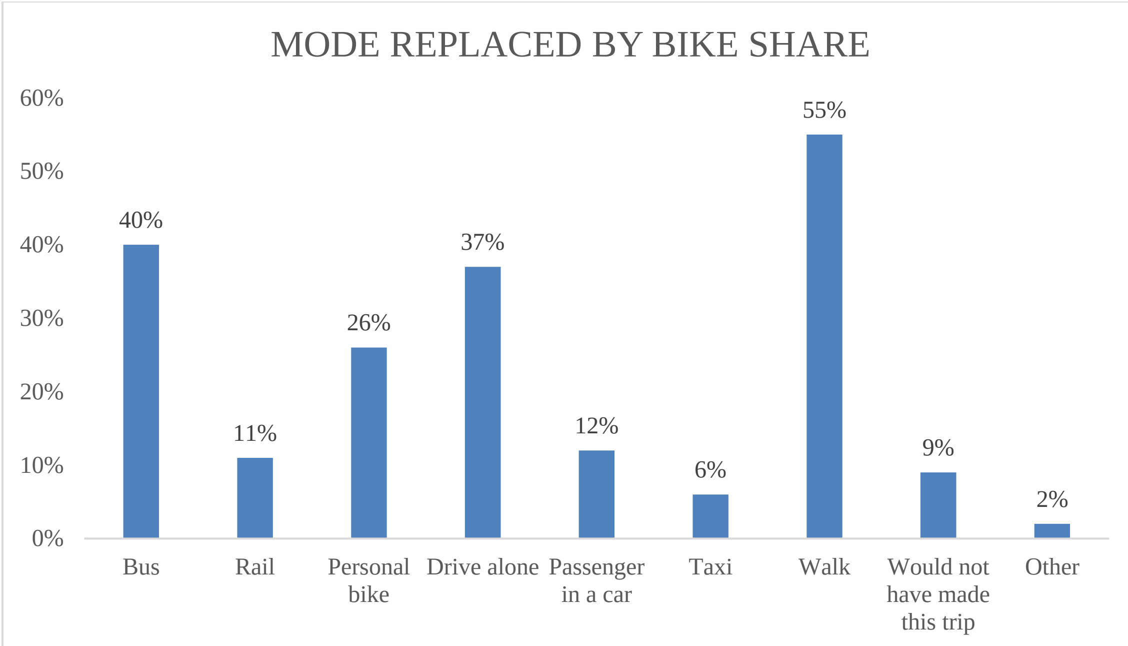

Figure 2 Mode Replace by bike share, Source: Nice Ride Minnesota, 2011, Note: Every user could pick the top two modes. Hence the cumulative percentage is 200.

In the same study, 80% of the bike share users said if it were not for the bike share they would have instead used transit or would have walked, as shown in Figure 2. About 14% of the users also said that they used bike share to arrive at their automobile which they then drove alone. This indicates that bike share is competitive to transit. If we can better link the two modes, then bike share and transit act in a complementary fashion rather than in a substitute fashion.

CHAPTER 2. LITERATURE REVIEW

2.1 Bike share overview

The concept of bike share started in Amsterdam on July 28th, 1965. In this system, regular bikes were differentiated using a standardized color scheme, and the system lacked security measures such as a present-day docking stations (Schimmelpennick, 2009). However, due to vandalizing and theft, the system collapsed within days (DeMaio, 2009). Since then, the growth of bike share has been categorized into three generations with the fourth generation of bike share just beginning (DeMaio, 2003, 2004). The subsequent generations are described below.

The second generation of bike share used sturdier bikes and a coin deposit system where users had to deposit a predetermined amount to use the bike (Gaegauf, 2014). The first example of this model was introduced in Denmark; the system was slowly phased in from 1991 to 1993 in three cities (Nielse, 1993). Initially, these systems were restricted to fewer bikes due to cost constraints, and cycles had solid rubber tubes to prevent theft of parts. This solid space in the tires was also used for advertisement, which led to investments from commercial sponsors to expand the system with time. In 1995, “Copenhagen City Bikes” were introduced in Copenhagen, initially launched with 1,000 bikes and eventually expanded to 2,500 bikes. This was the world’s first organized bike share system that was open to the public (Shaheen, 2010 & 2011). Despite all the safety measures, there was still thievery as the users were allowed to remain anonymous (DeMaio, 2009). This led to the third generation of bike share systems in which tracking systems were implemented to monitor bike locations.

This third-generation system was introduced at Portsmouth University in England in 1996 and was called the "Bikeabout" program. The program deployed magnetic strips with user's information attached to them as a means to track the user (DeMaio, 2010). With time, various other technologies were introduced to the third-generation bike share such as GPS tracking, mobile phone access, smart cards and electronic bike locks (Gaegauf, 2014, Martin, 2014).

Most of the earlier growth of bike share was outside the United States. Bike share was introduced to North America only in 1994. Since its introduction in the US, the popularity of bike share has continuously grown. As of 2017, there were 119 bike share systems with more than 4,830 hubs in the USA (Malouff, 2017). The location of these systems can be seen in figure 3 below. Although the most extensive systems are seen in the northeast and Chicago, bike share systems are available in nearly every state.

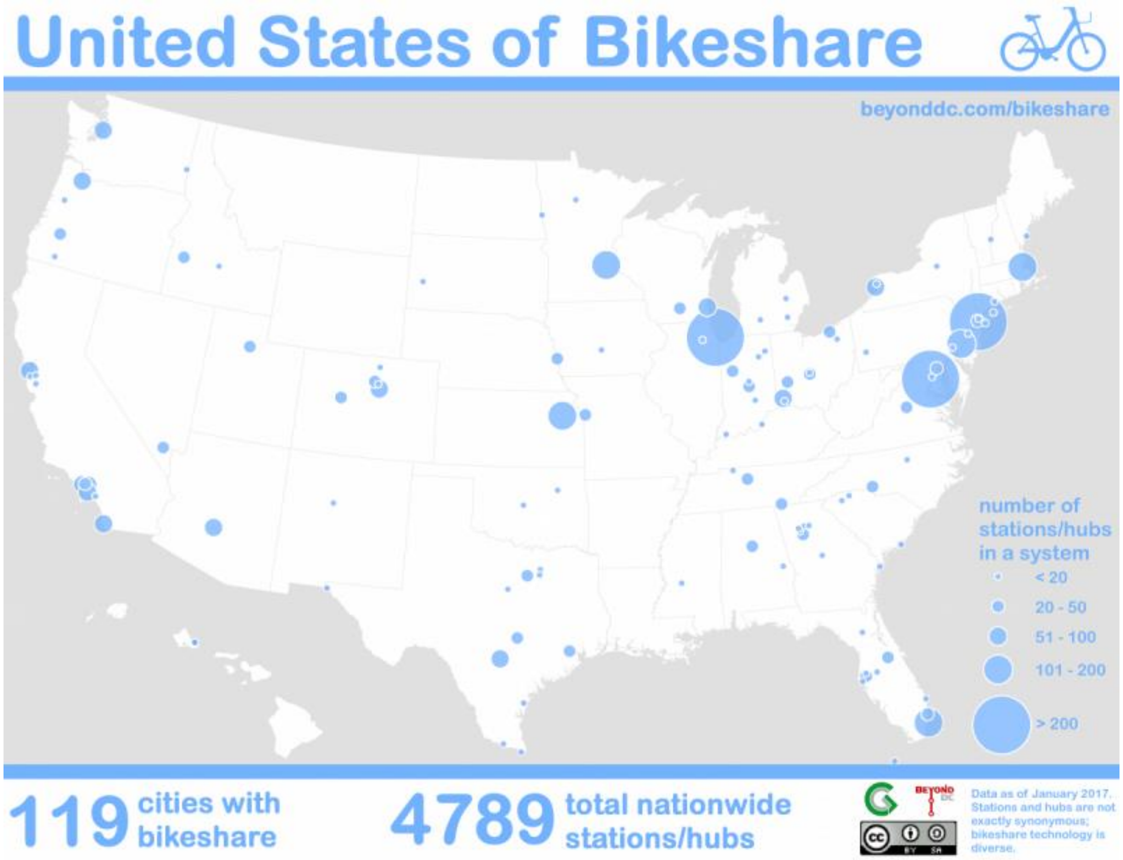

Figure 3 Bike share programs in the United States as of January 2017, Source: Beyond DC, 2014

Most of the bike share programs that began before 2000 had to terminate due to vandalism and high operational costs, and it is only recently that the US has seen an increase in successful programs (Erikson, 1995 & Bagwell, 1996). The current third generation bike share also requires high operational costs and to sustain these operational costs, third generation bike share programs have needed larger systems operating in urban centers to be successful. Starting a large system requires high capital costs and maintaining them necessitates operational expenses. To compensate for potential financial losses, bike share programs must often charge high fees or be subsidized by the government (Dusseau, 2014; Campanile, 2014). It is not viable for every government to subsidize for yearly losses, thus leading to some bike share programs relying on private sponsorships, like that of the New York’s Citi Bike program. This program utilizes funds from Citibank and Mastercard for advertising as a way of reducing their losses and subsidizing the costs of maintaining a bike share program (Gaegauf, 2014). Financial problems have led to the closure of bike share programs in Seattle and Lansing and some bike share programs in bike share friendly cities such as Toronto are actively losing riders (Alter, 2013).

Despite the difficulties to sustain a bike share program over time, it is essential to maintain them as they aid in decreasing taxi and car usage in favor of bicycling (Martin 2014). This shift is highly critical in a car-centric environment as it reduces congestion, emissions of greenhouse gases, noise, and air pollution (Fuller, 2013). The basis for most of the health benefits of bike share is that they promote an alternative for single occupant car users in the form of bike share or privately-owned bikes, however for the majority of the bike share programs that is not the case (Fishman, 2013). These increased bike trips are not always a result of a decrease in driving, in fact, about 48% of the new users were transit users in Washington DC. Similarly, 50% of the bike share users used to be transit users in Montreal. As the bike share programs grow in size, they tend to act as a substitute for the sustainable mode of transportation (Midgley, 2011). So, it is under question to say that bike share reduces congestion (Fuller, 2013; Martin, 2014).

2.2 The conflict between bike share and transit

Along with the health benefits, the integration of bike share and transit is also integral to widen the overall service area, thus potentially expanding transit patronage. This can compliment feeder bus service in regions with low ridership, allowing planners to improve the quality of service (Krizek and Stonebraker, 2011). There are various ways to use a bicycle as a feeder mode for transit such as transporting the owner's bicycle on board (bike on bus), using one's bike and locking it at the transit access station (Bike to transit) and bike share. Doolittle and Porter (1994) compared various ways in which bike commute is connected to transit, and the majority of the regular users preferred to carry their bikes on bus. This better aids the patron because bike on bus aids both first- and last-mile travel to and from transit stops, unlike bike to transit. Bike to transit had another added disadvantage of anxiety that the bike might be stolen. However, contrary to user preference, bike on bus is often not the most suitable mode of integrating the two modes of travel, as only a few users can be served with each bus due to rack space. The cost of investment is also much higher compared to the value of returns (Krizek and Stonebraker, 2011). A study conducted by Hagelin and Datz (2005) showed that 72% of bike on bus users commute to work within a very narrow time frame, which means that bike racks are full most of the time. Bike share could prove as a solution to this as it can be available at both origin and destination and patrons need not be worried about theft. Users were also comfortable using bike share as a link, given that the bike share was within 800 feet of their workplace. So, if bike share stations were spread out based on cycling transit users' needs, bike share can act as a viable feeder for bus networks.

In addition to giving access to jobs, goods, and services, linking bike share to existing transportation networks offers multiple benefits such as overall reduced travel cost, minimized fuel consumption, increased mobility, increased health benefits and mitigation of pollution (Shaheen and Martin, 2015). However, as mentioned earlier, the majority of the bike share programs in North America rely on public and private funding to operate. To qualify for these funds, they usually have to meet specific criteria such as advertising and coverage of particular regions. More often than not, these criteria tend to restrict the natural flow of bike share, and this compromises the link to existing transportation networks during the planning phase (Griffin and Sener, 2016).

When bike share systems are implemented on this opportunistic basis, they tend to act as a replacement for transit rather than as a feeder mode. The common claim regarding integration of transit and bike share is that, although bike share may serve as a substitute for some transit trips, the users often still obtain a transit pass, thus retaining their transit user status (Fishman, 2013). However, multiple authors have found that bike share does replace unlinked transit trips, especially in the urban core (Fuller, 2013; Buck, 2013; Shaheen, 2013; Tang, 2011; Murphy, 2015). This is counter-intuitive because of the initial belief that bike share would act as a feeder network to transit and allowing even more residents to use the transit network by providing convenient access to and from transit stations as first- and last-mile access proves to be a common problem for many communities (Chow, 2014; Griffin 2016).

Residents using bike share in place of transit suggests that bike share is providing a travel option that is faster than transit. However, this also means that bike share is often taking riders out of the public transportation system rather than from cars (Rosenthal, 2015; Martin and Shaheen, 2014). Taking riders off public transit rather than cars downplays the overall health benefit, and it also puts pressure on the financial operation of transit.

Bike share acting as a substitute for transit is a common phenomenon as studies conducted in various cities such as Washington DC, Montreal, Toronto and New York exhibit similar results (Shaheen 2012, Fishman 2013 and Ricci 2015). A survey conducted by Martin and Shaheen (2014) in Minneapolis and Washington DC revealed that bike share aided rail transit in sub-urban regions such as Minneapolis while diminishing rail ridership in urban centers such as Washington DC; however, in both the regions, bike share caused residents to shift away from bus service in the region. As another example, Campbell and Brakewood (2017) conducted a study in New York showing that for every 1,000 bike share trips, unlinked bus trips dropped by 2.42%. This implies that these two modes are intertwined, and this relationship can be used to develop more integrated transportation networks by efficiently placing bike share stations (Transitwire, 2017). Taking transit station locations into consideration, while planning bike share stations, could make the relationship between modes complimentary and extend the service boundary of transit (Martens, 2007). The result of the study conducted in Montreal, Toronto, Twin cities, and Washington, D.C. is that bike share aids transit in the bike share's beginning phase when their fleet size is limited. However, as bike share starts to grow, it shifts away users from transit rather than from automobile usage (Shaheen, Martin and Cohen, 2013).

As public bicycle systems are introduced to be a part of the urban transportation network, a portion of their success can be determined by the ability to extend public transportation access. For any bike share program to be successful in this aspect, the locations and distribution of bike share station must be carefully considered (Lin and Yang, 2011). There have been various studies regarding placement of bike share stations, but they have been general recommendations on installing the stations rather than selecting the location (Garcia-Palomares, 2012 and NACTO Station Siting Guide, 2016).

2.3 Bike share station siting

Bike share station siting is highly dependent on the preliminary goals of the system (Frade, 2015). Based on these preliminary goals, a demand analysis can be performed using variables such as the population of the catchment area, non-motorized transportation networks, transit networks, modal split, and profiles of residents that are more inclined to use bike share (Aoun et al., 2015). Such a price-elasticity of demand analysis might prove to be rigorous to conduct, so the alternative that is commonly used is a fixed uptake rate. In the fixed uptake method, a fixed percentage of the population is estimated to utilize the bike share system (Bike Share Planning Guide, 2015). For instance, during the planning phase of New York Citi Bike share, three scenarios of three percent uptake, six percent uptake, and nine percent uptake were considered. Based on the results, the city settled upon six percent uptake (New York City Department of City Planning, 2009). Even when transit networks in the region are considered during the planning phase, this only depicts how transit will alter bike share ridership and neglects the change in transit ridership. As an example, Clark (2016), who investigated Metro bike share in Los Angeles, California. There is potential that because the bike share has not integrated itself with the transit system in the region, it has not aided in reducing automobile ridership, and the usage of the bike share program has been in decline as well.

Various studies have proposed different models to rectify the issue of bike share station siting. To ensure smooth operation, Martinez et al. (2012) suggest a model where bike share stations are designed using discrete choice modeling. Additionally, Martinez et al. (2012) suggest minimizing the distance between stations, which would reduce the distance walked by the user while also aiding redistribution of bikes between stations to reduce costs of redistribution (Martinez, Caetano, Eiro and Cruz, 2012). However, similar to existing models, this treats bike share as a stand-alone system. The model suggested by Lin and Yang incorporates the relationship of bike share with transit. They proposed a system where the stations were aligned along the existing bike trails in the catchment area (Lin and Yang, 2010). This model considers the ease of use for the end user while also considering the investor’s requirements. Though the model addresses the relationship with transit, the existing transit network is only viewed as an optimization point that would help in increasing bike share ridership and ignores the impact on transit ridership.

Similarly, Garcia-Palomares et al. (2012) compared two models, one where the entire region is covered equally, and another where the stations are concentrated in areas with higher demand. A combination of results from the models was used to suggest station locations. Taking into consideration the relationship between bike share and transit, they recommend installing bike share stations at some transit hubs, but still, fail to consider the impact this would have on transit ridership. Also, the model neglects regions that are scarcely populated (Garcia-Palomares et al., 2012).

Though these studies take into consideration the local built environment, they neglected the characteristics of the users. Daddio (2012) developed a regression model using the current user characteristics. The data from the Capital bike share's pilot program was used to provide guidelines for the expansion of the same system (Daddio, 2012). Schoner conducted a similar study with Nice Ride Minnesota (Schoner, 2013), which used proximity to transit as a defining variable to predict bike share ridership better through a regression model. However, they still failed to quantify the impact of bike share on transit ridership.

The model proposed by Rosenthal considers bike share and transit to be a connected mode of travel. In this model, a combination of the value of time and actual travel cost was used to calculate mode split. The model compared a free-flow pattern with various degrees of congestion to estimate the number of automobile users that diverted to transit because of bike share. Unlike a regular logit model, this mode choice optimization did not use any demographic data, limiting the results to rough estimates (Rosenthal, 2015).

It is essential to study the interdependence of the two modes to plan a mutually sustaining transportation network. The aim of this study is to build a model that is similar to Rosenthal's (2015) to validate if change in ridership is a viable method to plan bike share station locations, but also integrate Daddio's method (2012) of taking into account the neighborhood characteristics in the form of demographics. If the selected demographics have a sizeable impact on transit ridership, then the results can be used to choose block groups to introduce bike share stations in. By doing this, we can mitigate the impact on transit ridership caused by introducing bike share in the neighborhood. This would also allow both the modes to work in a complementary fashion.

CHAPTER 3. METHODOLOGY

3.1 Background on San Francisco Transportation

The bus network in San Francisco is operated by the “San Francisco Municipal Transportation Authority (SF Muni).” SF Muni also operates trolleys, light rail, cable car, and a heritage streetcar line. The bus fleet consists of 827 vehicles and has a daily ridership of approximately 400,000 riders (Transit Center, 2017). Similar to the national trend, the daily ridership has been declining. It peaked in 2001 and then dropped by 15% between 2001 and 2016 (Transit vital signs, 2017), which has been associated with slow travel times. To counter this, Muni opted to implement an all-door boarding system which aided in steadying ridership temporarily (Jaffe, 2015). Further between 2016 and 2017, unlinked trips have dropped by six percent. Along with various factors, the introduction of the Ford GoBike bike share system has also been considered to be a cause for the drop-in ridership (Eskenazi, 2017).

Ford GoBike started as Bay Area bike share in 2013 with about 1,000 bikes, and the system is expected to expand to 7,000 bikes as a result of a partnership with Ford Motor Company (Etherington, 2017). The pilot program was a moderate success with an average of 418 trips per day with the majority of the trips happening during AM and PM peak on weekdays (Alson, 2015).

3.2 Data Collection and Assembly

Daily stop-level data of boarding's for three months (September through November) in a year, over the period of 2011 to 2015 was collected. With the help of R and PowerPivot in Excel, the 7.5 GB file was then converted into monthly boarding's at the stop level for ease of access.

The ridership has not been stable since 2011; overall the ridership has dropped by 15 percent between 2011 and 2015 as it can be seen in Figure 4.

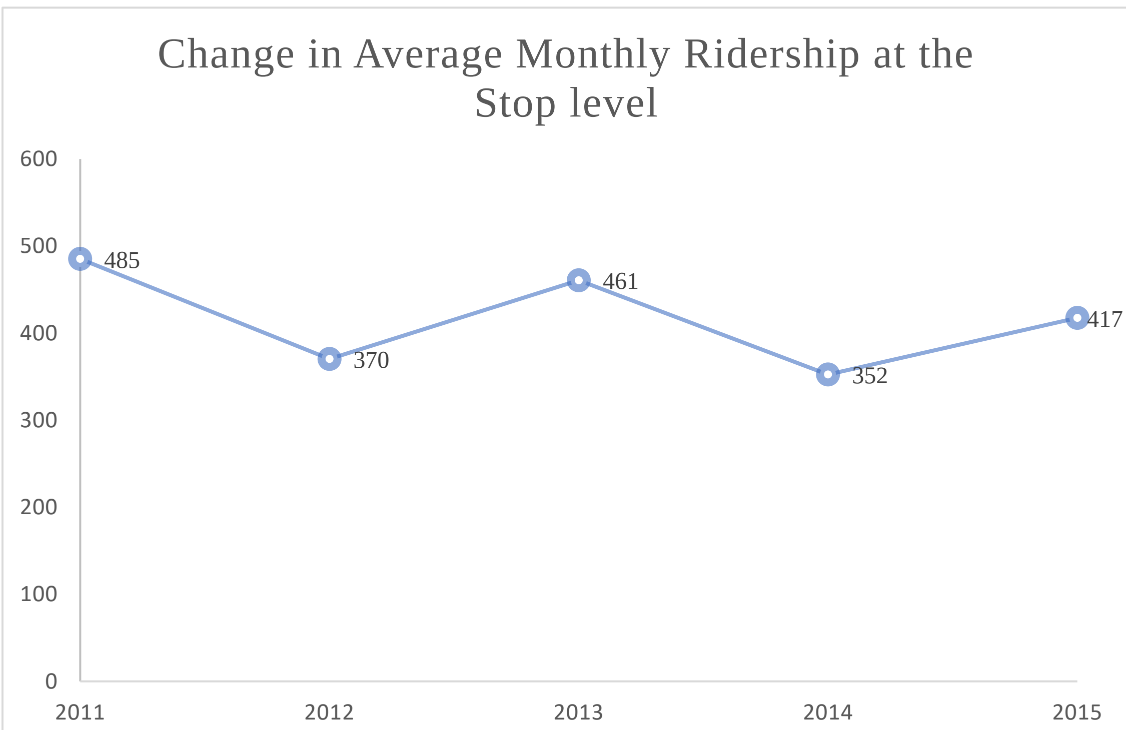

Figure 4 Change in Monthly ridership from 2011 to 2015, Source: SFMTA

The change in ridership can be attributed to various reasons such as economic seasonality, gas price, transit fare, safety and average headway (Alam, Nixon & Zhang et al., 2015). However, the data provided consisted only of stops where data was collected for the entire five-year period. Hence, this does not represent the overall ridership of San Francisco Muni bus system.

Using ArcGIS to compare the change in ridership between stops that were linked to bike share and stops that were not connected to bike share, the stops were divided into two groups. The stops were mapped using their latitude and longitude along with the bike share station locations obtained from the open data source. Any bus stop within two blocks (2,000 feet) of a bike share docking station was classified as “Associated with bike share” and the rest were classified as “Not associated with bike share.” The distance of 2,000 feet is the recommended distance suggested by the Bureau of Transportation Statistics as the boundary for considering bike share as associated with transit (USDOT, 2016). This distance is the maximum distance that a majority of the population is comfortable traversing on foot while changing modes of transportation within a single trip (Smallen, 2016). The resultant distribution of bus stops is shown in Figure 5.

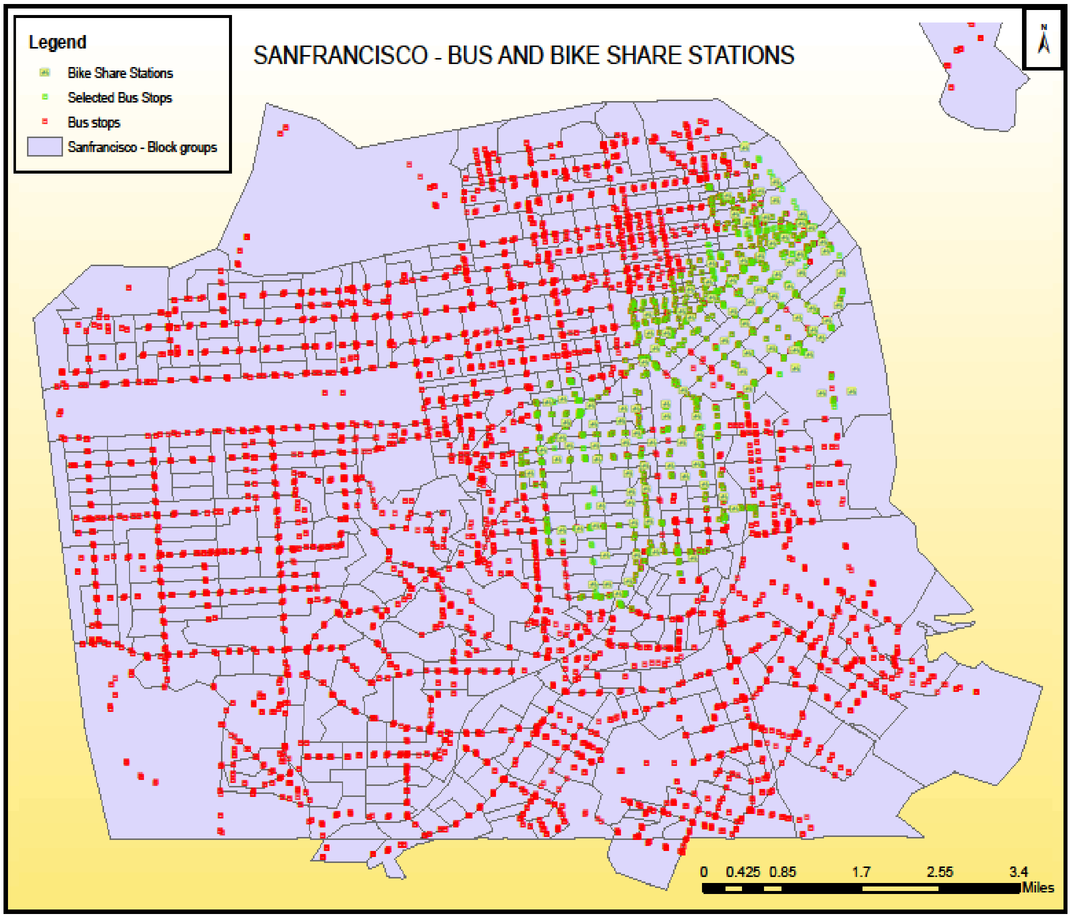

Figure 5 San Francisco - Bus and Bike share stations Source: SFMTA

3.3 Dependent Variable

Average transit ridership per month collected from SFMTA at the stop level was the primary dependent variable of interest in the model. Monthly ridership values ranged from 0 to 19,851 per stop with a median value of 107. To eliminate outliers, the mean and standard deviation of the dataset was computed, and then the data points that were larger than four standard deviations from the mean were eliminated to ensure that these extreme values do not affect the predicted values of the regression (Songwon Seo, 2006).

3.4 Explanatory variables

The explanatory variables address a variety of demographic and cost of travel variables that could have affected the ridership. A control variable for the year was used to treat natural changes over time. The demographic data were obtained from American Community Survey databases of 2010 to 2015. The geographic unit, variable-type, central tendency, and spread of the data is explained in Table 2.

Table 2 Variables Used

Variable Description	**Geographic Unit**	**Variable Type**	**Data Source**	**Min**	**Max**	**Median**
Monthly Boardings	Stop	Continuous	San Francisco Muni	0	19581	107
Bike share dummy	Stop	Binary	San Francisco Muni	0	1	0
Year Dummy	City	Continuous	San Francisco Muni	2011	2015	2013
Monthly Gasoline cost	City	Continuous	US-Energy-Information Administration – Data Navigation portal	2.95	4.48	3.92
Adult Ticket cost	City	Continuous	San Francisco Muni	2.00	2.25	2.00
Density of Pop per Sq. Mile	Block group	Continuous	US-Census Bureau - ACS	0	27	3
Male 18 to 34 (Count)	Block group	Continuous	US-Census Bureau - ACS	0	2343	192
Female 18 to 34 (Count)	Block group	Continuous	US-Census Bureau - ACS	0	2244	186
Median age	Block group	Continuous	US-Census Bureau - ACS	0	78	39
Minority Population count	Block group	Continuous	US-Census Bureau - ACS	0	5412	619
Average Per capita income	Block group	Continuous	US-Census Bureau - ACS	0	218465	44134

Table 3 Variables Used (cont)

Variable Description	Geographic Unit	Variable Type	Data Source	Min	Max	Median
No. of Households in poverty	Block group	Continuous	US-Census Bureau - ACS	0	697	56
No. of residents that walk to work	Block group	Continuous	US-Census Bureau - ACS	0	987	41
No. of residents that drove to work	Block group	Continuous	US-Census Bureau - ACS	0	1766	308
Percentage of population with a diploma or higher	Block group	Percentage	US-Census Bureau - ACS	0.00	1.00	0.90
Employment rate	Block group	Percentage	US-Census Bureau - ACS	0.00	1.00	0.93
White Population count	Block group	Continuous	US-Census Bureau - ACS	0	3462	660
Count with Diploma or over	Block group	Continuous	US-Census Bureau - ACS	0	6943	914
Poverty %	Block group	Percentage	US-Census Bureau - ACS	0.00	0.72	0.10
Population	Block group	Continuous	US-Census Bureau - ACS	0	8874	1338
Workers	Block group	Continuous	US-Census Bureau - ACS	0	5822	737
Households	Block group	Continuous	US-Census Bureau - ACS	0	4,177	563
Labor force	Block group	Continuous	US-Census Bureau - ACS	0	6,185	818
Employed	Block group	Continuous	US-Census Bureau - ACS	0	5,843	751
Bike to work	Block group	Continuous	US-Census Bureau - ACS	0	604	10
Minority-Pop Percentage	Block group	Percentage	US-Census Bureau - ACS	0.00	1.00	0.49

Note: Though the table is broken across various pages, it’s still a single table.

3.5 Transit-related Variables

The three transit-related explanatory variables used are a bike share dummy, a year dummy, and an adult ticket cost. Bike share dummy was used as a way to track the impact on transit ridership by bike share. Year dummy was used to account for natural growth or decline in transit ridership over time.

Ticket price is commonly associated with a change in ridership (Brakewood et al., 2015). To account for this change in ridership, a regular adult ticket cost was included as an independent variable. A single adult fare was $2 in 2011 and was increased to $2.25 in 2014 (SF Muni, 2014).

3.6 External Factors

In general, population and density of population in a region impact ridership, especially when a new system such as bike share is introduced into the neighborhood (Campbell, 2017). To track how a change in population affects ridership, annual estimates of population and block group area size were collected from the American Community Survey conducted by U.S Census Bureau from 2011 to 2015. Population and block group area was used to calculate the density of population. From the same data set, population of male and female between the age 18 to 34 was also calculated. This particular age group was known to use the bike more often than the rest as a part of their regular commute (Pedbikeinfo, 2012). Also, the first year of usage data of FordGo bike showed that the morning and evening peak hours were its busiest times. This could be a result of bike share being used to travel to work or school. To account for the same educational attainment, labor force and the number of people employed were also added to the model. To assess racial and economic differences in ridership changes, white population, minority population, poverty count and poverty rate were also included in the model.

3.7 Analysis methods

3.7.1 Ordinary least squared regression

An Ordinary Least Squares (OLS) regression to compute the difference between the control group and the experimental group. Ordinary Least Squares regression is a statistical model that is used to predict unknown parameters and to predict future variables. Ordinary Least Squares predict the dependent variable as a linear function of the independent variables used and then compares it to the observed variable. The tightness of fit is measured using the sum of the squares of all the difference between the observed and predicted variables. The smaller the difference, the better the fit (Greene, 2002). An OLS regression analysis was used to calculate the impact of the change in each demographic value in a year upon a change in ridership per year at the stop level. There are various ways to choose the variables used in an analysis. In this paper, a stepwise approach was used to choose the variables solely based on the t-statistic of the regression. Stepwise regression is a method used to find the best-fit of regression model by choosing the predictive variables through an automatic procedure. Stepwise regression either adds (forward) in or eliminates (backward) variables with each step based on the directionality of the method. Any variable that does not contribute to the overall adjusted R-squared is eliminated to maintain the overall integrity of the model. For this paper, bidirectional stepwise regression was utilized since there is potential for high correlations between variables. A bidirectional elimination acts similar to forward stepwise regression where it adds a variable at each step, but it also has a possibility of deleting a selected variable at each stage if there is any underlying multicollinearity between the variables. (Wright, Brownlee, Buswell, et al., 2016)

3.7.2 Interacted Variables

The OLS regression was helpful to understand the impact of the change in demographics on transit ridership, but we were unable to distinguish how much of this impact was caused by bike share. To calculate the same, an Interaction Regression was used as it would allow us to separate the coefficient (impact on transit ridership) into two parts, namely, the impact caused by bike share and the rest. Interaction regression does this by introducing interaction terms along with the independent variables to measure the combined impact of the multiple variables on the dependent variable. Usually one or both of the interaction variables are in binary form (0 and 1), and the result obtained from such an interaction variable and a measurement variable is called slope dummy variable since this provides the test difference between the two groups (Hamilton, L.C, 1992). Such a method can also be used to show the variation between multiple groups, for instance, years can be used as a dummy variable to track the difference concerning each year.

CHAPTER 4. RESULTS AND DISCUSSION

4.1 Impact of bike share on transit ridership at stop level

In this analysis, the bus stops were divided into bike share and non-bike share based on their proximity to a bike share station. Any bus stop that was within a two-block distance to a bike share station was denoted as a "bike share," and the rest were denoted as non-bike share. This was added to the data using a dummy variable "Experimental Group Dummy" where every "bike share" bus stop received a "1," and the "non-bike share" bus stops received a "0". Similarly, another dummy variable named "Time Dummy" was introduced. Since bike share was introduced in early 2013, any data point before that was allotted a "0," and the rest was allotted a "1" to differentiate the data points as before and after. To measure the impact caused by bike share over time, another variable called "Time * Exp Group dummy" was also introduced. This was used as an interaction variable that was the result of the product of the two dummy variables. Then a regression analysis was conducted where ridership at the stop-level was the dependent variable and Time dummy, Experimental group dummy, and Time * Exp Group dummy where the independent variables. Along with a regression analysis, an analysis of variation (ANOVA) was also conducted to ensure that the variation in the values did not occur purely due to chance. The results of this analysis are explained in the following section.

4.1.1 Regression results

As shown in Table 3, the mean square of values explained by the three variables is significantly larger than the residual values. The low p-values reject the null hypothesis that there is no variation in ridership with respect to time or whether if the bus stop is within two block radii of a bike share station. Though the extremely low p-values show that both the change in time and the introduction of bike share had an impact on transit ridership, the adjusted R-square is extremely low. This low adjusted R-square shows that bike share or change in time has little to no effect upon a change in ridership at the stop-level.

Table 4 Difference in difference - Regression statistics

Regression Statistics	
Multiple R	0.16
R Square	0.03
Adjusted R Square	0.03
Standard Error	901.99
Observations	94050

Table 5 Difference in Difference - Analysis of Variance

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	2039491484	679830494.6	835.60	0
Residual	94046	76513957505	813580.13		
Total	94049	78553448988			

Table 6 Difference in Difference - Coefficients

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	332.16	4.71	70.59	<0.001
Time Dummy	39.36	6.79	5.80	<0.001
Experimental Group dummy	352.95	9.48	37.23	<0.001
Time * Exp Group dummy	-29.64	13.63	-2.17	<0.05

The p-value and relative coefficient of the time dummy variable safely rejects the null hypothesis that the ridership before and after the installation is the same. At the same time, the standard error is relatively high showing that the independent variables used, namely time and bike share, do not account for the majority of the variation in the data. This undermines the findings from the overall analysis. From Table 5, the coefficient of the intercept explains the average ridership that is not defined by either change in time or bike share. This finding can be seen as the average ridership of non-bike share stops before bike share was installed. The coefficient of Experimental group dummy is the difference between "Experimental" group and "Treatment" group irrespective of the outside interference. The high positive value dictates that the ridership was extremely high in these block groups even before bike share was installed. The coefficient of the time dummy denotes the change in ridership over time for both groups and during this five-year period the ridership has increased by almost 40 per bus stop per month in San Francisco. The coefficient of "Time*Exp Group dummy" is the difference in ridership between bus stops that are associated with bike share stations and bus stops not associated with bike share stations. The negative coefficient shows that the growth in bike share bus stops is slower than non-bike share bus stops. When non-bike share bus stops ridership increased by 39.36 the bike share bus stops ridership grew by only 9.71. The overall R-squared and p-value of "Time*Exp Group dummy," showing uncertainty in the significance that bike share tends to take away patronage from bus networks. This result could be the result of bike share acting as a substitute for the users and thus take away riders, or it could be because the ridership has reached its peak. It possibly could be a combination of both as well, but the overall statistic of the model is extremely low for suggesting that bike share and bus network are interrelated.

4.2 Impact of bike share on transit ridership over the years

One flaw of the previous analysis is that both the groups are assumed to have a linear pattern of change over time irrespective of their “origin”. This is because intermediate years were not taken into consideration and the overall values were averaged as before and after. To correct for the this, a similar analysis was repeated, where the change in ridership over each year was taken into consideration rather than averaging it into just before and after. Rather than having a binary variable to separate the data into before and after, the data was instead categorized by years based on when the data was collected. The data was set up where a dummy variable for each year was introduced (excluding 2010). The year 2010 was excluded because that was the initial year of the data and thus treated as the intercept. Like the previous analysis, the time dummy and interaction variables for each year were also introduced. Instead of using one data point before the intervention and one after, three data points before and after were used by treating each year as a dummy variable. Along with this, a dummy variable for interaction was also introduced to separate the groups into “Experimental,” and “Control” groups, similar to the previous regression analysis of variance was conducted here as well. The result of this regression analysis is tabulated below.

Table 7 Change in ridership over the years - Regression statistics

Regression Statistics	
Multiple R	0.18
R Square	0.03
Adjusted R Square	0.03
Standard Error	898.27
Observations	94050

Table 8 Change in ridership over the years ANOVA

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	12	2.67E+09	2.23E+08	301.3376	0
Residual	94038	7.59E+10	806895.3		
Total	94050	7.86E+10			

Table 9 Change in ridership over the years - Coefficients

	Coefficients	Standard Error	t Stat	P-value
Intercept	331.75	8.25	40.19	<0.001
Experimental Group dummy	324.19	16.63	19.50	<0.001
2011	32.70	11.45	2.86	<0.01
2011-Exp	102.33	23.13	4.42	<0.001
2012	-33.45	11.62	-2.88	<0.01
2012-Exp	-18.18	23.34	-0.78	0.44
2013	14.37	11.46	1.25	0.21
2013-Exp	59.67	22.97	2.60	<0.01
2014	-23.66	11.58	-2.04	<0.05
2014-Exp	-146.66	23.31	-6.29	<0.001
2015	162.02	12.56	12.90	<0.001
2015-Exp	107.76	25.23	4.27	<0.001

Similar, to the previous analysis, Table 6 rejects the null hypothesis, but the 0.03 value of Adjusted R-squared in table 5 means that 97% of the ridership is explained by factors that are not taken into consideration making the overall result unreliable. These results give a basic understanding of how bike share affects transit ridership, but it is difficult to make decisions based on these results because there are external factors that cause a higher impact on ridership. To further explore Table 7 the coefficient was plotted as a graph that can be seen in Figure 7.

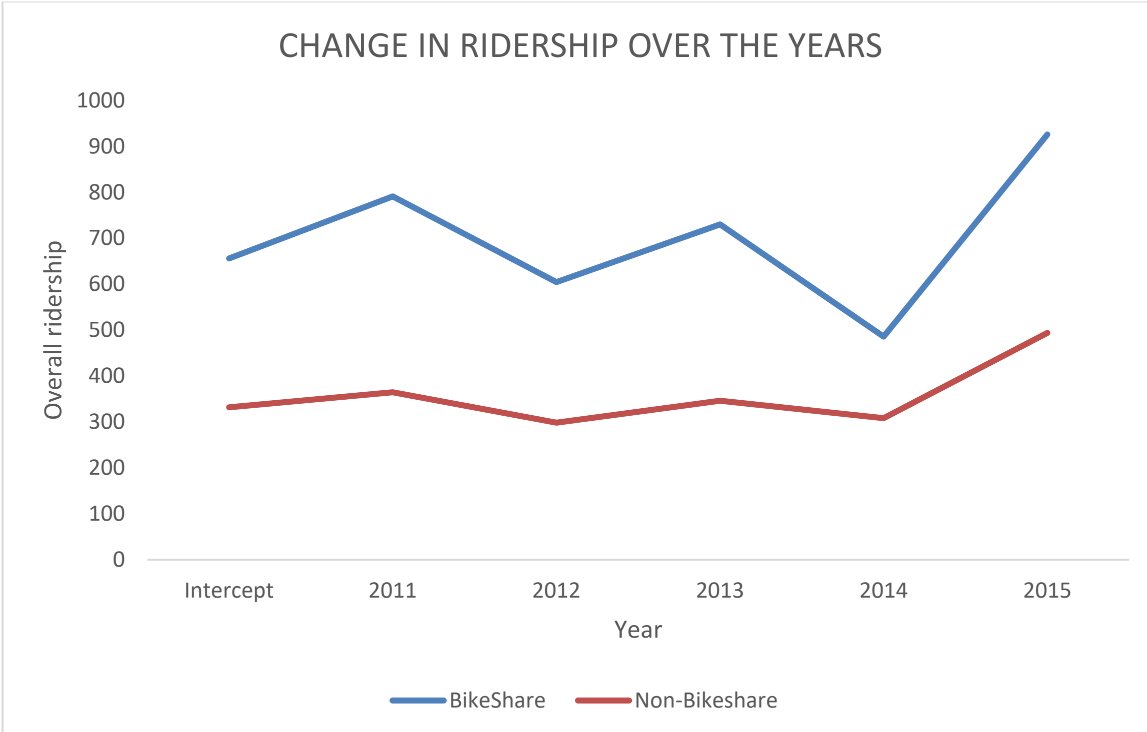

Figure 6 Change in ridership over the years

As can be seen in Figure 7, the results did not follow any noticeable patterns over the years. Another key takeaway is that both before and after the treatment, the results in the experimental group follows the same direction as the control group (increase or decrease) but at an accelerated rate. This is potentially due to the higher rate of activity in the bike share stations where similar external changes are resulting in accelerated results in these regions when compared to non-bike share stations.

Though the regression results show that bike share does not have a major impact on transit ridership, it does not take into account the neighborhood characteristics of each stop. There might be underlying factors causing high or low ridership at a particular stop. To account for this, the change in monthly ridership for each stop was calculated. Change in ridership was preferred over actual ridership to measure only the impact caused by bike share on transit. As mentioned earlier, most of the stops associated with bike share had the high ridership to begin with, this could affect the results irregularly, hence change in ridership is a better measure to track change. Using change in ridership will show the impact caused by the independent variables in the model. Since the change in ridership is calculated by subtracting the monthly ridership of the subsequent month of the previous year from the current year's ridership it also helps us to eliminate seasonal disparities. Similarly, the change in demographic variables was also computed as explanatory variables.

4.3 Impact of each demographic on Transit Ridership

4.3.1 Stepwise Regression

After plotting the independent variables against the dependent variable, the graphs followed a linear pattern with an absence of any quadratic or cubic relations. Hence, the relationship between independent and dependent variables will be estimated using an Ordinary Least Squares model.

An ordinary least square model can be represented as:

$$Y = \beta_0 + \beta_{ij}X_{ij} + \varepsilon$$

Where Y is the dependent variable, X_{ij} is the independent variables, β_0 is the intercept of the model, β_{ij} is the vector of the estimated coefficients and ε represents the error term of the model.

To choose the independent variables a bidirectional stepwise regression method was used. A forward stepwise regression starts the model without any variables and then adds the variables to see if they add to the predictability of the model, and any variable that does not add to the overall p-value is eliminated. In backward stepwise regression, the model starts with all candidate variables and variables are eliminated if the loss in integrity of the model is insignificant because of elimination of the said variable. A bidirectional stepwise regression uses a combination of both the models and the same was used to eliminate any variable that did not contribute to the model significantly. The statistics of these results are presented in Table 9, and the final results are tabulated along with the interaction regression results in Table 11.

Table 10 Stepwise Regression Statistics

Regression Statistics	
Multiple R	0.25
R Square	0.063
Adjusted R Square	0.062
Standard Error	352.1
Observations	53671

4.3.2 Stepwise Interaction Regression

An interaction regression was used to discern the impact of demographics on ridership directly and the impact caused by the same demographic because it came in interaction with bike share. To do the same, an interaction variable was added for each demographic in the model. Then, a bidirectional elimination process was used to remove all the variables that did not contribute to the overall t-static of the model. The complete results are shown in the Appendix. For comparison purposes, the statistics of the results from the bi-directional stepwise regression of non-interaction regression and the interaction regression are presented in a tabulated format in Table 11.

Table 11 Bidirectional Stepwise Regression with Interaction Variables results

Regression Statistics	
Multiple R	0.28
R Square	0.078
Adjusted R Square	0.077
Standard Error	349.3
Observations	53671

4.4 Comparing results

The coefficients from the regression analysis were tabulated side-by-side to compare the effect of each independent variable on bus ridership in neighborhoods that have access to bike share and neighborhoods that do not have access to bike share.

Table 12 Comparing results from Interaction and Non-interaction regressions

	Combined	Standalone	Bike share
Bike share dummy	38.9*** (4.26)	36500** (11100)	#N/A (#N/A)
Year Dummy	79.7*** (1.62)	77.5*** (1.70)	-18** (5.53)
Gasoline Cost	-5.52. (3.75)	#N/A (#N/A)	25.7** (9.84)
Adult Ticket Cost	-594*** (15.20)	-414*** (16.90)	-809*** (37.40)
Density of Population	9.88* (4.29)	-9.37 (6.12)	41.1*** (10.50)
Male 18 to 34	0.0623. (0.03)	0.0887** (0.03)	#N/A (#N/A)
Female 18 to 34	0.187*** (0.03)	0.202*** (0.03)	-0.253** (0.09)
Workers	0.398*** (0.09)	0.2* (0.09)	#N/A (#N/A)
Poverty %	2058*** (58.10)	494*** (68.70)	-552*** (153)
Employment rate	-103** (31.70)	-74.5* (34)	653*** (197)
Median Age	2.15*** (0.42)	1.37** (0.44)	13.7*** (1.56)
Minority Population Percentage	-79.6** (26.80)	-119*** (27.30)	352** (114)
Per Capita income	0.000446* (0.000196)	#N/A (#N/A)	#N/A (#N/A)
Employed	-0.293*** (0.09)	-0.162. (0.09)	-0.872*** (0.25)
Households in poverty	-0.213* (0.09)	-0.966*** (0.12)	1.44*** (0.21)
Walk to work	-0.138*** (0.04)	-0.122* (0.05)	0.308** (0.09)

Table 13 Comparing results from Interaction and Non-interaction regressions (cont)

	Combined	Standalone	Bike share
White	-0.141*** (0.02)	-0.162*** (0.02)	0.174* (0.08)
Drove to work	#N/A (#N/A)	-0.0666* (0.03)	#N/A (#N/A)
Percentage with a diploma or higher	#N/A (#N/A)	78. (42.70)	-96.8. (56.90)
Labor force	#N/A (#N/A)	#N/A (#N/A)	1.14*** (0.24)
Population	#N/A (#N/A)	0.0981*** (0.02)	-0.565*** (0.06)
Households	#N/A (#N/A)	0.116* (0.05)	#N/A (#N/A)

Note: Though the table is broken across multiple pages, it is a single table. Since not all the variables were used in both the models so #NA was used as a space filler for variables that are not significant. Robust standard errors in parentheses. '***' p<0.001, '**' p<0.01, '*' p<0.05, '.' p<0.1

Aside from the external demographic variables, the year dummy denotes that there is a decline in ridership by 18 riders per month per stop at bus stops that are within a two-block radius of a bike share station.

4.4.1 Cost factor

The cost factors had a very predictable outcome, as the increase in transit ticket led to an overall drop in ridership and bike share facilitated the decline even further. Similarly, increase in gasoline cost (automobile travel) led to a significant increase in ridership in bus stops that are linked to bike share. This could be a result of choice riders and captive riders; more choice riders can make the switch from automobile to transit as bike share provides them with the ability to traverse the last mile to resolve the connectivity issue.

4.4.2 Population

Variation in net population did not have a significant impact on ridership at the stop-level. And like net population, net households did not have a sizeable impact on transit ridership as well. However, the density of population had a considerable effect on transit ridership. With the increase in population density, bike share was better able to act as a complementary mode of transportation to transit. This shows that irrespective of the size of the block group that the bus stop serves, it is the density of population that has an impact on transit ridership.

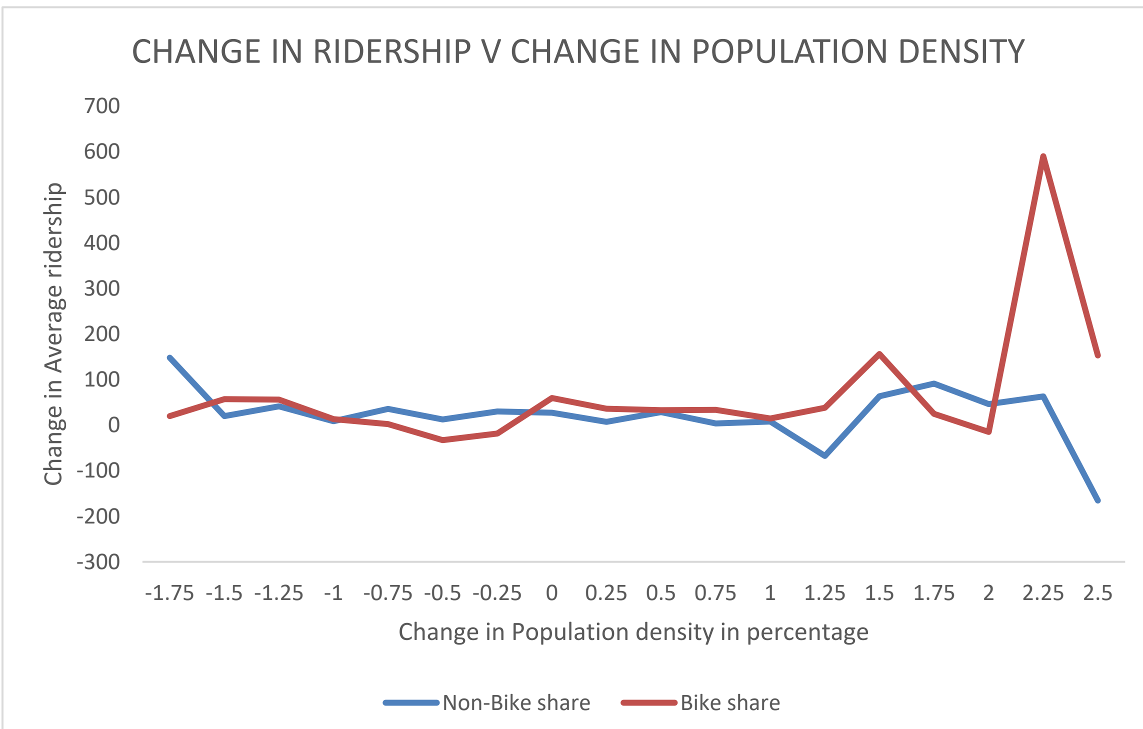

Figure 7 Average Change in Ridership vs. Average Change in Density of Population

4.4.3 *Employment*

The change in the net number of employed people in a region has an opposite effect on transit ridership, which is aggravated by the addition of bike share. Ridership loss due to increase in employed personnel in stations linked to bike share is five times larger than stations that are not connected to bike share. Though not as significant, labor force which is a combination of both employed and unemployed population has the opposite effect as the increase in labor force population increased ridership in bus stops that are within two block radius of bike share stations. Compared to net employment count, employment rate had the opposite effect. In general, residents tend to shy away from transit in a block group as more people get employed. Adding bike share to these regions not only retains these riders but also adds in new riders.

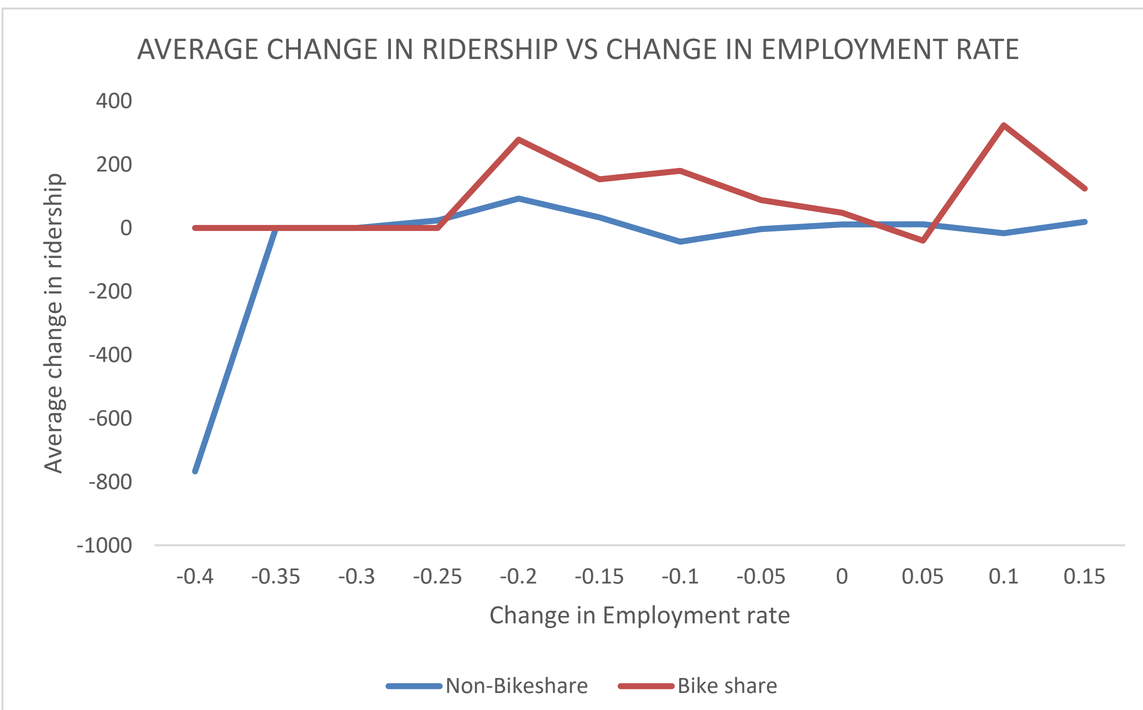

Figure 8 Average Change in Ridership vs. Average Change in Employment rate

4.4.4 *Education*

Percentage of the population with a high-level degree has a direct relationship with transit, as more educated people tend to use transit in general. However, when there is an alternative (bike share) available, the population with a diploma or higher tends to have an adverse effect on transit ridership. This could be due to patrons preferring a sustainable mode of transportation that is also beneficial to their personal health.

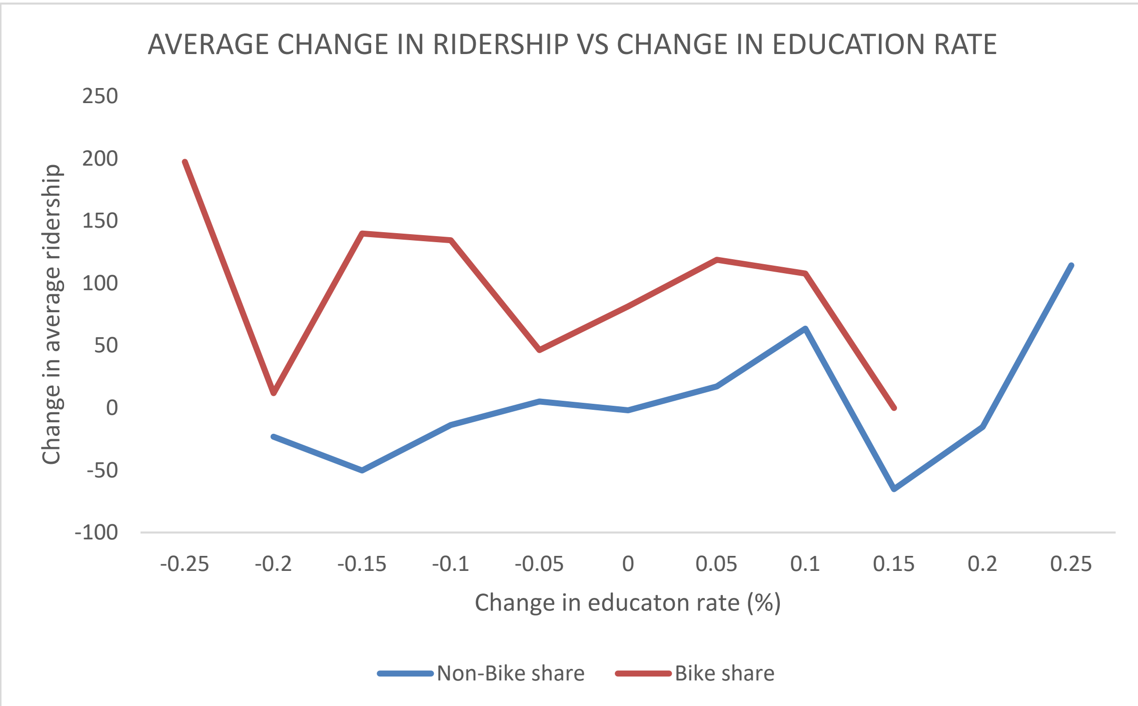

Figure 9 Average Change in Ridership vs. Average Change in Education rate

4.4.5 *Poverty*

Poverty percentage increased the ridership at the stop-level likely due to the affordability of a car. However, bus stops that are within two-block radii of a bike share station had a significant decline in ridership. This could be because bikes are available all around the day and cost almost the same for a single trip. This could be a potential reason for a user to prefer bike over bus and the lack of transfer could be because most of the riders are willing to traverse much longer distance on the bike rather than paying two separate fares. This could be corrected by allowing free- or subsidized-transfers between the two modes of transportations. Unlike poverty percentage, the number of households in poverty variable had a direct correlation to transit ridership if the stop was within two-block radii of the bus stop. This could be the result of fewer cars in the household and bike share providing them an option to traverse the "first-mile/last-mile" to reach the transit network.

4.4.6 Age

Overall with an increase in median age, average ridership at the stop-level increases. Adding bike share to the network further facilitates this increase. The rise in ridership for an increase in age by one year is amplified by a factor of ten if the bus stop is within a two-block radius of a bike share. To further analyze, the independent variable was split into Male and Female population between the age of 18 to 34 as mentioned earlier. This age group was more prone to using bike share bikes. With male population, adding a bike share system did not have any significant impact on the transit ridership. Concerning female population, for every unit increase in female population in the block group, the ridership fell by 0.25. This shows that females are more prone to using bike share as a replacement for transit.

4.4.7 Minority Population

In general, as a neighborhood had an increase in the proportion of minority population, transit ridership took a dip. However, at bus stops that are associated with bike share, transit ridership increased by 352 for every one percent increase in the minority population. This result establishes that bike share facilitates a better transportation option for the minority population.

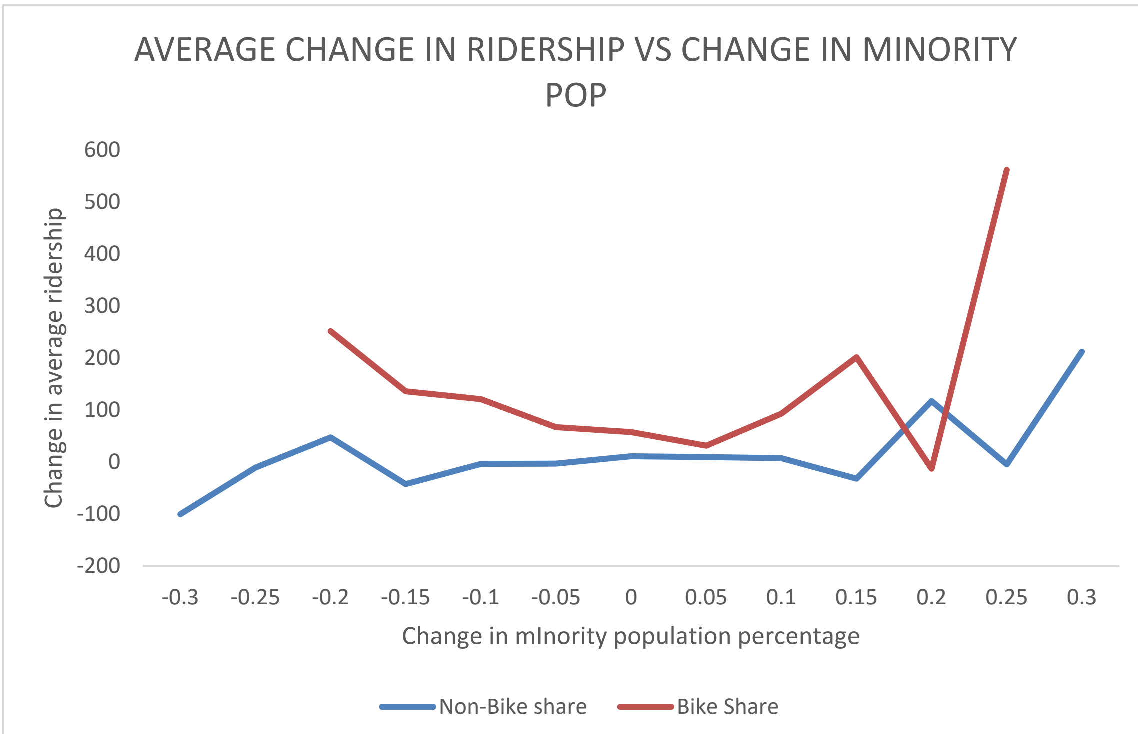

Figure 10 Average Change in Ridership vs. Average Change in Minority Population

4.4.8 Travel mode

Biking to work or driving to work did not have a significant impact on the overall ridership, however, introducing bike share in block groups where more people tend to walk to work aided the transit network in increasing its ridership by a small margin.

CHAPTER 5. CONCLUSIONS

Bike share is a complex mode of transportation that is relatively new to North America. Though the current planning practices ensure maximum ridership, these practices treat bike share as a standalone form of transportation. As explained earlier, integrating it with the existing transit network would better aid the region. The goal of this thesis was to assess if a change in transit ridership caused by bike share is significant enough to alter the way bike share stations are placed. This would allow bike share to better integrate with the other transportation modes of the city. Such integration would allow bike share to be used as a tool to further support transit as a reliable and sustainable mode of transportation, especially in cities where last mile access still proves to be a hindrance.

Based on the findings it is impossible to say with certainty that transit ridership is a good tool for bike share station siting. The extremely low R-squared value means that there are various other external factors that affect transit ridership, once we account for the same the impact caused by bike share might be very minimal. This shows that it is better to consider bike share as a stand-alone mode of transportation at least when it comes to bus networks. We can use the impacts caused by demographics as guidance for few stations to help improve equity in the city, but we would need results with far higher accuracy to alter the current OD matrix method used for selecting locations for bike share stations.

Bike share systems in Boston (Hubway), Minnesota (Nice ride), Denver (B-cycle) and Reston (Capital bikeshare) have added bike share stations to low-income neighborhoods even though demand and revenue projections did not support them. Such exceptions can be administered to improve bike share's connection with transit and to support the neighborhoods that need bike share. Suggestions for the same are explained in the "Recommendations" section.

5.1 Recommendations

5.1.1 Density

The bike share should not always be centered around dense neighborhoods, it should be distributed in locations where there is no bus service or near bus stations that serve highly densified neighborhoods. Targeting dense neighborhoods alone to ensure that there is higher usage means that a large section of the population is unserved by this service. Also, when a new mode of transportation is introduced to a region that is already densely populated with short trip lengths, there is a conflict between the two modes of transportation, and thus they tend to act as substitutes to one another rather than working in a complementary fashion. This is also true for block groups with a high count of the population within the age of 18-34, as they are capable of traversing longer distances using a bike. Thus, they tend to act as substitutes rather than compliments to transit.

5.1.2 *Income Category*

Based on the results bike share is an excellent tool for captive riders to access their closest bus routes. It is not always possible to provide bus services that provide access to the entire population. When there are regions that are where the users do not have direct access to transit but would prefer to use transit, bike share can prove to be the first mile and last mile connectivity tool for these users.

5.1.3 *Minority population*

Along with low-income groups, bike share can be largely helpful for block groups with a large number of minority population, as they seem to access transit more than usual once bike share is introduced into their community.

5.1.4 *Trip Distance*

When the average travel distance of the neighborhood is shorter (walk/bike) than usual, bike share helps users to traverse the entire trip with the aid of bike share. This could potentially take riders away from the existing network. However, in regions where the average travel distance is longer than average (drove to work), bike share helps them to change their travel behavior by being part of their daily commute. Thus, by concentrating bike share stations in regions with predominantly long-distance trips, more users can utilize a more sustainable form of transportation.

5.1.5 Cost of travel

Neighborhoods with a higher than average percentage of minorities and lower median age tend to use bike share as a replacement for transit. This finding could be due to the cost of travel if they were to pay for both the service as stand-alone trips. To truly integrate the ride, the payment for both the trips must integrate too, thus making it easier for users to make a more independent decision about using multiple modes of transportations in a single ride.

5.2 Future Research Opportunities

Though there has been an overwhelming amount of work done in the field regarding what the impact of bike share on other modes or vice versa is, there has been very little work regarding how this can be used to alter the users travel experience. One of the significant shortcomings of this thesis was the inability to provide geographical locations that are suitable for modal integration. Because the explanatory variable was quite small, it is impossible to project at future value. However, the same can be rectified by adding more variables that help us to explain bus ridership better.

Along with demographic characteristics of the region, various other factors can be used as well, such as quality of bike paths, proximity to the closest bike station, average number of dockings in the station, etc., No analysis is without fault - to cross-check the results and to improve upon the analysis it would be crucial to expanding upon the analysis using ridership data from other cities in the future.

APPENDIX

Table 14 Stepwise Regression Results

	Coefficients	Std.Error	T-Stat	P-Value
Intercept	-1.61E+05	3.27E+03	-49.128	<0.001
Bike share dummy	3.89E+01	4.26E+00	9.127	<0.001
Year Dummy	7.97E+01	1.62E+00	49.133	<0.001
Gasoline Cost	-5.52E+00	3.75E+00	-1.472	>0.1
Adult Ticket Cost	-5.94E+02	1.52E+01	-39.155	<0.001
Density of Population	9.88E+00	4.29E+00	2.305	<0.05
Male 18 to 34	6.23E-02	3.25E-02	1.919	<0.1
Female 18 to 34	1.87E-01	3.21E-02	5.819	<0.001
Workers	3.98E-01	8.60E-02	4.62	<0.001
Poverty %	2.05E+02	5.81E+01	3.528	<0.001
Employment rate	-1.03E+02	3.17E+01	-3.245	<0.005
Median Age	2.15E+00	4.16E-01	5.17	<0.001
Minority Population Percentage	-7.96E+01	2.68E+01	-2.966	<0.05
Per Capita income	4.46E-04	1.96E-04	2.281	<0.05
Employed	-2.93E-01	8.64E-02	-3.389	<0.001
Households in poverty	-2.13E-01	9.05E-02	-2.356	<0.05
Walk to work	-1.38E-01	4.04E-02	-3.422	<0.001
White	-1.41E-01	2.06E-02	-6.88	<0.001

Table 15 Bidirectional Stepwise Regression with Interaction variables results

	Coefficients	Std.Error	T-Stat	P-Value
Intercept	-1.56E+05	3.43E+03	-45.487	<0.001
Bike share dummy	3.65E+04	1.11E+04	3.271	<0.05
Year Dummy	7.75E+01	1.70E+00	45.488	<0.001
Year Dummy X Bike share	-1.80E+01	5.53E+00	-3.26	<0.05
Gasoline cost X Bike Share	2.57E+01	9.84E+00	2.617	<0.05
Adult Ticket Cost	-4.14E+02	1.69E+01	-24.501	<0.001
Adult Ticket Cost X Bike share	-8.09E+02	3.74E+01	-21.635	<0.001
Density of Population	-9.37E+00	6.12E+00	-1.531	>0.1
Density of Population X Bike share	4.11E+01	1.05E+01	3.929	<0.001
Male 18 to 34	8.87E-02	3.29E-02	2.698	<0.05
Female 18 to 34	2.02E-01	3.48E-02	5.808	<0.001
Female 18 to 34 X Bike share	-2.53E-01	9.48E-02	-2.669	<0.05
Workers	2.00E-01	8.98E-02	2.23	<0.05
Poverty %	4.94E+02	6.87E+01	7.184	<0.001
Poverty % X Bike share	-5.52E+02	1.53E+02	-3.612	<0.001
Employment rate	-7.45E+01	3.40E+01	-2.194	<0.05
Employment rate X Bike share	6.53E+02	1.97E+02	3.319	<0.001
Median Age	1.37E+00	4.40E-01	3.12	<0.05
Median Age X Bike share	1.37E+01	1.56E+00	8.745	<0.001
Minority Population Percentage	-1.19E+02	2.73E+01	-4.381	<0.001
Minority Population Percentage X Bike share	3.52E+02	1.14E+02	3.09	<0.05
Drove to work	-6.66E-02	3.32E-02	-2.005	<0.05
Drove to work X Bike share	5.55E-01	8.70E-02	6.377	<0.001
Percentage with diploma or higher	7.80E+01	4.27E+01	1.826	<0.1
Percentage with diploma or higher X Bike share	-9.68E+01	5.69E+01	-1.702	<0.1
Labor force X Bike share	1.14E+00	2.43E-01	4.677	<0.001
Employed	-1.62E-01	9.13E-02	-1.771	<0.1
Employed X Bike share	-8.72E-01	2.55E-01	-3.425	<0.001
Population	9.81E-02	2.27E-02	4.318	<0.001
Population X Bike share	-5.65E-01	6.35E-02	-8.899	<0.001
Households	1.16E-01	4.65E-02	2.485	<0.05
Households in poverty	-9.66E-01	1.22E-01	-7.921	<0.001
Households in poverty X Bike share	1.44E+00	2.09E-01	6.863	<0.001
Walk to work	-1.22E-01	5.19E-02	-2.344	<0.05
Walk to work X Bike share	3.08E-01	9.48E-02	3.25	<0.05
White	-1.62E-01	2.24E-02	-7.233	<0.001
White X Bike share	1.74E-01	8.00E-02	2.179	<0.05

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