PROFILES, PREFERENCES, AND REACTIONS TO PRICE CHANGES OF BIKESHARE USERS: A COMPREHENSIVE LOOK AT CAPITAL BIKESHARE DATA

by

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ABSTRACT

PROFILES, PREFERENCES, AND REACTIONS TO PRICE CHANGES OF BIKESHARE USERS: A COMPREHENSIVE LOOK AT CAPITAL BIKESHARE DATA

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In the decade since 2007, public bikeshare systems (PBS) have disrupted the landscape of urban transportation systems all over the world. The rapid pace at which urban systems are enduring this disruption due to PBS has left cities and researchers play catch up on understanding various factors impacting the usage and impacts of PBS. Comprehending the profiles and preferences of bikeshare users have a substantial role to play in policy-making, planning and operational management at all bikeshare systems. However, the research is scant related to these factors.

As its first major objective, this research evaluated the impact of pricing on bikeshare ridership and revenue. As a case study, the introduction of single-trip fare (STF) for $2 by Capital Bikeshare (CaBi) was studied. Aggregate analysis results showed that the first-time casual (short-term) users increased by as much as 79% immediately after the introduction of STF. Jurisdiction-level analysis indicated a statistically

significant increase in casual user ridership for identical 12-month periods before and after the introduction of STF. The introduction of STF did not impact ridership and revenues of registered (annual or monthly) members. Casual user revenues before and after the introduction of STF were also compared at the station-level, while controlling for seasonal and weather factors. The results showed a statistically significant increase in ridership and decrease in revenue per ride for casual users after the introduction of STF.

Even though casual bikeshare users account for a large share of revenue, literature provides very little insights about the casual users. As the second major objective of this research, profiles and preferences of bikeshare users (registered members and casual users) were obtained by conducting an intercept survey of CaBi users. Survey findings indicated that, when compared to casual users, registered members are more likely to earn more and are more sensitive to service as reflected by station density. A typical White user has 2.4 times greater odds of being registered member than a user of different race. Analysis also revealed that each additional increase in the number of monthly trips leads to about 18% increase in the odds of the bikeshare user being a registered member.

As the third major objective, this research evaluated price sensitivities and elasticities of bikeshare fare products using monadic design implemented in the survey instrument. Higher household income groups and White users were found to be less sensitive to price compared to other income groups and other races/ethnicities. Pivot-price elasticities revealed that females are about 30% and 10% more price sensitive than males for single-trip fare (STF) and annual membership, respectively. Also, sightseeing

trips are 30% less price sensitive than work trips for STF purchasers. Results from this study would be useful in policy-making, planning and operations for bikeshare systems.

1 INTRODUCTION

Innovative transitions in mobility (e.g., shared mobility services such as ride-hailing, carsharing and bikesharing) and the associated infrastructure shifts have transformed the form, function, and sustainability of urban systems (Venigalla et al. 2018). Dubbed as a "large-scale tactical urbanism" (Marshall, Duvall, & Main 2016), bikesharing is a worldwide disruptive urban transportation phenomenon.

1.1 Motivation

Bikeshare operators routinely explore options to improve ridership and revenue by examining their pricing, service, operations and revenue. The goal of this research is to analyze various factors effecting the ridership and revenue of the public bikeshare systems. The pricing structure and ridership of the bikeshare program in the metro Washington DC region, known as the Capital Bikeshare (CaBi) were studied with the following objectives.

1. Examine the impact of pricing and transit disruptions on bikeshare ridership and revenue through aggregate analysis of ridership and revenue data.
2. Assess the impact of pricing on bikeshare usage and revenue through station-level disaggregate analysis of big data.

3. Study the profiles and preferences of bikesharing members and casual users by analysing data from a user intercept survey.
4. Evaluate service and price sensitivities of bikeshare users through ordered logit regression and monadic design methods.

1.2 Dissertation Organization

This dissertation is a manuscript-style document, where in each chapter primarily addresses a specific research issue in detail. Each chapter begins with an introduction to the problem, leads to the research objective followed by some common sections including literature review, methodology, analysis, results, and conclusions. Chapters 3 through 6 are modified versions of research articles, which are either published in, or currently under peer-review by different high-impact scientific journals. All chapters combined, this dissertation presents a collective body of work related to understanding the profiles, preferences, and reactions to price changes of bikeshare users. The data used in the analyses were obtained from Capital Bikeshare (CaBi), which is the public bikeshare system operating in the Washington DC metro area.

Chapter 2 begins with a brief discussion on evaluation and trends of public bikeshare systems in the past decade all over the world. The chapter synthesizes various findings and sheds light on how the decade-long disruption caused by the introduction of bikeshare into the landscape of urban transportation systems. It also summarizes a list of research studies on user surveys and big data on public bikeshare systems. This chapter concludes with research questions that are answered in the subsequent chapters.

Chapter 3 is a modified version of the paper that examines the impact of introducing new fare (single-trip fare for $2) option by CaBi on bikeshare ridership and revenue. Aggregate ridership and revenue of the identical 12-month periods before and after the introduction of single-trip fare (STF) were analyzed. This chapter also investigates impact of metro works within quarter and half mile radius of bikeshare stations.

Chapter 4 further examines the impact of STF at station-level while controlling for seasonal and weather factors. This chapter evaluates the influence of changes made to bikeshare fare-products by performing disaggregate analysis of system-wide data on revenue and ridership in the Capital Bikeshare system.

Chapter 5 is a self-contained research paper, which inspects profiles and preferences of bikeshare users (registered members as well as casual users) by analyzing the data from an intercept survey conducted at CaBi locations. The primary goal of this chapter is to provide detailed insights on users of the Capital Bikeshare (CaBi) by portraying similarities and differences between casual users and members. This chapter also outlines, compares and contrasts the pricing preferences of both casual users and members of the CaBi system.

Chapter 6 is also a self-contained research paper, which presents the evaluation results of price sensitivities, and pivot-price elasticities of bikeshare fare products (STF and annual membership) using monadic design implemented in the survey instrument. The main objective of this chapter is to examine bikeshare users' sensitivity to changes in price and preferences on service. Additionally, the chapter also presents the results of price elasticities analysis of bikeshare fare products.

Chapter 7 summarizes the findings and major conclusions from the body of work presented in this dissertation. Furthermore, this chapter provides avenues for future research work.

2 BACKGROUND AND RESEARCH OVERVIEW

This chapter synthesizes selective literature related to the decade-long disruption caused by the introduction of bikesharing into the urban ecosystems and how it has changed the dynamics of natural, social, and engineered subsystems through interaction among multiple subsystems and across multiple scales. The main focus of the synthesis is on topics that are relevant to the research questions that are addressed in this dissertation.

2.1 Trends

Shaheen, Guzman & Zhang (2010) reviewed the history of bikesharing and categorized them into four generations. First generation bikesharing started with White Bike plan in Netherlands in 1965. Fifty bicycles were painted in white and left permanently unlocked for the public to use them for free. Similar free bike system was implemented in France in 1974 and U.K. in 1993 under Green Bike scheme. However, these programs were unsuccessful as the majority of the bikes were stolen or damaged. Second generation bikesharing systems have designated docking stations where the bicycles can be locked, borrowed and returned using coin-deposit systems to unlock a bike. These systems were first introduced in 1995 in Europe with 1,100 specially designed bicycles at designated bike racks. Third generation systems use advanced technology to check-in and check-out bikes at various docking stations. These systems are responsible for growth of public bikeshare systems (PBS) all over the world in the past decade. Fourth generation bikesharing involves “dockless” bikes, which offers flexibility to park anywhere and has GPS-enabled lockbox eliminating the need for a docking station (Shaheen et al., 2012). These dockless bikes are expanding rapidly since 2016 in both developing and developed countries due to their low installation and maintenance costs.

2.1.1 Europe

The third-generation bikesharing was launched in Lyon, France’s third largest city in the year 2005 with 1,500 bicycles. Following its success, Velib was launched in Paris in 2007 with 10,000 bicycles at 750 stations (Larsen, 2013). As of 2018, Velib’ Metropole operates with mechanical and electric bicycles that are charged at stations in approximately 60 locations in greater Paris area (Velib, 2018). Netherlands has single nationwide bikesharing program since 2003 called “OV-fiets” with 8,500 bikes in 252 stations spread across the country.

Bicing, the bikesharing program in Barcelona, Spain, was inaugurated in March 2007 with over 6,000 bikes in 424 stations. Bicing introduced a total of 45 electric bicycle stations distributed throughout the city in early 2007 (Bicing, 2018). London bicycle sharing system was launched in July 2010 with 5,000 bikes located across 315 stations, spread at approximately 300 m intervals across 45 km^2 of Central London (Goodman and Cheshire, 2014). Other major bikeshare programs exist in Ireland, Switzerland, Sweden, Norway, Germany, and Denmark.

2.1.2 North America

2.1.2.1 United States

SmartBike was the first IT-based bikesharing program implemented in North America in August 2008 with 120 bicycles at 10 rental locations in Washington, DC. This program was replaced by Capital Bikeshare (CaBi) in late 2010. By August 2018, CaBi has grown to over 4,300 bikes at more than 500 stations spread across the District of Columbia, and the states of Virginia and Maryland. Four large station-based systems, namely, CitiBike in New York City, Divvy in Chicago, Capital Bikeshare in Washington DC and Hubway in Boston generated the vast majority (74%) of the bikeshare trips in 2017 in United States (NACTO, 2017).

In the 8-year period since the city of Denver, CO unveiled Denver B-Cycle in April 2010, which is the first of many modern bikeshare systems (*aka* the 3rd generation bikeshare) in the United States; over 100 PBSs were launched in cities and universities across the United States (GGWASH, 2017). NACTO (2017) reported that between 2010 and 2017, over 123 million bikeshare trips were made in the US. In 2017 alone, bikeshare users made over 37 million trips (up from 28 million in 2016), which far exceeded the 31.7 million annual ridership of entire Amtrak system (Amtrak, 2017), and the number of people visiting Walt Disney World each year (NACTO, 2016). These statistics clearly establish that bikesharing has become a disruptive force in the urban transportation systems in the USA. Despite the availability high quality data on over 100 million individual bikeshare trips in the USA, the role of bikesharing within the context of sustainable urban systems has not been studied at a scale and level of detail necessary for advancing urban systems science.

A report by Mineta Transportation Institute (MTI) classifies public bikesharing business models in North America into non-profit, privately owned and operated, publicly owned and operated, public owned/contractor operated, and vendor operated (Shaheen et al., 2014). There can be an overlap among these operating models due to variations in ownership, administration, and operations. Major bikeshare programs in U.S. including CitiBike, CaBi, Divvy, Hubway have the ‘publicly owned and contractor operated’ business model adapted for their bikeshare system meaning that local government is responsible for funding and administering the system whereas operations are contracted to a private operator.

In addition to station-based ‘dockable’ public bikesharing, more than five major dockless companies (Jump, Limebike, Ofo, Spin etc.) are currently operating in approximately 25 cities and suburbs by the end of 2017. Though dockless bikes account for about 44% of all bikeshare bikes available in the U.S., only 4% of the trips were made on dockless bikes in the U.S. in 2017 (NACTO, 2017).

2.1.2.2 Canada

BIXI was the first bikesharing company in Canada, which was launched in Montreal in 2009. BIXI then expanded to Toronto with 800 bicycles at 80 stations in 2011. As of 2011, BIXI was North America’s largest bikeshare program with 5,050 bicycles at 405 docking stations within an area of 46.5 square kilometers (Fuller et al., 2013). Mobi, the bikeshare system in Vancouver, Canada, was launched in the summer of

2016. Owned and operated by CycleHop, Mobi had 125 stations over 1,200 bikes and 650,000 trips covering over 2 million kilometers by fall 2017. Mobi plans to expand its coverage by installing 500 new bikes at 50 new stations by spring 2018 (City of Vancouver, 2018).

2.1.2.3 Mexico City

Ecobici is Mexico City's PBS which started its operation on February 2010 with 84 bike stations and 1,200 bicycles. By end of 2016, the system has grown to more than 400% due to user's demand with 454 bike stations and 6,000 bikes and more than 100,000 users benefit from this service inside 35 km^2 area (Ecobici, 2018).

2.1.3 Asia

While bikeshare programs have grown rapidly in Europe and North America, their expansion in Asia, except China has been very limited. Mateo-Babiano, Kumar, & Mejia (2017) conducted a survey to determine the difficulties in the implementation of PBS programs in Asia. The survey results showed that majority of the respondents strongly feel that presence of numerous technical, financial, and regulatory barriers deterred the bikeshare execution in Asian cities. Also, lack of cycling infrastructure in Asia limits bikesharing as mode of transportation. The study also recommends updating "Share the road" policies, creating budgetary allocations for non-motorized travel, and including bicycle infrastructure into transportation plans will help in the implementation and usage of PBS in Asia.

2.1.3.1 Singapore

TownBike in Singapore was the first bikeshare program in Asia, which was launched in 1999 that operated until 2007 (Shaheen, Guzman & Zhang, 2010). Singapore-based dockless company oBike has started its services in Singapore with 1,000 bicycles in January 2017. As of 2018, oBike has more than million active users and has expanded to 20 countries (Abdullah, 2018). Other dockless bikesharing companies including Mobike, SGBike, and Ofo have inaugurated their programs in Singapore in 2018.

2.1.3.2 China

Hangzhou, the largest PBS in China, was launched in 2008 with 40,000 bikes and 1,600 stations. Currently Hangzhou has surpassed Velib' as the largest bikeshare program in the world. Hangzhou plans to expand its system to 175,000 bikes by 2020 (Larsen, 2013). Shanghai PBS has over 19,000 bikes in 600 stations and is very popular among tourists. Taiyuan bikeshare expanded from 20,000 to 41,000 bikes in around 1,000 stations since its launch. Other major cities in China with bikeshare program include Wenzhou, Guangzhou, Guilin, Nanning, Shaoxing etc. Mobike and Ofo are two of the biggest Chinese companies in dockless bikesharing market. As of 2017, they have more than 7 million bikes in operation in over 150 cities, mostly in China and are expanding their operations all over the world (Denyer, 2017).

2.1.3.3 Korea

The first bikeshare program in South Korea, known as Nubija, was established in Changwon in 2008 with 3,300 bicycles at 165 stations (Lee et al., 2012). Seoul bikesharing systems emphasize cycling for recreation rather than commuting purpose due to the poor connectivity of the bikepaths throughout the city (Dunbar, 2013). Seoul Metropolitan Government (SMG) launched a bikesharing system in Seoul after constructing bike lanes along the Han River in 2015. Seoul Traffic Vision 2030 states that the capital city would provide free public bicycle service throughout the city and extend the bike paths to public residential areas by end of 2030. Also, this plan aims to expand the public bicycle rental service to enable people to bike anywhere in the city.

2.1.3.4 India

India took its first step into bike sharing in June 2017 with the launch of 450 bicycles located in 48 docking stations around Mysore, a historic city in Southern India (Global Briefs, 2017). PBS is currently available in nine major cities in India and is rapidly expanding to other cities. Mobycy has launched India's first dockless bikesharing in 2017. As of 2018, this system has 700 bicycles in 15 cities and makes 2,000 rides a day (Pant, 2018). Mobike, the Chinese dockless bikesharing company introduced its services with 1,000 bicycles in Pune city in June 2018 (Parekh, 2018).

2.1.4 Other Continents

2.1.4.1 South America

Ecobici bikeshare program in Argentina first opened in 2010 with just 3 stations and 72 bicycles with manually operated bikeshare stations. As of 2015, the system has become more efficient and easier to use with 200 new fully automated stations with 3,000 bikes (ITDP, 2015). Bikesantiago started its services in October 2013 in the metropolitan area of Santiago, capital city of Chile with 30 stations and 300 bicycles. The system has expanded to 132 stations and 1,882 bikes by the end of 2015 and is still in a process of rapid expansion. Public Bike System Company (PBSC) urban solutions has rolled out an initial network of 2,600 bikes in 260 solar powered stations spread across South America's largest city, Sao Paulo in Brazil in January 2018 (PBSC, 2018).

2.1.4.2 Australia

Public bikesharing programs were introduced in two major Australian cities (Brisbane and Melbourne) for the first time in 2010. Both cities have showed low bikeshare usage levels compared to other bikeshare programs around the world. The most influential barriers for such low usage in Australia include motorized travel being too convenient and docking stations not sufficiently close to home and work locations (Fishman et al., 2014).

2.1.4.3 Africa

Morocco's "Medina Bike" program was launched in November 2016 with 300 bikes distributed across 10 stations and is the first known modern bikesharing program to be launched in the African continent. This program was launched by United Nations Industrial Development Organization (UNIDO), which reflects the North African county's policy to combat climate change according to COP22 (Conference of the Parties) (Kirk, 2016). University of Nairobi, Kenya launched its bikeshare program with 20 bicycles in February 2017 funded by UN-Habitat.

2.1.5 Summary

The rapid pace at which urban systems are enduring this disruption due to PBS has left cities and researchers playing catch up on understanding of PBS' impact on social system (mobility, health and economic equity), natural environment and engineered urban systems (transportation network and transit facilities and usage). Furthermore, capital markets are witnessing large investment interests in the bikesharing service providers. For example, recently Washington Post (2018) reported that ride-hailing provider Uber has acquired Jump, an e-bike startup company, for about $100 million and expanded Uber's shared mobility options to bikesharing. Also, Lyft has acquired Motivate, which is the largest private operator of PBSs in the USA, for $250 million (Small, 2018). The full extent of policy implications of such large business initiatives in mobility services is yet to be known. It is conceivable that public bikesharing in the US would eventually play a secondary role to private bikesharing systems. Prior to any such major shift, to effectively address all operational, economic equity, environmental and other policy implications of public and private bikesharing systems at city, state, and national levels, it is imperative that policy makers, practitioners and researchers comprehensively study large amounts of publicly available data on multiple urban bikeshare programs that has been garnered in the last 8-years.

2.2 Discoveries

Shaheen et al. (2014) identified potential benefits of bikesharing as: 1) increased mobility; 2) lower transportation costs; 3) reduced traffic congestion on roads and public transit during peak periods; 4) reduced fuel use; 5) increased use of public transit and alternative modes (e.g., rail, buses, taxis, carsharing, ridesharing); 6) economic development; 7) health benefits; and 8) greater environmental awareness. Discoveries pertaining to bikeshare users, usage and systemic impacts on mobility, human health and social systems, urban systems, sustainability, and scientific methods are summarized in the following section.

2.2.1 User Surveys

For analyzing bikeshare demand and to get a sense of who will use it and at what scale, the Institute for Transport Development and Policy recommends creating profiles of current and potential bikeshare users (ITDP & Gauthier 2013). In this context, bikeshare user surveys play an important role in bikeshare policy-making, planning and operations. National Association of City Transportation Officials (NACTO) even provides a number of bikeshare intercept survey templates to analyze travel behavior of the riders, barriers to bikeshare, demographics, economic impacts, pricing, and perceptions of bikeshare (NACTO, 2018). Table 2.1 represents list of research studies on user surveys on PBS.

Table 2.1: Representative list of research studies on user surveys on PBS

Study	**Public Bikeshare System (PBS)**	**Findings**
Ahillen et al., 2015	DC Capital Bikeshare and Brisbane Citycycle	Providing helmets, reducing subscription fees, and adding flexible subscriptions to users may have contributed to a 50% increase in Citycycle ridership in just six months.
Bachand-Marleau, Lee and El-Geneidy, 2012	Montreal PBS	Bike users who earn <$40,000 per year are 32% less likely to use bikeshare than other income groups and women have about 0.6 times the odds of using the bikeshare.
Braun et al., 2016	Spain PBS	Bicycle commuting has positive connection with access to bikeshare station and negative association with access to public transport stops.

Table 2.1: Representative list of research studies on user surveys on PBS

Study	Public Bikeshare System (PBS)	Findings
Buck et al., 2013	DC Capital Bikeshare	CaBi short term users are more likely to be female and young who have lower household income and use bicycle for utilitarian purpose compared to the area cyclists.
Buehler, 2011	DC Capital Bikeshare	Average CaBi casual user is a well-educated, Caucasian female between the ages of 25 and 34 and a domestic tourist
Campbell et al., 2016	Beijing PBS	E-bikeshare is more tolerant of trip distance, high temperatures, and poor air quality compared to traditional bikeshare system.
Fishman et al., 2014a	Nice Ride Minnesota, Melbourne PBS, DC Capital Bikeshare, London PBS	Overall reduction in motor vehicle use due to bikeshare was observed in Melbourne, Minneapolis, Washington, DC and increase in motor vehicle use in London's bikeshare program.
Fishman et al., 2014b	Australia PBS	Convenience associated with car usage and the inconvenience of docking station are key barriers to bikeshare membership.
Godavarthy and Taleqani, 2017	North Dakota Great Rides Bikeshare	Bikeshare users conveyed their readiness to utilize bikeshare in the winter season when the bike paths and sidewalks could be cleared of snow.
Goodman and Cheshire, 2014	London PBS	Introduction of casual use has encouraged women to use bikeshare and the percentage of income-deprived users doubled as the bikeshare expanded its system to poorer areas
Judrak, 2013	Boston Bluebikes, DC Capital Bikeshare	Registered members exhibit higher cost sensitivity around the 30 and 60-minute pricing boundaries compared to the casual users.
Kaviti et al., 2018	DC Capital Bikeshare	Introducing new fare option (single-trip fare for $2) increased the first-time casual users and casual users' monthly ridership by 79% and 41% respectively.
McNeil et al., 2017	New York Citi Bike, Chicago Divvy, Philadelphia Indego	Low-income bike users who become members through discount membership may use bikeshare as often as white, high income users.
Murphy and Usher, 2012	Dublin's bikeshare	Vast majority of Dublin bike users were male (78%), 58.8% of whom were between 25-36 years of age and about 17.2% of the survey respondents earn <30,000 euros/year.
Ogilvie and Goodman, 2012	London PBS	Registered individuals are more likely to be male, live in low deprivation areas and high cycling prevalence. Females made 1.63 fewer trips per month than males.
Shaheen et al., 2015	Bay Area Bikeshare	Majority of the bikeshare users have a bachelor's degree, an annual household income of $50,000 or more, and are Caucasian.
Wang, Akar and Chen, 2018	New York Citi Bike	Weather related variables, land-use and built environment characteristics have significant effects on the overall bike sharing usage.
Zhang et al., 2016	China's PBS	Expanding the system attracts first time users and extends the ability to reach new areas for existing users.

2.2.2 Effects on Mobility

User surveys indicate that the extent of shift to bikesharing from other transportation modes varies widely across cities. For example, it has been reported that about 35% of Denver B-cycle; 21% of Capital Bikeshare (Washington DC); and 10% of CitiBike (NY City) users make their trips by bikeshare in lieu of an automobile trip (including personal auto, or taxi/Uber/Lyft) (Duvall 2012; Capital Bikeshare 2016; and Campbell & Brakewood 2017).

2.2.3 Impacts on Human Health and Social Systems

Numerous research studies in medical sociology affirm that bicycling decreases obesity rates, lowers body weight, decreases cardiovascular risks, and improves overall health (Bassett et al. 2008; Pucher et al. 2010; Wanner et al. 2012; Matthews et al. 2007; Otero et al. 2018; and Oates et al. 2017). Furthermore, bicycling is also an affordable way to improve community connectivity and livability (Smith 2013). Through many examples like these, it has been established in the literature that the health benefits of bicycling, when combined with a reduction in automobile travel and the near zero carbon footprint of bicycle transportation, demonstrate that bikesharing is a positive force in urban systems.

2.2.4 Sustainability Impacts

Marshall, Duvall, & Main (2016) estimate that in 2015 Denver bike-sharing system alone is responsible for 1.7 million fewer vehicle-miles traveled and 80,000 fewer gallons of gasoline consumed. DDOT (2018) estimated that since its inception in 2010, Capital Bikeshare users "travelled 42 million miles, reduced 28.64 million pounds of carbon dioxide, saved 1.72 million gallons of gasoline, and burned an astonishing 1.8 billion calories". Zhang & Mi (2018) used big data analytics to study the impact of bikesharing on energy use and emissions and estimate that in 2016 bikesharing in Shanghai saved 8,358 tons of gasoline and decreased CO_2 and NO_X emissions by 25,240 and 64 tons, respectively.

2.2.5 Impacts on Science and Analytical Methods

2.2.5.1 Big Data Analytics

Big data analytics may be defined as the convergence of advanced analytical techniques operating on big datasets to uncover hidden patterns or to address salient research questions. A summary of literature from a narrow-perspective of big-data analytical techniques for bikeshare with emphasis on sustainable urban systems is presented Table 2.2.

Table 2.2: Representative list of research studies on big data on public bikeshare systems

Study	**Public Bikeshare System (PBS)**	**Big data analytical technique(s) used**	**Findings**
Bao et al. 2017	New York Citi Bike	K-means clustering, agglomerative hierarchical clustering, DBSCAN	Top trip purposes for New York PBS are eating, shopping, and transfer to other transit systems. People living around bikeshare stations use it for commuting purposes during peak hours.
Biehl et al. 2018	Chicago's Divvy	Generalized linear models	Station-level analysis has superior predictive capability than the community-level analysis.
Campbell and Brakewood (2017)	New York Citi Bike	Ordinary least square regression	Every thousand bikesharing docks along a bus route is associated with a 2.42% fall in bus trips in Manhattan and

Table 2.2: Representative list of research studies on big data on public bikeshare systems

Study	Public Bikeshare System (PBS)	Big data analytical technique(s) used	Findings
			Brooklyn.
Caulfield et al. 2017	Ireland PBS	Multinomial logistic regression	Frequent users have shorter travel times. Number of trips is found to be greater during clear weather conditions.
El-Assi et al. 2017	Toronto's PBS	Multilevel/Linear mixed effects model	Bike ridership has positive correlation with higher temperatures, lower humidity and snow levels, sufficient bicycles and docking stations, proximity to university campuses and transit stations.
Gebhart and Noland 2014	DC Capital Bikeshare	Regression analysis	Fewer trips were made in rain and trips increase with higher temperatures. Metro availability may cause a reduction in cycling trips during rain and chilly weather conditions.
Hyland et al. 2017	Chicago Divvy PBS	K-means clustering; multilevel mixed regression model	Station usage increases with the number of PBS stations within 1-5 km for member trips and 2-8 km for non-member trips.
Ma et al. 2014	DC Capital Bikeshare	Regression analysis, ArcGIS	Metrorail stations are important source of origin and destinations for bike trips and an increase in bike trips would increase transit ridership.
Rixey 2013	DC Capital Bikeshare, Denver B-cycle, NiceRide Minnesota	Regression analysis	Bikeshare ridership has positive correlations to population and retail job density; presence of bikeways; bike, walk, and transit commuters.
Rixey and Prabhakar 2017	DC Capital Bikeshare	Linear regression model	Bikeshare station pairs connected by links with a higher percentage of low-stress facilities are correlated with higher bikeshare ridership
Venigalla et al. 2018	DC Capital Bikeshare	General linear models	Controlled experimental data testing revealed the introduction of a new single-trip fare product resulted in statistically significant increase in casual user ridership and decrease in revenue.
Vogel and Mattfeld 2011	Vienna's Citybike Wien	Time-series modeling, k-means clustering	Stations with similar temporal activity patterns are geographically connected and station activity depends on its location.
Wang et al. 2015	Nice Ride Minnesota	Regression models	Proximity to Central Business District, campuses and parks; access to off-street paths have highest marginal effects on the bikeshare station use.
Zamir et al. 2017	DC Capital Bikeshare	K-means and agglomerative hierarchical clustering algorithms	Most of the bike pickups and drop-offs happen during morning/afternoon peak during weekdays and 41% of the stations are relatively self-balanced during the

Table 2.2: Representative list of research studies on big data on public bikeshare systems

Study	Public Bikeshare System (PBS)	Big data analytical technique(s) used	Findings
			day.
Zhang et al. 2016	Zhongshan PBS, China	Multiple linear regression models	Demand for bike trips is positively correlated with population density, length of bike lanes, and diverse land-use types near the station.
Zhao et al. 2015	China's Jiangning PBS	Z-score, visual analytic techniques, chi-statistic	Residential areas and rail stations are primary sources of bikeshare trip generation and attractions respectively.

2.3 Research Questions

Rather extensive literature survey conducted for this dissertation revealed that there is limited understanding of sensitivities of bikeshare users to price and service. Research that associates bikeshare patronage to rail transit usage and how disruptions to rail service impact bikeshare ridership is scant. Furthermore, research on price elasticities of bikeshare fare products is also scarce. To address these knowledge gaps, the following research questions are addressed in the following chapters.

1. What impact does the introduction of new fare product have on ridership and revenue of public bikeshare systems? Given the concurrency of the launch of new bikeshare fare product with metro works (SafeTrack), how do disruptions to Metrorail service impact the bikeshare ridership?
2. Is there statistically significant change in revenue and ridership at station level (disaggregate analysis) due to the introduction of new fare product at bikeshare systems?

3. How, and in what way the casual (short-term) user is different or similar from the registered (annual or monthly pass) member? What are the pricing preferences of the bikeshare users?
4. Which variables influence the price and service sensitivities of the bikeshare users? What are the price elasticities for different bikeshare fare options available?

Literature that is pertinent to each of these research questions is presented in the respective chapters.

3 IMPACT OF PRICING AND TRANSIT DISRUPTIONS ON BIKESHARE RIDERSHIP AND REVENUE

3.1 Introduction

In recent years, shared mobility services such as Uber, Lyft, Zipcar, and bikesharing systems have been gaining popularity all over the world. These services have become hallmarks of the so-called 'shared economy' and are seen as supporting sustainable transportation goals. A typical public bikesharing program usually has multiple docking stations and allows users to rent and return bicycles at various locations at a fixed-fee. Public bikesharing systems are affordable, convenient and provide a sustainable mode of transportation for short trips. Furthermore, the introduction of information technology has led to the increased awareness and rise in usage of public bikesharing in North America (Shaheen et al. 2013).

The bikeshare program in the metro Washington DC region, known as Capital Bikeshare (CaBi), is a public bikeshare system that operates in the District of Columbia (DC), Northern Virginia and Montgomery County, Maryland with over 470 stations and more than 3,900 bikes (as of September 2017) that continues to grow. CaBi is operated by 'Motivate', a private operator, through a contract with District Department of Transportation (DDOT) and Arlington County Commuter Services. Motivate currently manages some of the largest bikeshare systems in the United States including CitiBike (NewYork City and Jersey City, NJ), Divvy (Chicago), Ford GoBike (San Francisco Bay

Area) etc. CaBi bikes and station equipment are produced by “Public Bike System Company” and “8D technologies”, respectively. The pricing model for the CaBi system consists of a fixed ‘subscription fee’ that provides access to the system and a variable usage fee for rides that exceed 30 minutes.

SafeTrack is an initiative of the Washington Metropolitan Area Transit Authority (WMATA) aimed at addressing safety recommendations and rehabilitate the Metrorail system in the region. Through SafeTrack, WMATA completed three years worth of rail-track maintenance work in less than one year. The program was announced just one month before it started. Given the Washington DC metro region’s dependence on the Metrorail system, various agencies responsible for transit, traffic and transportation operations in the region took many measures aimed at alleviating the adverse impacts of SafeTrack on commuters. In this context, CaBi introduced an experimental single-trip fare (STF) product that allows riders to take a bikeshare trip of up to 30 minutes for $2. Prior to STF, users had the option of purchasing two other casual fare products - a 24-hour pass and a 3-day pass. In addition to alleviating the advese impacts of SafeTrack, the single-trip fare product was also aimed at drawing more people towards bikeshare use.

Additional rationale for the introduction of STF came from the 2014 CaBi member survey report (Capital Bikeshare, 2014). The CaBi membership survey was administered via e-mail request to all registered members and therefore a self-reported sample. (Registered members are those users who purchased monthly or annual membership products). The 2014 CaBi member survey report indicated that 58% of CaBi survey respondents rode Metrorail less often than they used to. Registered members who use CaBi frequently reported the greatest reduction in the use of non-bicycle modes. For example, 70% of respondents who made 11 or more CaBi trips in the month prior to the survey reported that they reduced their use of Metrorail. This compares to 46% of respondents who made one to five CaBi trips in the prior month, which reflects a net additional reduction of 28 percentage points for frequent riders. The survey also revealed that CaBi members would ride more if the system had more bikes and docks available. However, none of the biennial CaBi member surveys conducted thus far addressed the issue of user sensitivity to bikeshare pricing. Furthermore, there is limited research that associates bikeshare patronage to rail transit usage and how disruptions to rail service impact bikeshare ridership.

Using this background, this study aims at addressing the following research questions.

1. What impact does the introduction of the single-trip fare product have on ridership and revenue?
2. Given the concurrency of the launch of single-trip fare with SafeTrack operations, how do disruptions to Metrorail service impact the bikeshare ridership?

3.2 Relevant Studies

Public bikesharing systems have many documented benefits. Buehler and Hamre (2015) observed that users and businesses had monetary and non-monetary benefits from CaBi. The users benefit by reducing their overall travel cost and time. Businesses in the vicinity of bikeshare stations and along bike paths benefit from increased customer traffic. Ricci (2015) studied various benefits of bikeshare and concluded that bikesharing is used as commuting function, to carry out other economic, social, and leisure activities. The advantages of using bikeshare include improved health, increased transport choice, convenience, and improvement in overall travel experience. Also, bikesharing systems can generate economic benefits to users through reduced travel time and costs and improve local economies by connecting people to employment, retail and other places. The linkages between bikeshare and transit have also been explored in the literature. Ma et al. (2014) demonstrated that bike-sharing programs can help increase transit ridership. The analysis showed that Metrorail stations have been the source of important origin and destinations for CaBi trips and concluded that an increase in CaBi trips would also increase transit ridership. Shaheen et al. (2013) analyzed modal shift resulting from individuals participating in bike sharing systems in North America. The study showed decline in bus and rail usage because of bike sharing in Montreal, Toronto, and Washington DC but increased rail usage in the Twin Cities, Minnesota. Martin and Shaheen (2014) observed that bikesharing improves urban mobility and acts as a substitute of public transit in denser cities and ascertained that public bikesharing solves the first-mile / last-mile problem and provides access to and from the public transit system. Bachand et al. (2011) conducted an online survey in the Montreal region to analyze potential integration of bikeshare with transit and observed that facilitating bike parking at transit stops and allowing transit users to bring bicycles on board increased bikeshare ridership. These studies show that bikeshare programs complement or even act as substitute for transit services. In this context, the District Department of Transportation, considers Capital Bikeshare as a transit service (Capital Bikeshare, 2014).

A few studies analyzed the effects of weather conditions on bikeshare ridership. El-Assi et al. (2017) performed analysis on Toronto's bikeshare system and revealed that higher temperature and lower amounts of snow resulted in higher bike ridership. This study also substantiated that public bikeshare stations located near university campuses and transit stations have generally high ridership levels. Gebhart and Noland (2014) analyzed the effect of weather on the Capital Bikeshare system. The results showed that fewer trips are made in rain and trips increase with higher temperatures up through 32 degrees Celsius. This study established that the availability of Metrorail service might cause a reduction in cycling trips during rain and cold weather conditions.

There is very limited research with focus on the impact of bikeshare systems during disruptions to rail service. Pu et al. (2017) analyzed the shift in modal behavior after a WMATA rail service disruption on March 16, 2016. The results showed a 30% increase in bus ridership in downtown DC and CaBi ridership increased by 21%. However, there is no research on the impact of bikeshare ridership during periodic rail service disruptions for shorter or longer duration.

Numerous studies discussed factors affecting the bikeshare ridership but very few of them studied pricing as one of the factors. Ahillen et al. (2016) described metrics which examine neighborhood performance and temporal and spatial ridership trends for Washington, DC's Capital Bikeshare and Brisbane's CityCycle. The study found providing helmets, expanding hours of operation, reducing subscription price and adding stations in suburbs with few or no stations could increase bikeshare ridership. Judrak (2013) studied the time-specific cost structure of the public bikesharing system of Boston and Washington, DC. The study observed that registered users exhibit higher cost sensitivity than casual users and spatial topology does not play a key role in terms of usage patterns of both registered and casual members. There is scant research work on how the change in fare structure affects the bikeshare ridership. Goodman and Cheshire (2014) examined how the profile of users has changed in the first three years of London Bicycle Sharing System (LBSS) using total-population registration and usage data. The findings suggest that percentage of 'deprived' users (those who are in the top tenth nationally for income deprivation) have doubled as the LBSS system expanded to poorer areas. However, a recent increase in price has resulted in reduction in usage of the system for the deprived users.

In summary, the literature review identified scant studies (very limited in number and narrow in focus) that researched how changes in pricing impact bikeshare ridership. Furthermore, no studies on the impact of public bikeshare ridership during major planned or unplanned disruptions to line-haul transit services such as Metrorail were identified. Thus, the research questions of this study address this knowledge-gap.

3.3 Data

The five most popular fare products adopted by CaBi are listed in Table 3.1. It should be reiterated here that, throughout this paper those CaBi riders who have purchased monthly or annual membership are referred to as 'registered' users, whereas those who have purchased a 24-hour pass, 3-day pass or single-trip ride are referred to as ‘casual’ users. All fare products except STF offer unlimited trips for rides under 30-minute duration. If a rider exceeds 30-minutes of bike usage, a usage fee is assessed. The usage fee depends on the duration of the ride and type of fare product purchased.

Table 3.1: Popular fare products offered by CaBi

Pass Type	Subscription fee	Validity
Single-trip	$2	Single-trip under 30 minutes.
24-hour pass	$8	Unlimited trips under 30 minutes valid for a day.
3-day pass	$17	Unlimited trips under 30 minutes valid for 3 days.
Monthly pass	$28	Unlimited trips under 30 minutes valid for a month.
Annual pass	$85	Unlimited trips under 30 minutes valid for a year.

The monthly revenue summaries from January 2015 through May 2017 were obtained from DDOT. The revenue data consists of summaries of subscription and usage fees of registered and casual members, categorized by jurisdiction. CaBi ridership data containing anonymous individual trips (available at http://www.capitalbikeshare.com/trip-history-data) was downloaded for this analysis. The subset of ridership data used for the analysis includes only the trips made during the period June 1, 2015 through May 31, 2017. This subset covers ridership for 12-months ‘before’ and 12-months ‘after’ the introduction of STF in early June 2016. By analyzing data for, and making comparisons over exactly the same 12-month ‘before’ / ‘after’ periods, seasonal variations in ridership trends are minimized. The variables considered for ridership analysis include start- and end-dates of each trip (full time stamp); start-station and end-station; and whether the user is a casual user or registered member. Advanced analysis tools in spreadsheets are used to derive ridership summaries at different levels of aggregation such as daily or monthly or even for specified periods at specified locations. The daily weather data was obtained from Weather Underground, a website which offers historical weather data for different regions. (http://www.weatherunderground.com). Primary variable of interest in the downloaded weather data is whether or not there was precipitation on a given calendar day during the analysis period.

3.4 Methodology

Monthly ridership and revenue were analyzed to study the impact of STF for both registered and casual members. The number of new registrations per dock for before and after STF were compared. Data fusion techniques outlined by Venigalla (2014) were used to conflate weather data with ridership data to identify and adjust for the days in which it rained or snowed. A two-tailed t-test on the means was performed to examine the changes in ridership and revenue after the introduction of the STF. Analysis of variance tests were performed to verify if there is a significant variation in the percentage change in revenue and ridership across jurisdictions and season. Linear regression models were developed to study the impact of daily ridership on temperature and season. Finally, ArcGIS tools were used to examine if SafeTrack surges have an impact on bikeshare ridership at nearby CaBi stations.

3.5 Analyses

The single-trip fare was introduced during the SafeTrack period to provide additional mobility options to commuters during the metro repairs and encourage CaBi ridership. The revenue analysis includes revenues from both registered and casual users for 12-month periods ‘before’ (June 2015-May 2016) and ‘after’ (June 2016-April 2017) the introduction of STF. The new registered and casual members were analyzed on a monthly basis to examine the difference in the number of first-time CaBi users after the launch of STF. Furthermore, monthly ridership was also analyzed to explore the impact of STF on both registered and casual members. The anlyses aggregates data for all four jurisdictions served by CaBi, which include two urban jurisdictions – District of Columbia (DC), Arlington, Virigina (located adjacent to and south of DC); and two suburban jurisdictions – City of Alexandria, Virginia (located southeast of DC) and Montgomery County, Maryland (located northwest of DC).

3.5.1 Normalization and Control for Independent Variables

Concurrent with the availability of STF, a number of other variables could also have an influence on revenue and ridership. Therefore, an attempt was made to control for some of those variables so that the true impact of STF on revenue and ridership can be isolated and measured. As a part of planned CaBi system expansion, from May 2016 to May 2017 the number of docks increased by about 23%. It is to be expected that ridership and revenue would increase with increased system supply. The number of docks was selected as a suitable surrogate for system supply. To account for the change in number of docks, both revenue and ridership data are normalised on a ‘per dock’ basis for each month in the analysis period (total ridership or revenue divided by the number of docks for the considered month). Additionally, by choosing the same 12-month periods for 'before' and 'after' the introduction of STF, differences due to seasonal factors are minimized.

Given the aggregate nature of data, it is difficult to know if the differences in revenue and ridership are attributable to general increase in the awareness and usage of the bikeshare system, or due to the introduction of STF. To control for such 'noise' and background growth due to background factors other than STF, growth rates of new registrations for each calendar month in the 12-month periods 'before' the introduction of STF (June 2014-May 2015 and June 2015-May 2016) were compared to corresponding growth rates 'after' the introduction of STF (June 2016-May 2017). The analyses also included an examination of CaBi ridership using GIS tools during disruptions to the Metrorail service.

3.5.2 New Registrations per Month

Table 3.2 summarizes and Figure 3.1 illustrates the year-over-year calendar month growth in number of first-time users (or new registrations) per dock 'before STF' period (June 2015-May 2016) and one 12-month 'after STF' period (June 2016-May 2017). As seen in Figure 3.1, growth rates for first-time casual users (including single-trip users) are generally positive. The data shown in Table 3.2 indicates that there was an overall increase (summed over the 12-month period) of about 34% before STF (from May 2015 to May 2016). However, the growth in first-time casual members is 79% 'after' the launch of STF, which is more than double the growth for the 12-month period ‘before’ the launch. At the same time, there was a decline in the growth, about -7%, of new registered users for the 12-month period ‘after’ the launch of STF (-3% before STF). These trends may be indicative of STF attracting more people to try CaBi as an alternative mode of transportation.

For 8 of the 12 calendar months (namely, June, Sept, Oct, Nov of 2016, Jan, Feb, Apr and May of 2017), the growth or percentage change in casual users ‘after STF’ is noticeably higher than the corresponding growth recorded for the same month ‘before STF’. For example, for the month of September 2016 (after STF), casual users increased by 56.1% over the casual users in September 2015 (before STF). In comparison, the percent increase for September 2015 over September 2014 (both before STF) was 39.1%. This 17-percentage-point increase in casual members for September month may or may not be attributable to the availability of the STF product in September 2016. However, there was a decrease of about 10.9% registered members for September 2016 (after STF) when compared to September 2015 (before STF). This change in registered members compares to a corresponding 2% increase for September 2015 over September 2014 (both before STF).

Furthermore, for 11 of the 12 months ‘after’ the introduction of STF, casual members registered a positive growth. Only March 2017 (after STF) showed a decline in casual users when compared to March 2016 (before STF). This may be attributable to the unusually cold weather for many days in March 2017. In contrast, positive growth was noted only for five of the 12-months ‘after’ the introduction of STF in new registered members. Also, after the introduction of STF growth rate for casual members for any calendar month is generally higher than the comparable month growth rate for registered users.

A paired t-test (one-tailed) of the calendar month growth rates before STF and after STF indicated that the growth rate in casual users was positive and was significantly higher after the introduction of STF ($t = 1.69$, $p < 0.1$). On the other hand, the paired t-test on calendar month growth rates in registered members 'before' and 'after' STF was inconclusive ($t = 0.60$, $p = 0.72$). The combination of these observations provides additional credibility to the hypothesis that the introduction of STF has led to statistically significant growth in number of first time casual users. However, the analysis is inconclusive on whether or not the growth in new registered members is impacted by the introduction of STF.

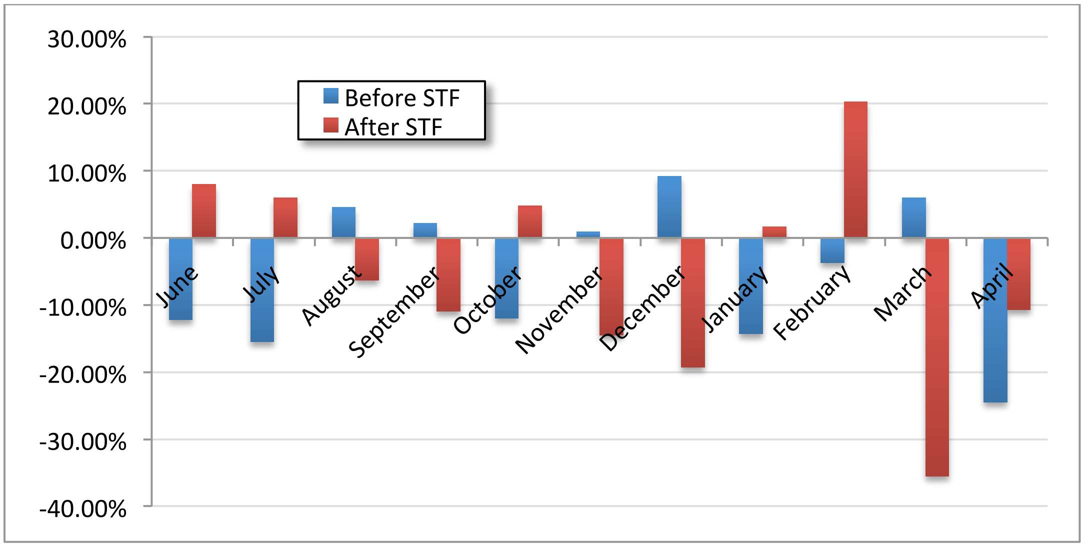
Table 3.2: New registrations per month before and after the introduction of STF

	New Registrations Per Dock				Year-Over-Year Growth Rate for the Specified Month / Period		
	2014	2015	2016	2017	2014 - 2015	2015 - 2016	2016 - 2017
	Registered Members						
January	-	0.2096	0.1797	0.1827	-	-14.3%	**1.7%**
February	-	0.1861	0.1793	0.2157	-	-3.7%	**20.3%**
March	-	0.4671	0.4949	0.3193	-	6.0%	-35.5%
April	-	0.7953	0.6004	0.5362	-	-24.5%	-10.7%
May	-	0.6350	0.7588	0.5671	-	19.5%	-25.3%
June	0.6534	0.5739	0.6196	-	-12.2%	**8.0%**	-
July	0.5767	0.4871	0.5161	-	-15.5%	**6.0%**	-
August	0.5836	0.6102	0.5716	-	4.6%	-6.3%	-
September	0.6323	0.6460	0.5758	-	2.2%	-10.9%	-
October	0.4589	0.4041	0.4235	-	-12.0%	**4.8%**	-

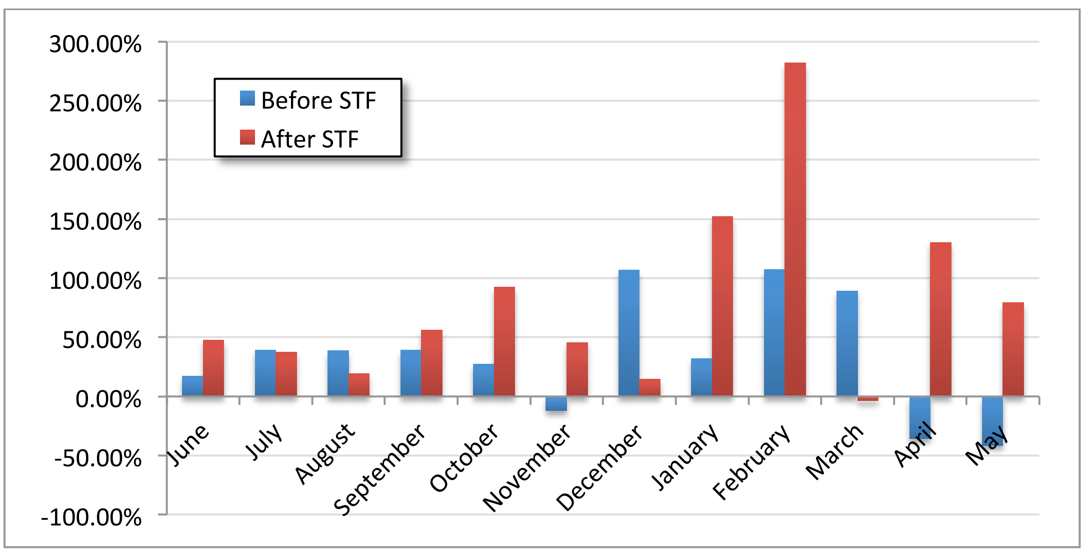
Table 3.2: New registrations per month before and after the introduction of STF

November	0.2596	0.2619	0.2240	-	0.9%	-14.5%	-
December	0.1587	0.1733	0.1399	-	9.2%	-19.3%	-
Winter Months	0.2091	0.2077	0.1807	0.1992	-0.7%	-13.0%	10.2%
Non-winter Months	0.5810	0.5774	0.5701	0.4742	-0.6%	-1.3%	-16.8%
Yearly	0.4747	0.4541	0.4403	0.3642	-3.26%	-4.10%	-9.90%
Year-Over-Year Growth Rate Before STF and After STF				Before STF (June 2015 to May 2016): -3.32%		After STF (June 2016 to May 2017): -6.81%	
	Casual Members						
January	-	0.6833	0.9036	2.2766	-	32.2%	**152.0%**
February	-	0.5215	1.0824	4.1360	-	107.5%	**282.1%**
March	-	2.4989	4.7267	4.5523	-	89.2%	-3.7%
April	-	6.9028	4.4489	10.2410	-	-35.6%	**130.2%**
May	-	7.4652	4.3757	7.8517	-	-41.4%	**79.4%**
June	4.3801	5.1313	7.5817	-	17.2%	**47.8%**	-
July	5.1805	7.2217	9.9320	-	39.4%	37.5%	-
August	4.7973	6.6477	7.9321	-	38.6%	19.3%	-
September	3.5500	4.9386	7.7094	-	39.1%	**56.1%**	-
October	2.9582	3.7635	7.2444	-	27.2%	**92.5%**	-
November	2.8155	2.4775	3.6012	-	-12.0%	**45.4%**	-
December	0.8470	1.7509	2.0045	-	106.7%	14.5%	-
Winter Months	1.8312	1.3583	1.8979	3.2063	-25.8%	39.7%	68.9%
Non-winter Months	4.1732	5.5712	6.7439	7.5483	33.5%	21.1%	11.9%
Yearly	3.504	4.166	5.128	5.81152	36.60%	38.75%	128%
Year-Over-Year Growth Rates Before STF and After STF				Before STF (June 2015 to May 2016): 34.01%		After STF (June 2016 to May 2017): 79.43%	

- Shaded cells represent months or periods 'after' the launch of STF.
- Negative growth rates are highlighted in red.
- Boldface emphasis indicates that Y-O-Y growth rate for 'after STF' is higher than growth rate for 'before STF'



(a) Registered Members

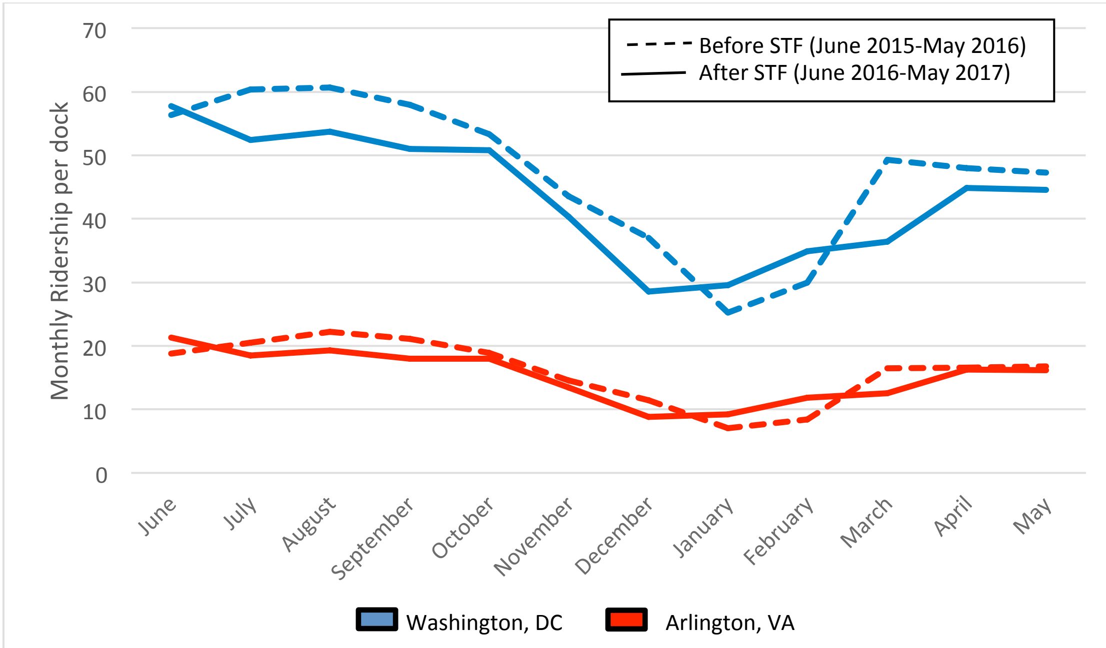


(b) Casual Users

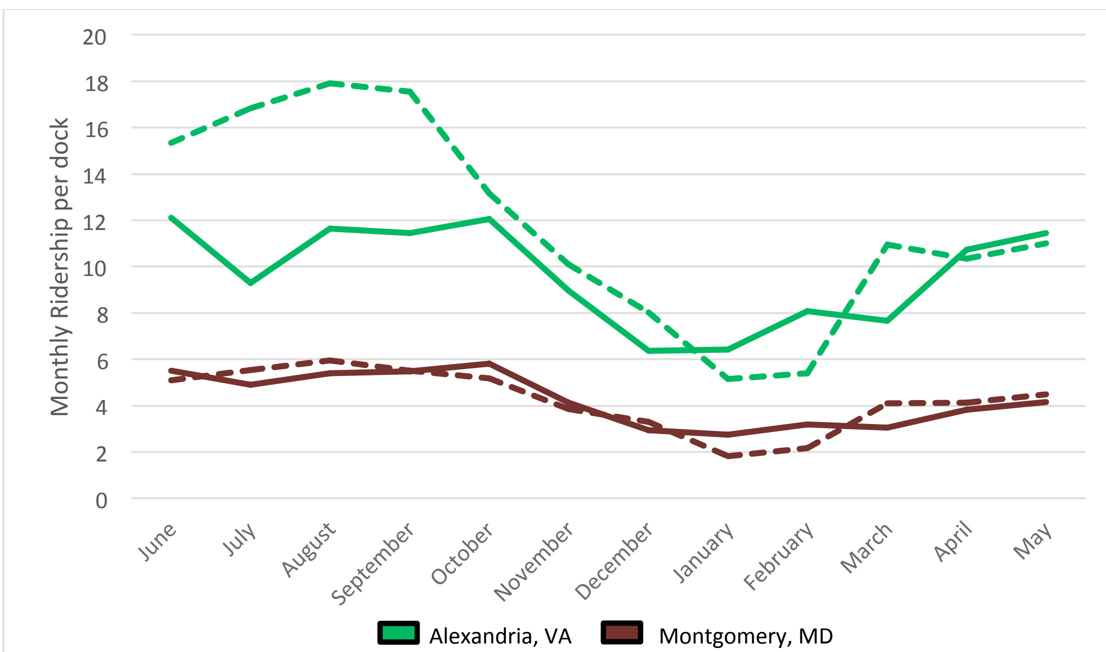
Figure 3.1: Percentage growth in new members per dock before and after the introduction of STF

3.5.3 Monthly Ridership

Monthly ridership for each jurisdiction was computed by aggregating monthly trips by user-type (casual or registered) originating at all CaBi stations located in the jurisdiction and then dividing those aggregate trips by the number of docks in the jurisdiction for that month. Figure 3.2 shows monthly ridership of the registered users 'before' and 'after' the introduction of STF. As indicated earlier, for most months in the analysis period, the launch of STF corresponds with a notable decrease in the number of registered members. However, the monthly ridership levels by registered users do not provide any visible evidence of the impact of single-trip fare. Monthly ridership of the registered members in Montgomery County showed an overall increase of 4% after STF. There was a general decline in the registered member ridership for District of Columbia (DC), Arlington, and Alexandria 'after' the STF launch.



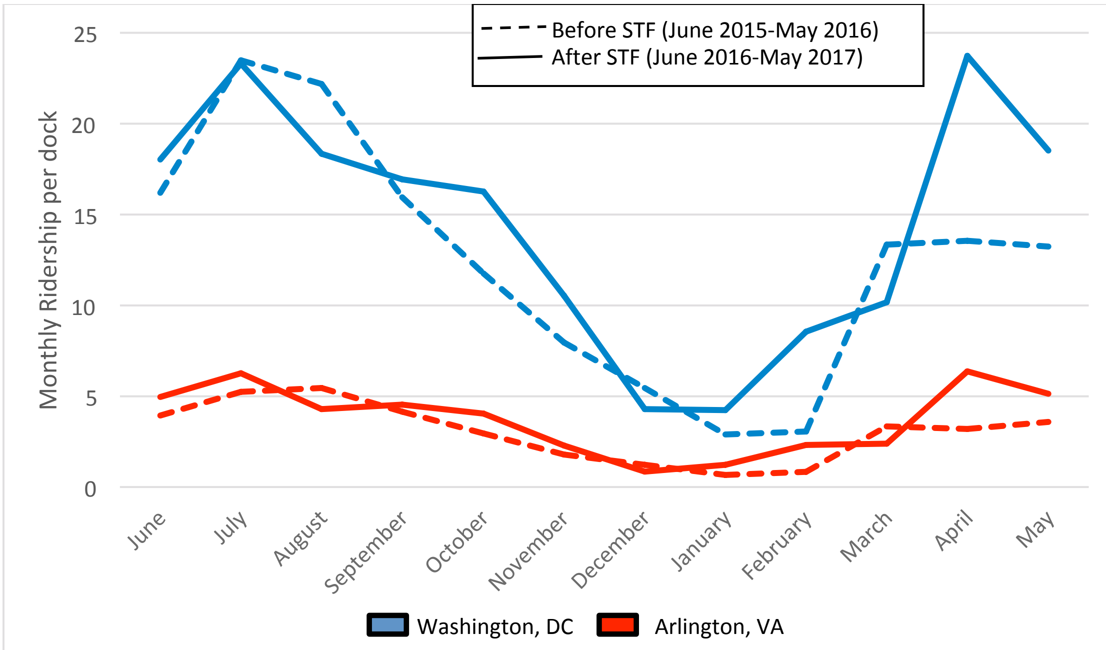
(a) Urban Jurisdictions



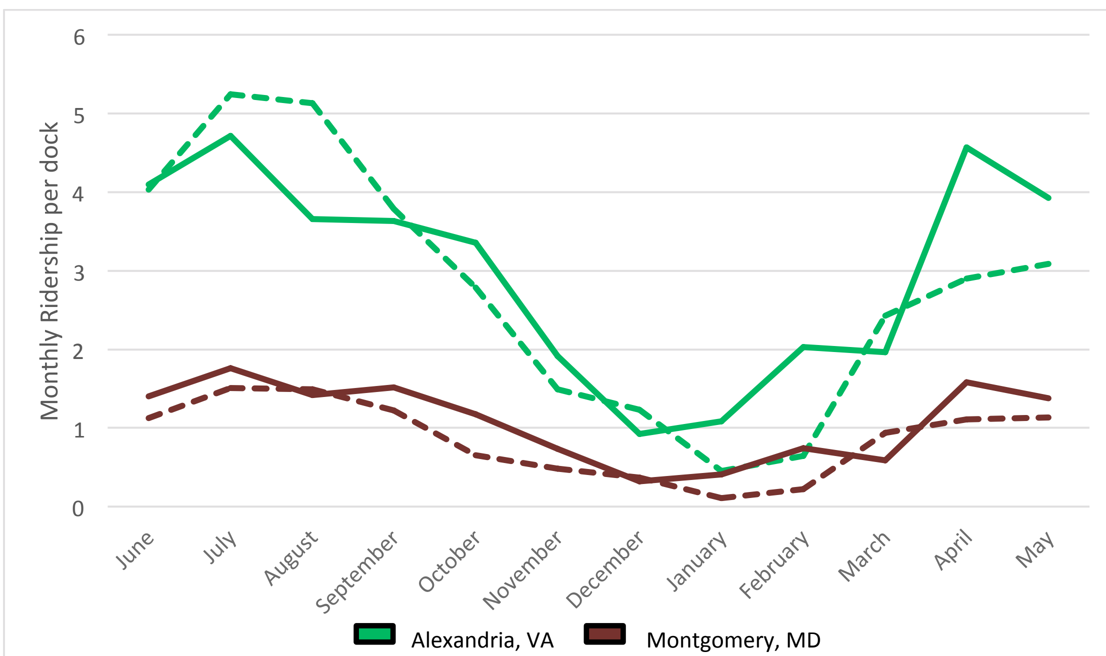
(b) Suburban Jurisdictions

Figure 3.2: Monthly ridership of the registered users before and after the introduction of STF

The monthly ridership of casual users 'before' and 'after' the introduction of STF is illustrated in Figure 3.3. In contrast to the lack of any obvious trend in ridership of registered members, an increase in the ridership levels for casual members is discernible 'after' the launch of STF. An increase in the monthly casual user ridership can be seen in the urban jurisdictions – DC and Arlington County – by about 31% and 37%, respectively. Casual-user ridership in Alexandria and Montgomery County is seen to increase by about 34% and 61%, respectively. For all jurisdictions combined, the monthly increase in ridership by casual users 'after' the introduction of STF was about 41%. The National Cherry Blossom Festival (NCBF), which is normally held during late March and early April of every year, attracts more than 1.5 million visitors to DC and Arlington (NCBF, 2018). Considerably large increase in casual user ridership is noted during the NCBF days in April 2017 over the NCBF days in Mach 2016. This increase may be due to the combined effect of STF product availability during NCBF. However, further analysis is required to analyze the impact of weather and special events such as NCBF on the ridership levels of both casual and registered users.



(a) Urban Jurisdictions

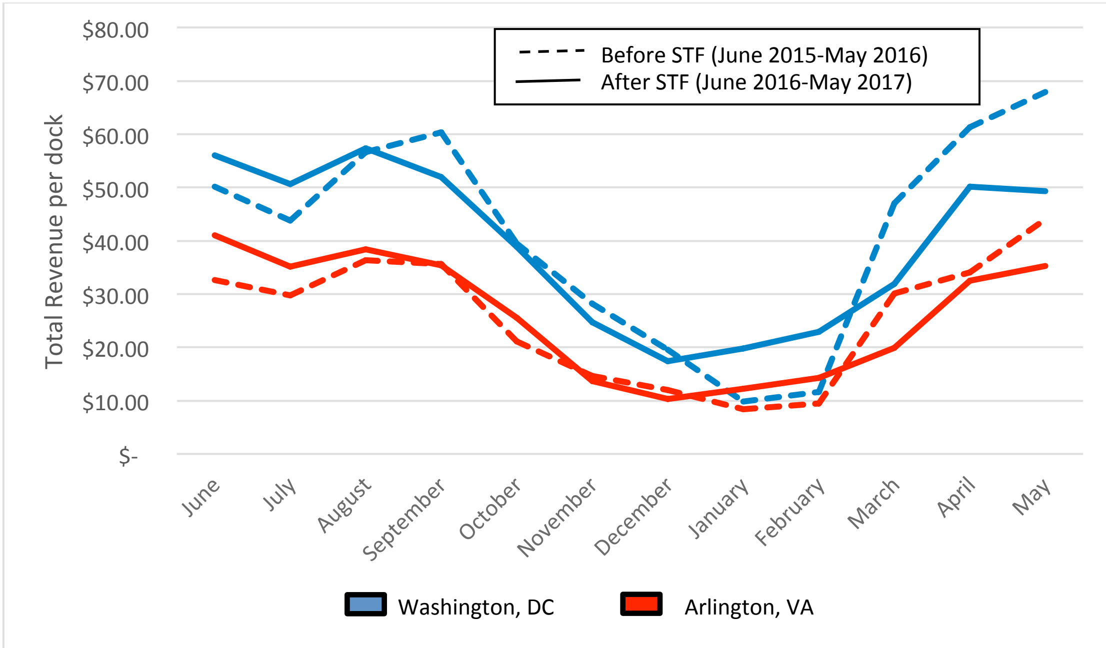


(b) Suburban Jurisdictions

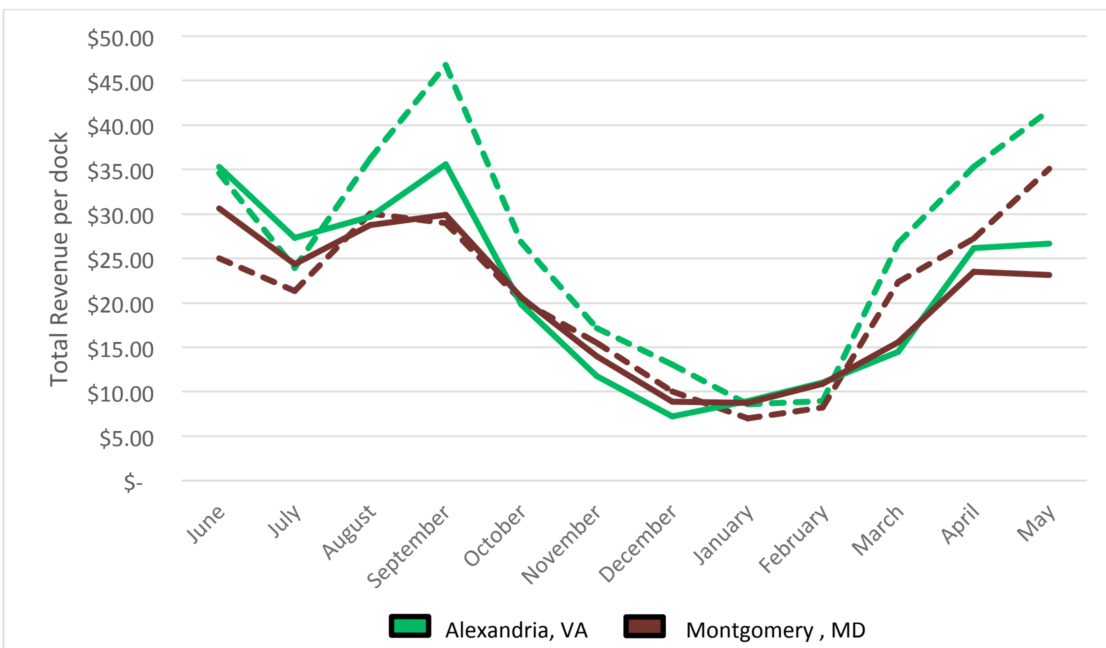
Figure 3.3: Monthly ridership of casual users before and after the introduction of STF

3.5.4 Revenue Analysis

The revenue data were also analyzed at the individual jurisdiction-level to examine the impact of STF launch on revenues. Figure 3.4 shows total revenue from registered members before and after the introduction of STF for all CaBi jurisdictions. The percentage increase in the revenue after STF from registered members for DC and Arlington is about 9% and 7%, respectively. DC showed the maximum percentage increase in the total revenue of the registered users compared to other CaBi jurisdictions. This trend may be due to the fact that both DC and Arlington are densely populated, have the highest concentrations of jobs and the most work trips made by bikeshare in the region. During the analysis period, the number of CaBi stations has more than doubled for Alexandria, which led to the decrease in the overall revenue by about 17% (on a per-dock basis). This decrease may be because of the fewer users from the new CaBi stations installed in Alexandria. Montgomery County showed little change in overall revenue after the introduction of STF.



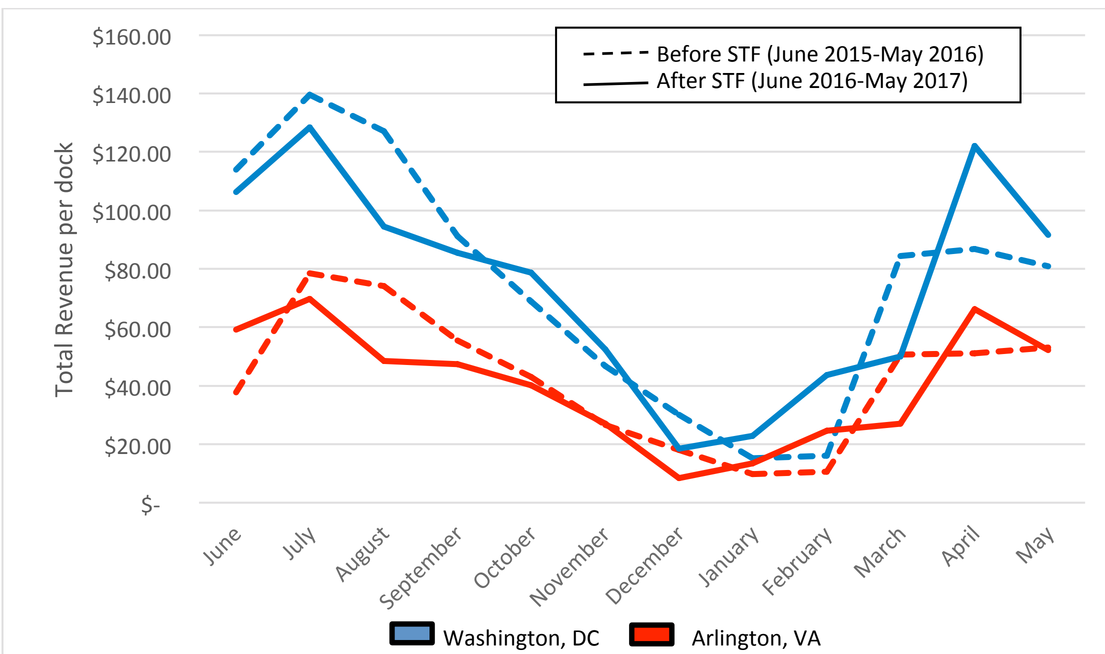
(a) Urban Jurisdictions



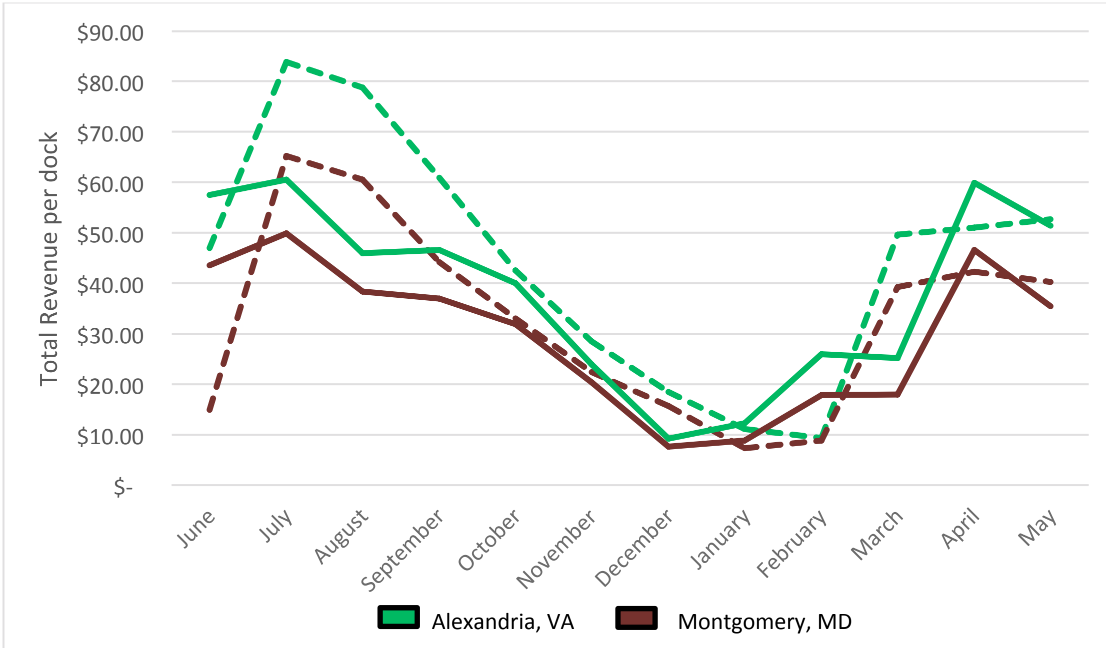
(b) Suburban Jurisdictions

Figure 3.4: Total revenue of the registered users before and after the introduction of STF

The total revenue from casual users before and after the introduction of STF for all jurisdictions is shown in Figure 3.5. The overall revenue from casual members does not follow a pattern after the STF launch. The urban jurisdictions, DC and Arlington, showed an overall increase in total revenue of approximately 19% and 12%, respectively. The revenue growth for the suburban jurisdictions, Alexandria and Montgomery County, was about 5% and 16%, respectively. Casual users accounted for a 13% growth in revenue (across all jurisdictions) after launching the STF.



(a) Urban Jurisdictions



(b) Suburban Jurisdictions

Figure 3.5: Total revenue of the casual users before and after the introduction of STF

Unlike the analysis of new monthly registrations, percent changes (or growth rates) in revenue for each calendar month 'after STF' could not be compared to the growth rates in the same month 'before STF' due to unavailability of data for June-Dec 2014. Therefore, it could not be established if the modest increases observed in revenues after the introduction of STF are in fact attributable to the introduction of STF. More in-depth analysis of revenue data is needed to ascertain the impact of STF on revenue. For example, disaggregate analysis of revenue and ridership from each type of casual users (those who purchased 24-hour pass, 3-day pass and STF) at individual station may provide more insights on true impact of STF on revenue than the aggregate analysis at jurisdiction level. Given this, the analysis about the impact of STF on revenue from casual users at the jurisdiction-level for the identical 12-month periods before and after STF is inconclusive.

3.5.5 Sample Means

A two-sample t-test on the means indicates that there is a significant increase in daily ridership (combined registered and casual users) 'after' the introduction of STF ($t = 3.93$, $p < 0.05$). However, t-tests do not show any significant increase in monthly ridership ($t = 0.93$, $p = 0.18$), monthly revenue ($t = 0.35$, $p = 0.63$) or daily revenue ($t = 0.36$, $p = 0.36$) 'after' the introduction of STF. Also, the t-tests showed a significant decrease in the daily revenue from 24-hour pass ($t = 6.135$, $p < 0.05$) and 3-day pass type ($t = 6.54$, $p < 0.05$) after the introduction of STF.

3.5.6 Analysis of Variance

Analysis of variance is performed on the effect of STF on change in revenue and ridership. The set of independent class variables used in the analysis includes jurisdiction, season considered, and CaBi membership type. Season is a dummy variable representing winter months (November through February as 0) and non-winter months (March through October as 1). The results showed that there is significant variation in the percentage change in revenue and ridership between jurisdictions and season. The results also showed that there is a significant variation in the percentage change in ridership based on the bikeshare membership type. The model variables and their parameters are listed in Table 3.3.

Table 3.3: Analysis of variance for change in revenue and ridership due to STF

Variable	Degrees of freedom	Sum of Squares	Mean Squares	F value	Prob (>F)
	Model 1: Monthly revenue percentage change				
Jurisdiction	3	3.675	1.225	3.614	**0.017633**
Season (Winter=0, Non-winter=1)	1	4.347	4.347	12.825	**0.000648**
Membership type	1	0.198	0.198	0.585	0.447046
Residuals	66	22.372	0.339		
	Model 2: Monthly ridership percentage change				
Jurisdiction	3	9.15	3.049	6.702	**0.000421**
Season (Winter=0, Non-winter=1)	1	10.16	10.156	22.327	**9.40E-06**
Membership type	1	7.52	7.521	16.534	**0.000109**
Residuals	82	37.3	0.455		

- Season (Winter=0, Non-winter=1): Winter months (November-February=0) and non-winter months (March-October=1)
- Membership type: Registered members (0) or Casual users (1)
- Boldfaced values indicate that the variable effect is significant on percent change in revenue or ridership due to the introduction of STF

3.5.7 Regression Analysis

A paired t-test of the calendar month growth rates discussed in the earlier analyses established that the launch of STF has resulted in positive growth rate for the casual users and has no measurable impact on the registered members. Also, the analysis is inconclusive on the impact of STF on revenue. While the above ridership analyses was controlled for number of docks, seasonality and background variations, other variables such as temperature, day of the week, and whether or not it is winter season may have an impact on ridership and revenue. To study the impact of these variables and develop models for predicting ridership, linear regression models were developed as a function of the aforementioned explanatory variables. The dataset used for this analysis includes daily trips from June 1, 2015 to May 31, 2017. The dummy explanatory variable set in the analyses includes: before or after STF; weekday or weekend; and season (November through February as winter months and March through October as non-winter months). After testing numerous models, a daily ridership model is proposed for its ability to explain variation in and estimating the daily ridership for given conditions. The model's variables and their parameters are listed in Table 3.4.

The positive sign for average temperature coefficient indicates its positive correlation with ridership. As would be expected, average precipitation negatively impacts daily ridership, which is evidenced by the negative coefficient for precipitation. The positive value of the coefficient for dummy variable STF (where 1 indicates 'after STF') is indicative of a positive impact of STF on daily ridership. Similarly, the positive value for the variable 'season' indicates higher ridership during the non-winter months than during the winter months. Lastly, daily ridership on a weekday is evidently higher than the weekend ridership (positive dummy variable coefficient).

Table 3.4: Regression model for daily ridership

Response Variable: Daily ridership (in 1000's)	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	4.118049	0.179373	22.958	**< 2e-16**
Average temperature (^{0}C)	0.205141	0.009608	21.351	**< 2e-16**
Precipitation (mm)	-3.71354	0.229576	-16.176	**< 2e-16**
Day of the week (Weekday=1/Weekend=0)	0.8911	0.143495	6.21	**8.95E-10**
STF (Before STF=0; After STF=1)	0.67606	0.129425	5.224	**2.30E-07**
Season (Winter=0, Non-winter=1)	1.809828	0.185406	9.761	**< 2e-16**
Multiple R-squared: 0.711		Adjusted R-squared: 0.709		
Note: Significant independent variables labeled in bold				

3.6 Effect of SafeTrack on Ridership

Zhu et al. (2017) noted that the SafeTrack maintenance work has compelled the regular metro riders to look for alternatives like bikeshare and metro bus. Also, it was noted earlier in this paper that STF was launched in conjunction with the announcement of 'SafeTrack surge' schedule. A 'surge' is essentially the period in which maintenance work is performed on a 24-hour basis at the specified section(s) of the Metrorail track while shutting down rail transit operations at the affected metro stations. This study made an attempt to measure whether or not SafeTrack surges have an impact on bikeshare ridership at nearby CaBi stations. The SafeTrack maintenance was planned in sixteen surges but only nine surges with proximity to bikeshare stations were considered for this analysis. The schedule for all nine SafeTrack surges and the metro stations affected are shown in Table 3.5.

Table 3.5: SafeTrack maintenance schedule

Surge #	Duration	Metro stations affected
Surge 1	June 4 –16, 2016	East Falls Church to Ballston
Surge 2	June 18 – 3, 2016	Eastern Market to Minnesota Ave and Benning Road
Surge 3	July 5 –11, 2016	National Airport to Braddock Road
Surge 4	July 12 – 18, 2016	Pentagon City to National Airport
Surge 5	July 20 – 31, 2016	East Falls Church to Ballston
Surge 6	August 1 – 7, 2017	Takoma to Silver Spring
Surge 7	August 9 –21, 2016	Shady Grove to Twinbrook
Surge 8	Oct 29 - Nov 22, 2016	Fort Totten to NoMa
Surge 9	February 11 – 28, 2017	Rosslyn to Pentagon

Metro stations under maintenance were grouped based on the SafeTrack schedule for Surge 1 to Surge 9. Using the Geographic Information System (GIS) tools, CaBi stations falling within the 0.25- and 0.50-mile radii of those Metro stations were isolated for SafeTrack impact analysis (Venigalla 1996; Venigalla and Baik 2007; Venigalla and Casey 2006). The purpose of this analysis is to examine the impact of each surge on daily ridership at CaBi staitons inside the specified buffers. Figure 3.6 illustrates the process of selecting CaBi stations within 0.50-mile radii of Metro stations impacted by SafeTrack surges. Metro stations that are affected by SafeTrack but do not have any CaBi stations located within the 0.50-mile radius were ignored in the analysis. It should be pointed out that very few bikeshare stations exist near the Surge 7 location and therefore data shows very low ridership levels for Surge 7

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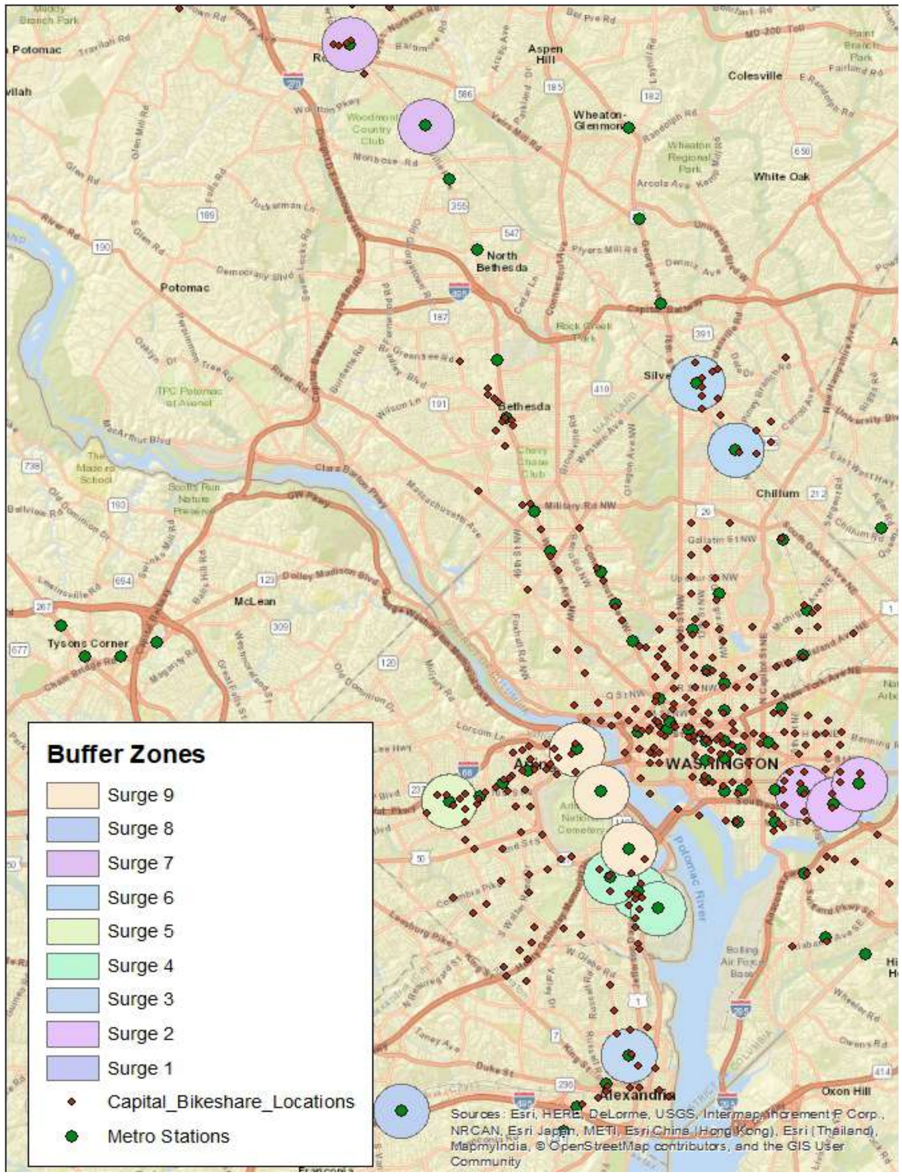
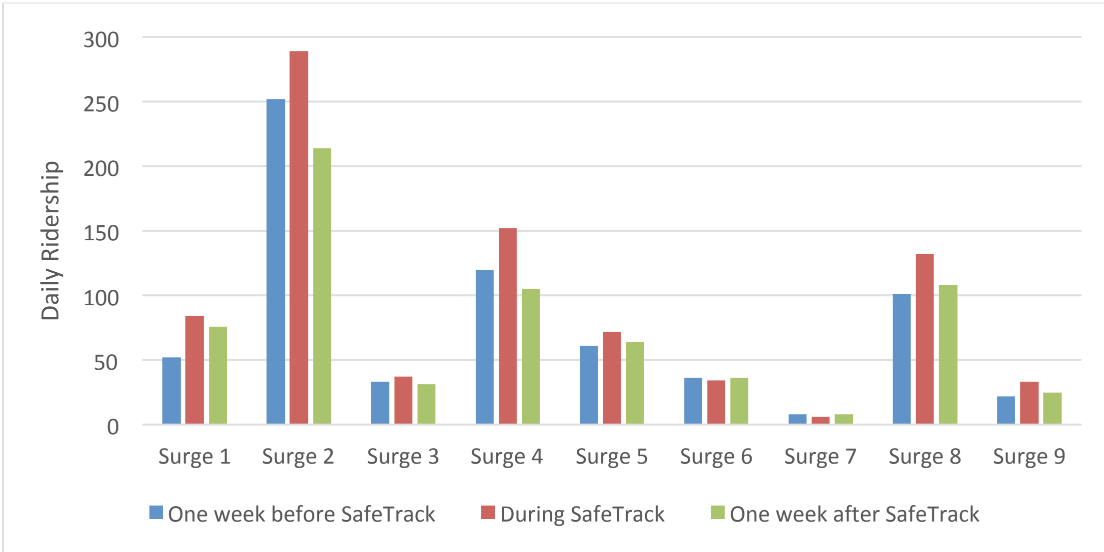


Figure 3.6: CaBi stations within 0.5-mile radius of metro stations impacted by SafeTrack

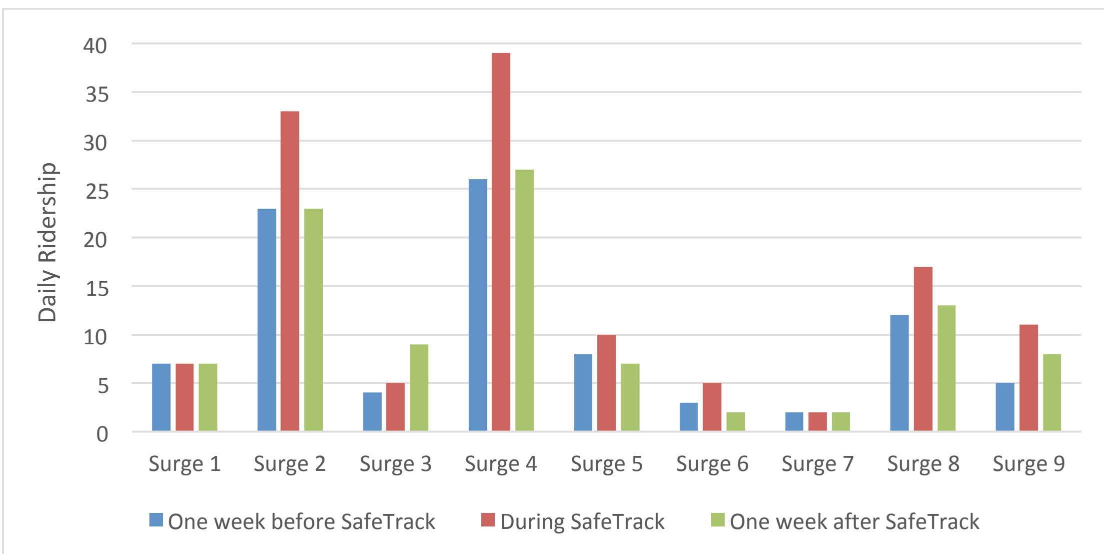
The SafeTrack impact analysis includes three time periods: 1) one week before the surge; 2) during the surge (usually one week); and 3) one week after the surge. To control for the impact of adverse weather events on bikeshare ridership, data for only those days with no precipitation and only weekdays were included in the analysis.

Comparisons were made among trips (both registered and casual users) made ‘before’, ‘during’ and ‘after’ each SafeTrack surge.

The daily bikeshare ridership trends at CaBi stations impacted by SafeTrack during, before and after SafeTrack for 0.25- and 0.5-mile buffers are illustrated in Figure 3.7 and Figure 3.8, respectively. It can be seen from Figure 3.7 that there is a noticeable increase in daily CaBi ridership during SafeTrack for both registered and casual members for the CaBi stations inside the 0.25-mile buffer. In this case, the aggregate percentage increase in CaBi ridership for registered users and casual users during SafeTrack was approximately 19.93% and 40.43%, respectively. In other words, the aggregate bikeshare ridership of casual members increased more than twice the increase seen for the registered members due to SafeTrack. However, it cannot be known for certain if this large difference is attributable to the availability of the new STF product or simply to the availability of all casual use fare products for bikeshare users. The aggregate percentage increase in ridership affected by the SafeTrack one week after the surge when compared to the ridership one week before the surge period for registered and casual users was about 4% and 18%, respectively. This consistent increase in ridership for all surges is somewhat indicative of the possibility of SafeTrack surges playing a role in attracting new bikeshare users (registered and casual) at bikeshare stations with the 0.25-mile buffer. But the increase is notably minor compared to the increase in ridership levels during the SafeTrack period.



(a) Registered Users

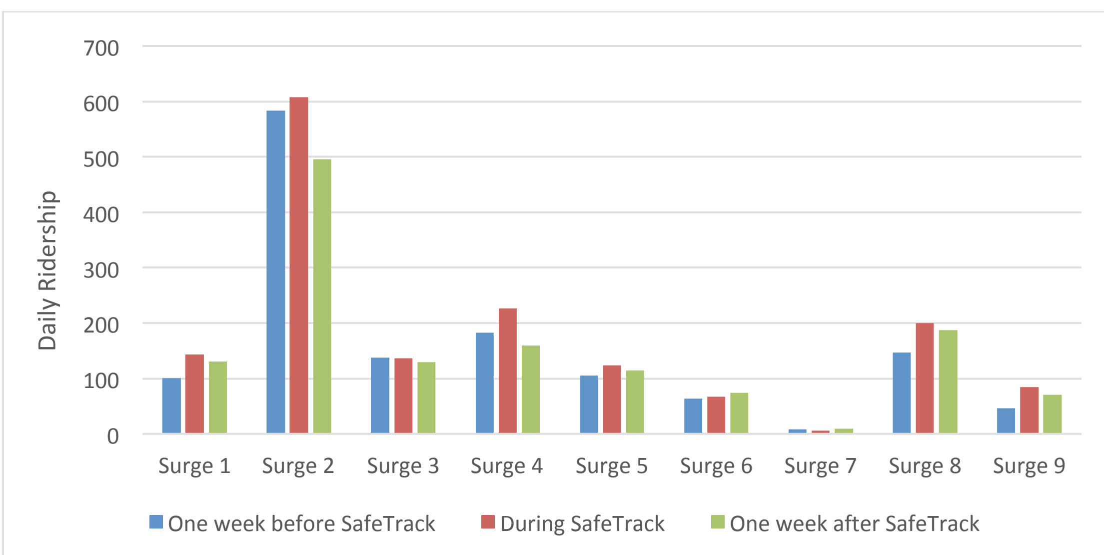


(b) Casual Users

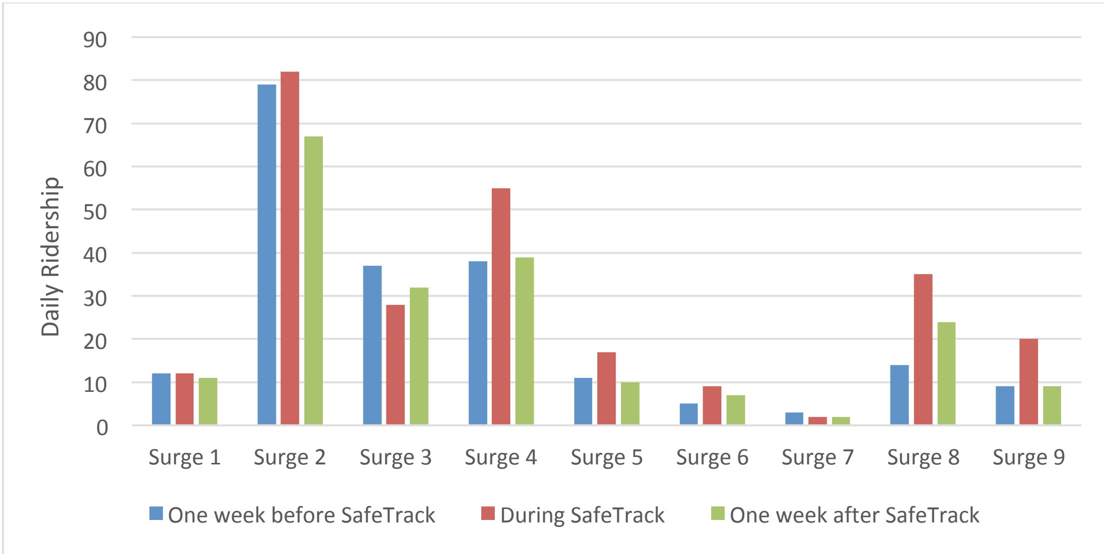
Figure 3.7: Daily ridership at CaBi stations within 0.25-mile radius of SafeTrack Metrorail stations

Figure 3.8 shows daily ridership of CaBi stations during, before and after SafeTrack at CaBi stations within the 0.5-mile buffer. The reason for considering 0.5-

mile buffer in addition to the 0.25-mile buffer is that any person would be willing to walk up to a maximum distance of 0.5-mile to get to the bikeshare station. In this case also there is a noticeable increase in the daily bikeshare ridership (for both registered and casual users) during SafeTrack. The overall increase in CaBi ridership inside the 0.5-mile buffer for registered users and casual users during the surge period was found to be about 20.2% and 42.6%, respectively. However, the increase in the CaBi ridership inside the 0.5-mile buffer appears to have not sustained after the track repairs were completed. Furthermore, one week after the SafeTrack surge, the ridership declined to levels seen just before the surge (in some cases even lower) indicating that SafeTrack surges may have driven more people to use CaBi until the track maintenance works were completed and return back to regular mode of transport after the works were finished.



(a) Registered Users



(b) Casual Users

Figure 3.8: Daily ridership at CaBi stations within 0.5-mile radius of SafeTrack Metrorail stations

A two-sample t-test was employed to test whether the daily ridership during SafeTrack surges are significantly different from the ridership recorded one week before SafeTrack surges. Results of the tests for the 0.25-mile radius show that CaBi ridership during SafeTrack surges is significantly more than the ridership before SafeTrack surges for registered users ($t = 1.92$, $p < 0.05$) as well as for casual users ($t = 2.12$, $p < 0.05$). However, the ridership levels after the SafeTrack surges do not show a significant increase with respect to ridership before the surges for both registered members ($t = 0.74$, $p = 0.77$) and casual users ($t = 1.01$, $p = 0.84$). This analysis supports the hypothesis that planned disruptions to Metrorail service would increase CaBi ridership. It also confirms the finding in the 2016 CaBi Member survey report, which showed that around 33% of survey respondents increased their use of bikeshare since Metro's SafeTrack began in June 2016 (Capital Bikeshare, 2016).

The analysis for the 0.5-mile buffer shows that the ridership during SafeTrack is significantly more than the ridership before SafeTrack for registered users ($t = 2.29$, $p < 0.05$) and casual users ($t = 2.32$, $p < 0.05$). However, the ridership levels after the SafeTrack surges do not show a significant increase with respect to ridership before the surges for both registered members ($t = 1.74$, $p = 0.95$) and casual users ($t = 1.33$, $p = 0.90$) for the 0.5-mile buffer.

This SafeTrack impact analysis on bikeshare ridership may be summarized in noting that disruptions to Metrorail services would increase ridership at the bikeshare stations within 0.5-mile radius of the affected Metrorail stations. However, there is no evidence that the increase in bikeshare ridership was sustained. One of the factors that may have contributed to this shift in modal usage from Metrorail to bikeshare is the availability of bike corrals (stations with dedicated attendants) during the SafeTrack periods.

3.7 Conclusion and Discussion

This research shows that introduction of a single-trip fare (STF) product can result in major changes to revenue and ridership as experienced at Capital Bikeshare. The analyses show that the STF product may have caused an increase in the first-time casual users by as much as 79%. The addition of STF product to fare options may also have contributed to the increase in the casual users' monthly ridership by 41%. These notable percentage increases in number of first-time casual members and their monthly ridership suggest that the STF product may have attracted more people to ride CaBi as an alternative mode of transportation.

Statistical tests show that there is a significant increase in daily ridership levels after the introduction of the STF. However, the tests also show a significant decrease in the daily revenue for riders with 24-hour pass and 3-day pass after the introduction of STF showing that a shift towards the use of single-trip fare ($2/trip) instead of the 24-hour pass (for $8) or the 3-day pass (for $17). Year-over-year calendar monthly growth rates of new casual users were significantly higher after the introduction of STF. Results of analysis of variance show that jurisdiction and season variables play a statistically significant role in the percentage change in revenue and ridership. Regression analyses indicate daily ridership to have a positive correlation with temperature and a negative correlation with precipitation.

Due to the concurrency of STF launch with SafeTrack, it may be surmised that the single-trip fare has created an opportunity for commuters to try CaBi as an alternative travel mode at an affordable price during the metro maintenance work. There is a statistically significant increase in the daily ridership for both registered and casual users of CaBi near Metro stations that affected by transit service disruptions during SafeTrack. The percentage increase in casual riders at these Metro stations was greater than that of registered users. It is possible that people may have taken the casual passes only for the SafeTrack duration instead of the monthly or annual membership. However, after the SafeTrack periods, the rise in CaBi ridership at the affected Metro stations did not sustain as hoped.

Several of these conclusions may be unique to Capital Bikeshare system because of its unique structure, geography and the user-base. Therefore, caution must be exercised when extrapolating the study findings to other cities with bikeshare systems. However, it is clear from the analysis that the single-trip fare acted as a catalyst for more people to try CaBi as an alternative mode of transportation. In order to understand the true impact of STF on system-wide revenues from casual users, a micro-scale analysis of revenue transactions at individual stations is needed. This research only examines the impact of one fare product, namely $2 per single-trip, on revenue and ridership. More research is needed to study on the impact of combinatorial changes in pricing on bikeshare ridership and how different pricing options affect bikeshare ridership and revenue.

4 ASSESSING THE IMPACT OF PRICING ON BIKESHARE USAGE AND REVENUE THROUGH STATION-LEVEL ANALYSIS OF BIG DATA

4.1 Introduction

Exponential growth of shared mobility services such as carpooling/ridesharing, ride hailing (e.g. Uber, Lyft), carsharing (e.g. ZipCar) and bikesharing in recent years has taken the sustainable transportation concept by a storm. Even though bikesharing has been in existence since early 1960s, worldwide movement toward bikeshare is “off and running” since the 2007 launch of the third-generation bikeshare system Vélib' by the City of Paris (Goodyear, 2018). In the decade since 2007, public bikeshare systems have caused major disruption to the landscape of urban transportation systems around the world. The fast-pace and large scales at which this disruption is taking place leaves researchers playing a catch-up in understanding this phenomenon’s undercurrents such as demographic characteristics of users, causes and effects of changes in revenue, ridership and even the viability of bikeshare systems.

Public bikesharing programs typically serve three user groups—*members* (users with an annual or monthly membership); *casual users* (short-term bikesharing users who purchase a single-trip or 24-hour or multiday passes); and *occasional members* (users with a special key to pay for a short-term pass) (Shaheen, Cohen and Zhody, 2016). Subscriptions from members provide a steady stream of revenue to bikesharing programs. Therefore, many bikesharing providers place an emphasis on catering to the preferences of members. On the other hand, for the year 2012 casual users of bikeshare programs in North America generate the largest source of revenue through membership and usage fees ranging from 44% to 67% of the programs total revenue (Shaheen et al., 2014). Casual users continue to account for a large percentage of total revenue (Venigalla et al. 2018).

Subscription products or 'fare products' and their pricing play a key role in policy and practice considerations at bikesharing systems. For, as in the case of a transit, the cost of ridership of a bikeshare trip plays a major role in mode choice behavior of users. To cater to the preferences of users, improve service and increase ridership, bikeshare providers routinely change pricing of existing fare products, introduce new products, and alter the menu of pricing models for all user types. Despite the importance of pricing to bikeshare patronage, few studies focused on the impact of pricing on revenue and ridership (Venigalla et al., 2018; Kaviti et al., 2018). The primary goal of this research is to examine the impact of changes made to bikeshare fare-products on bikesharing usage and revenue by analyzing large amounts of system wide data on revenue and ridership.

4.2 Motivation

The motivation to conduct this research came from the policy decision made by Capital Bikeshare (CaBi), the public bikeshare system in the Metro Washington DC area, to launch a single-trip fare (STF) product for its casual users. CaBi was the first big city bikeshare system in the United States to offer service to single-trip users. The coverage area of CaBi spans across several jurisdictions in District of Columbia (DC), and its northern Virginia and Maryland suburbs. Overseen by the District Department of

Transportation (DDOT), CaBi currently has over 500 stations and more than 4,000 bikes and is frequently expanding its coverage in the region (DDOT, 2015). CaBi serves three types of users; casual users, occasional members, and registered members. The casual users and registered members combined constitute more than 98% of the bikeshare users (Venigalla et al., 2018). As of March 2018, subscription prices of prominent fare products offered by CaBi include the following.

Casual users:

- Single-trip fare (STF) for $2, for trips up to 30 min duration (introduced in June 2016)
- 24-hour pass for $8, for unlimited trips of 30-min duration or less in the 24-hour period after the pass is purchased
- 3-day pass for $17, for unlimited trips of 30-min duration or less in the 72-hour period after the pass is purchased

Registered members/occasional members:

- 30-day (monthly) pass for $28, for unlimited trips of 30-min duration or less that is valid for 30 days
- Annual pass for $85, for unlimited trips of 30-min duration or less that is valid for 365-days

In addition to the subscription fee, CaBi riders incur usage fees for trip durations exceeding 30 minutes. CaBi added the STF product for casual users in June 2016, in conjunction with the first scheduled SafeTrack, which is a track maintenance initiative of the Washington Metropolitan Area Transit Authority (WMATA). The purpose of SafeTrack was to address safety recommendations and rehabilitate the metro rail system. During this rehabilitation process, metro rail had encouraged alternative travel options because of expected delays and capacity restrictions. CaBi's rationale for charging per-ride as opposed to offering only 24-hour and 3-day pass options for casual use was that fixed cost per ride could widen the appeal of Capital Bikeshare to new audiences seeking alternative travel options during SafeTrack beyond current subscriber base. The STF option was also aimed at potentially drawing new registered members towards regular bikeshare. Within a shorttime after its launch, STF has become a very popular fare option among the CaBi users (Venigalla et al. 2018). However, the potential effect of neither the price of STF, nor the timing of the launch on acceptance by CaBi users was studied before STF was introduced. However, a few months after the launch of STF, CaBi initiated this structured evaluation of the impact of STF on revenues and ridership at CaBi.

4.3 Research Objectives

The primary objective of this research work was to evaluate the impact of the introduction of this popular new fare product in the form of STF on revenue and ridership in the Capital Bikeshare system by conducting disaggregate analysis of revenue and ridership data. The objective was met by addressing two research questions:

Research question 1:

a) Is there a statistically significant change in revenue from casual users of Capital Bikeshare after the launch of STF?

b) If the answer to 1.a were 'yes', the follow up question would be, is this change attributable to the launch of STF or is it simply an extension of the background trend that existed before the launch?

Research question 2:

a) Is the change, if any, in usage of Capital Bikeshare (trips and duration) by casual users significantly different after the launch of STF?

b) If the answer to 2.a were 'yes', the follow up question would be, is this change attributable to the launch of STF or is it simply an extension of the background growth that existed before the launch of STF?

The availability of large amounts ridership and revenue data at individual trip-level and transaction-level, respectively, provided an opportunity to accomplish this objective.

4.4 Literature Review

Literature search was focused on two primary themes. First focus was on studies that employed disaggregate analyses of ridership and revenue data at the level of individual stations. Second emphasis on literature search was given to studies that examined the impact of pricing on bikeshare systems' ridership and revenues.

4.4.1 Station-level Analysis of Bikeshare Usage Data

Rixey (2013) studied the impact of demographic and built environmental characteristics on bikeshare ridership at station level for CaBi, Denver B-cycle, and NiceRide MN systems. The results indicated that bikeshare ridership has positive correlations with population and retail job density; presence of bikeways; and bike, walk, and transit commuters. The findings also showed that the minority population and days of precipitation have negative association with the station-level bikeshare ridership levels. El-Assi et al. (2017) conducted a similar study to identify factors affecting Toronto's bikeshare demand at the station level by developing trip generation models. The study further developed a station-pair regression model, which showed a positive correlation with the increase in infrastructure, decrease in number of intersections with major roads and negative correlation between distance and bicycle ridership. Ma et al. (2014) explored the linkages between bikeshare and transit at the station level and demonstrated that bike-sharing programs can help increase transit ridership. The analysis showed that Metrorail stations have been the source of important origin and destinations for Capital Bikeshare trips and concluded that an increase in trips would also increase transit ridership.

A few studies discussed how regression models could be used to determine the bikeshare ridership at the station level. Zhang et al. (2016) developed multiple linear regression models to study the effect of built environment variables on trip demand and ratio of demand to supply (D/S) at station level for public bikesharing system in Zhongshan, China. The results showed that both trip demand and D/S were positively correlated with population density, length of bike lanes, and diverse land-use types near the station. The findings also suggest that adding a new station with additional capacity within a 300 meters (m) radius of an existing station can improve the D/S at the station level. Wang et al. (2015) developed regression models to identify factors effecting bike station activity for Nice Ride Minnesota. The results showed that proximity to Central Business District, campuses and parks; access to off-street paths have the highest marginal effects on the station use whereas socio-demographic characteristics and economic variables have minimal marginal effects.

de Chardon and Caruso (2015) compared various aggregation models to calculate daily trips at different public bikeshare systems. The study developed day-aggregation, interval aggregation and station aggregation models to estimate the number of daily trips for eight major bicycle sharing systems in Europe and North America. The results showed that the daily aggregate model provides the better estimates of trips compared to other models.

Research on comparative assessment of aggregate and disaggregate models for the prediction of bikeshare demand is sparse. Biehl et al. (2018) developed two Generalized Linear Models at station and community level to predict average annual daily bicyclists for Chicago's Divvy bikeshare system. The results show that the station-level analysis has superior predictive capacity than the community-level analysis and averaging of disaggregate results to represent community areas has better accuracy than aggregate model. This is because disaggregate model contain more information regarding the bikeshare system, built environment and socioeconomic factors that impact the bike usage.

4.4.2 Studies Related to Impact of Pricing on Usage

Though numerous studies discussed factors affecting the bikeshare ridership, only very few studies included pricing as one of the factors (Kaviti 2018). Judrak (2013) analyzed the time-specific cost structure of the public bikesharing system of Boston and Washington, DC. The study observed that registered users exhibit higher cost sensitivity around the 30- and 60-minute pricing boundaries compared to the casual users. One of the recommendations of this study is that incentives should be provided to bikeshare users on specific congested roads with dynamic pricing based on the current traffic conditions. Goodman and Cheshire (2014) examined how the profile of income-deprived and women users changed in the first three years of operations at London Bicycle Sharing System (LBSS). The percentage of income-deprived users doubled as the LBSS expanded its system to areas with low-income populations and women users make a higher share of casual trips. However, these positive developments have been partially offset by increasing the then prevailing prices at LBSS by 50%. The study further argues that bikeshare fares should be in a reasonable range to maximize the bikeshare usage and to make the system more equitable to all the users.

A report by Venigalla et al. (2018) and research paper by Kaviti et al. (2018) discussed the impact of the launch of $2/trip STF by CaBi on its revenue and ridership at jurisdiction level. These two studies examined the interrelationship of revenue and ridership with other system variables such as supply (as measured by number of stations and bike racks or docks), jurisdiction, seasonality, transit disruptions, day of week and precipitation. Aggregate analysis performed at the level of two urban (Washington DC and Arlington, VA) and two suburban (Alexandria, VA and Montgomery County, MD) jurisdictions showed significant increase in casual user ridership for the two identical 12-month periods before and after the introduction of STF. However, the study found that the analysis on the impact of STF on revenue from casual users before and after STF at jurisdiction-level was inconclusive. Though notable changes were observed in revenues aggregated at the jurisdiction level, the paper could not verify if the changes observed in revenues after the introduction of STF were in fact attributable to the introduction of STF. The analysis performed by Kaviti et al. (2018) was primarily based on ridership and revenue data aggregated by month and jurisdiction, which has no fidelity at the daily level and station-level. Furthermore, in normalizing revenues and ridership on a 'per-dock' basis, the analysis by Kaviti et al. (2018) not only included new stations with sparse ridership, but also diluted the true impact of the introduction of single-trip fare at stations that have high ridership. Therefore, disaggregate analysis of the data at station level (i.e. analysis of individual trips and revenue transactions by station) could provide additional valuable insights on the impact of STF.

Ahillen et al. (2015) compared the policies and ridership trends of the Washington, DC's Capital Bikeshare and Brisbane's Citycycle. The findings show CaBi had few changes in its pricing policy since its launch in 2010. However, Brisbane CityCycle reduced the daily subscription fees from $11 to $2, introduced weekly subscriptions and provided free helmets at each of the stations. The results show providing helmets, reducing subscription fees, and adding flexible subscriptions to users may have contributed to a 50% increase in Citycycle ridership in just six months. Kaviti et al. (2018) studied the impact of introducing single-trip fare (STF) for $2 on CaBi ridership and revenue. The results showed that introducing this new fare option increased the monthly ridership for the first-time casual users and all casual users by 79% and 41% respectively.

4.4.3 Summary

The literature review identified only limited research on station-level analysis and the benefits of using the disaggregate analyses over aggregate analyses in the public bikeshare system. Studies on impact on pricing changes on bikeshare ridership are scant. This study attempts to fill these gaps by analyzing the impact of a single-trip fare on the Capital Bikeshare ridership and revenue at the station level. Also, this research compares the disaggregate models with that of the aggregate models for the newly introduced fare product.

4.5 Data and Methodology

4.5.1 Study Data

The study employs two primary data sources, which include data on individual CaBi trips and revenue transactional data for every CaBi revenue transaction during the period January 2015 through May 2017.

- Dataset 1 - CaBi ridership data. This data contains information on anonymous individual trips and is available to public at http://www.capitalbikeshare.com/trip-history-data. The dataset contains detailed information on each trip, which includes start and end stations, start and end times, duration of trip etc.

- Dataset 2 - Revenue transactional data. This data includes information on each revenue recognition transaction, including refunds issued to customers. This dataset is obtained exclusively for this study and is not available for public. Variables included in the dataset are transaction date (includes time to the second), fare product (single-trip, annual membership etc.), transaction amount, station at which the transaction occurred. To protect the security and identity of the users, DDOT (data provider) removed all personally identifiable data.

The ridership data (Dataset 1) identifies each trip-maker as only a casual or registered user. No details are available on the type of casual user (i.e. STF user, 24-hour / 3-day pass holder). This loss of detail handicaps the impact analysis of STF launch on other casual users. However, the details of casual user (e.g. type of casual user, time of purchase and station at which purchase is made) are present in revenue transaction data (Dataset 2), which could be successfully mapped into Dataset 1. Data fusion techniques outlined by Venigalla (2004) were employed to fuse datasets 1 and 2. This data-mapping exercise enabled further identification of each casual trip-maker as a single-trip user; the first-time user of a 24-hour / 3-day pass; or a repeat user of a 24-hour / 3-day pass (Venigalla et al. 2018).

Additionally, for the purposes of analysis control, daily weather data were obtained from Weather Underground history data website (http://www.weatherunderground.com) which offers historical weather data for different regions. The two primary data sets combined contain over 22 million records.

4.5.2 Station Selection for Analysis

In order to compare station-level metrics between the two 12-month periods 'before' and 'after' STF launch, of the then total 440 stations (currently over 500) only those 330 stations that existed all through the 24-month analysis period were selected. The Institute for Transport Development and Policy recommends an average spacing of 300 meters between stations for a bikeshare system to be successful (ITDP 2014). Using this recommendation as a guideline, if a new station were to be opened within 300 meters of an existing station during the analysis period, it would be appropriate to combine the data and analysis metrics for both those stations. However, CaBi opened no new stations within 300 meters of existing stations during the 24-month analysis period. While the analysis included 330 common stations, for the purpose of illustration of data and discussion of results, 20 stations with the highest ridership in June 2015 were also selected. Throughout this paper these 330 stations are referred to as 'common stations' and the 20 stations are referred to as 'top 20 stations'. Figure 4.1 illustrates the locations, density and the coverage of the 330 common stations, with top 20 of them highlighted in a different color.

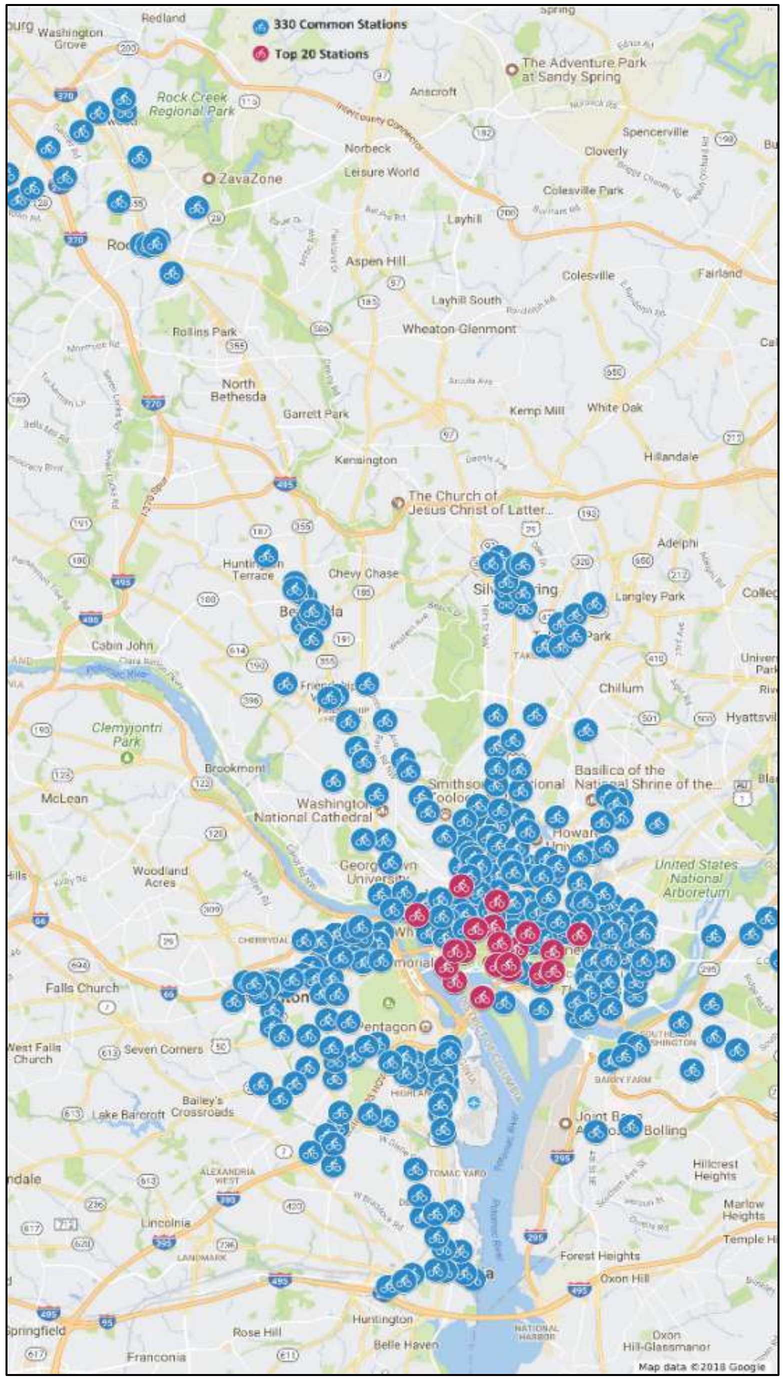


Figure 4.1: Common stations to the 12-month periods 'Before' and 'After' the introduction of STF

4.5.3 Time Periods of Comparison and Control Treatment

The single-trip fare option is available to CaBi users from June 2016. For making 'before' and after' comparisons using Datasets 1 and 2, the 12-month period June 1, 2015 through May 31, 2016 is termed as 'before STF'. The 12-month period from June 1, 2016 through May 31, 2017 is termed as 'after STF'. By comparing metrics for exactly the same months in the 'before' and 'after' time periods, seasonal variations in data are eliminated. Furthermore, to verify if the growth trends for revenue and ridership are impacted by STF launch, three identical 5-month periods (January through May for years 2015, 2016 and 2017) were identified. These three 5-month periods were used to compute revenue and ridership growth rates 'before' and 'after' STF launch. The analysis time periods are illustrated in Figure 4.2.

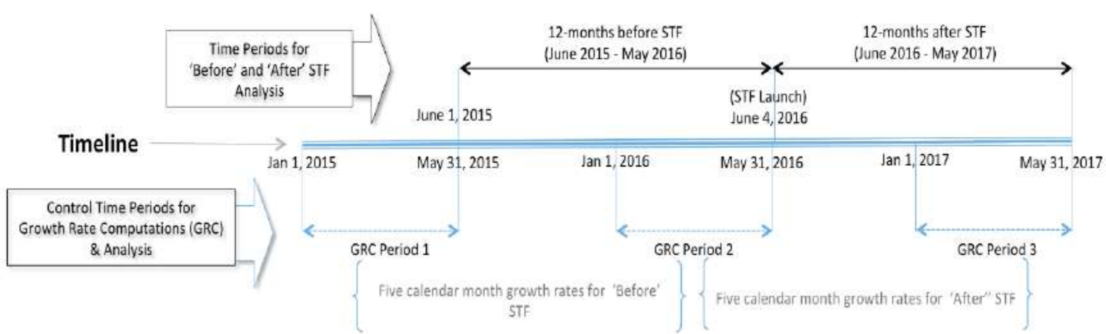


Figure 4.2: Schematic of time periods for revenue and ridership comparison and growth computations

If a statistically significant change in ridership and/or revenue were to be noted after the launch of STF, it is not known if the introduction of STF itself caused these changes or the changes merely reflect a continuation of the trend that was in existence from months prior to the launch of STF. Based on the available revenue and ridership data, hypotheses tests could be performed to verify if the growth trends have changed in a statistically significant way. To facilitate the hypotheses testing, the calendar-month growth rates for ridership and revenue were computed using the 5-month data for January through May for 2015, 2016 and 2017. For example, the ridership growth rates for a given station for January month 'before STF' launch would be difference in ridership between January 2016 and 2015 divided by the ridership in January 2015. Likewise, the ridership growth rates for January month 'after' STF launch would be ridership in January 2017 over its January 2016 ridership. The 5-month period was chosen because the station-level revenue data were available only from January 2015. The growth rates of revenue and ridership were analyzed for the 319 stations that existed during all three 5-months periods (which indicates that 11 of the 330 stations were opened during the January to May 2015 period).

4.5.4 Screening for Outliers

For analyzing system usage, it is important to identify and eliminate trips that are excessively long so that the analysis results are not skewed. For example, the longest CaBi trip in 2015 clocked over 14,911 minutes (over 248 hours or 10 days) and the 2017 data included a trip over 27,249 minutes (over 27 days). Such excessively long trips would unduly influence the analysis results. To determine a reasonable cutoff length for eliminating abnormal trips as well as for deriving trip length frequencies, the ridership data for 2015, 2016 and 2017 were scrutinized for trips of excessive length. The summary of this scrutiny is presented in Table 4.1. It can be seen that across the three analysis years, 1.2 to 1.6 percent of trips exceeded a length of 120 minutes, which is about 6 standard deviations away from the mean trip duration. Therefore, to avoid the influence of these long trips on analysis results, only trips that are 120 minutes or shorter in duration were included in the analyses.

Table 4.1: Frequency of trips by trip duration

Trip Duration	2015 Ridership Data		2016 Ridership Data		2017 Ridership Data	
	Number of trips	Percentage	Number of trips	Percentage	Number of trips	Percentage
> 300 min	3,628	0.11%	7,035	0.21%	4,256	0.20%
> 240 min	6,063	0.19%	10,193	0.31%	6,522	0.30%
> 180 min	12,997	0.41%	18,917	0.57%	12,893	0.60%
> 120 min[1]	38,472	1.20%	47,151	1.41%	34,600	1.61%
> 60 min	131,976	4.13%	149,247	4.48%	114,537	5.33%
> 30 min	329,412	10.32%	367,569	11.03%	279,435	13.00%
Total	3,192,908		3,333,786		2,149,340	

[1] Trips in the longest 1.5% of the tail are assumed to be outliers. Therefore, only trips that are shorter than 120 min are included in trip length analyses.

4.5.5 Response Variables

The response variables examined in the impact assessment analysis are system usage and revenue. The extent of system usage is reflected in the number of trips taken by users, and trip lengths or trip durations. However, trip length information is not available in the data. For this reason, only the trip duration variable was used as one of the three response variables. While total revenues are an indicator of the impact, true impacts on revenue may be captured only through revenue normalized for usage (or, revenue per trip). In summary, the set of response variables included in the analysis are the following:

- Ridership (number of trips)
- Usage (trip-length in minutes)
- Revenue (total revenue and revenue per trip)

The analysis was performed only on the casual user revenues and ignores revenues from registered members for two reasons. First, Kaviti et al (2018) established that the launch of STF has not impacted the ridership of registered users. Secondly, the revenue from registered users could not be sourced to individual stations where the registered users have made their trips.

4.5.6 Explanatory Variables

Variations in response variables were examined as a function of the following explanatory variables and their two-way and three-way interactions.

- Station: A single station or set of stations based on their location,
- Weekend/weekday: Whether or not the rides were taken on a week day where commute trip could be predominant, or on a weekend where recreation trips could be predominant
- Month: Month in which trips are taken to account for seasonality

4.5.7 Control Variables for Analysis

To enable a classical 'before-and-after' experimental set up for evaluating the true impact of STF on response variables, other variable that could potentially influence the outcomes must be controlled for. These controls and treatments for the experimental setup and evaluation included the following:

- The station-level disaggregate comparative analysis is conducted by pairing variables only at 330 stations that are common to the 12-month periods 'before' and 'after' the launch of STF. This direct comparison excludes stations that are open only for partial time in the 24-month analysis period and also eliminates the impact of seasonality.
- Days with precipitation are excluded from the analysis.
- No adjustments were made for temperature variations. However, by including calendar month as an independent variable, seasonal effects on ridership were controlled for.

4.6 Before and After Analysis Results

Descriptive statistics on the differences in response variables before and after the introduction of STF are presented and discussed in this section.

4.6.1 Trips, Trip Durations at Top 20-Common Stations

To assess the impact of STF on number of trips, the trips starting at all common stations were summarized from the ridership data. Table 4.2 provides a glimpse at the changes observed in trips and usage after the launch of STF at the top 20 stations. The highest increase in casual member ridership (36%) after the introduction of STF occurred at Smithsonian-National Mall / Jefferson Dr & 12th St. The corresponding change in trip duration at Smithsonian-National Mall / Jefferson Dr & 12th St is about 33%. On the other hand, among the top 20 stations, the station at 21st St & Constitution Ave NW registered the most decrease in ridership (29%) with a corresponding 24.5% decline in hours of usage. The top 20 stations experienced a combined 3.5% and 4.5% increase in trips and trip-duration, respectively.

Table 4.2: Casual user trips and usage at 20 stations with the highest ridership

Station Name	Number of Casual Trips			Trip-hours		
	Before STF	After STF	% Change	Before STF	After STF	% Change
Lincoln Memorial	54,064	45,536	-15.8%	31,886.5	27,269.5	-14.5%
Jefferson Dr & 14th St SW	43,594	43,503	-0.2%	25,705.7	26,253.6	2.1%
Jefferson Memorial	22,086	24,959	13.0%	11,215.3	12,944.5	15.4%
Smithsonian-National Mall / Jefferson Dr & 12th St	17,726	24,196	36.5%	12,295.2	16,328.6	32.8%
4th & C St SW	14,418	15,655	8.6%	7,864.6	8,663.0	10.2%
New York Ave & 15th St NW	13,150	13,789	4.9%	7,766.1	7,824.5	0.8%
Constitution Ave & 2nd St NW/DOL	12,316	14,554	18.2%	6,202.1	7,768.3	25.3%
Ohio Dr & West Basin Dr SW / MLK & FDR Memorials	11,770	12,918	9.8%	6,919.8	7,577.0	9.5%
10th St & Constitution Ave NW	10,370	10,660	2.8%	5,456.5	5,808.2	6.4%
19th St & Constitution Ave NW	9,666	7,529	-22.1%	5,473.4	4,467.4	-18.4%
Massachusetts Ave & DuPont Circle NW	9,591	10,406	8.5%	4,811.3	5,004.3	4.0%
Washington & Independence Ave SW/HHS	8,530	7,725	-9.4%	4,247.8	3,899.4	-8.2%
17th & G St NW	8,507	9,829	15.5%	4,648.1	5,577.4	20.0%
21st St & Constitution Ave NW	8,455	6,006	-29.0%	4,522.5	3,414.0	-24.5%
14th & D St NW / Ronald Reagan Building	7,828	10,277	31.3%	4,412.3	5,755.4	30.4%
7th & F St NW / National Portrait Gallery	7,137	8,387	17.5%	3,743.7	4,428.7	18.3%
Georgetown Harbor / 30th St NW	6,886	8,288	20.4%	4,224.1	4,905.7	16.1%
Columbus Circle / Union Station	6,677	8,132	21.8%	3,247.3	3,631.7	11.8%
USDA / 12th & Independence Ave SW	5,889	6,037	2.5%	3,671.0	4,019.3	9.5%
Thomas Circle	5,839	5,937	1.7%	2,737.5	2,810.2	2.7%
Totals	**284,499**	**294,323**	**3.45%**	**161,051**	**168,351**	**4.53%**

4.6.2 Casual User Revenues at Top 20-Common Stations

Aggregate analysis based on monthly summaries of revenues presented in a prior study shows a decline in revenue from casual users (Vengialla et. al. 2018). However, due to normalization by number of docks, the aggregate analysis did not adequately explain the impact of STF on revenue from casual users. To closely examine the STF at individual stations, revenues recognized from casual users at kiosks located at each of the 330 common stations are analyzed. Only the revenues that are marked as '*Product*' sales at a CaBi station (the designation indicates a sale at a station kiosk) are included in the analysis. Usage fees and refunds are excluded.

Casual user revenues recognized at kiosks located at the top 20 of the 330 common stations are presented in Table 4.3. The table indicates that the introduction of STF resulted in notable reduction in revenues at almost all 20 stations. The declines in revenues from 24-hour and 3-day passes are 42% and 34%, respectively, which indicates a shift in casual usage towards the STF product. After the launch of STF, revenues from all casual users at these stations declined by 21%, despite a 3.5% increase in ridership (Table 4.2). A closer examination of revenues at individual stations indicates that all but two of the top 20 stations (Jefferson Memorial; and 14th & D St NW / Ronald Reagan Building) experienced decline in revenues. Declines in revenues at individual stations range from about 12% at Columbus Circle / Union Station to over 40% at 21st St & Constitution Ave NW (computations are not shown in the table). A visual observation of the ridership and revenue trends at the other 310 common stations showed similar trends.

Statistical verification is needed if these changes could be attributed to the introduction of STF.

Table 4.3: Revenues from casual fare products at the top 20 stations

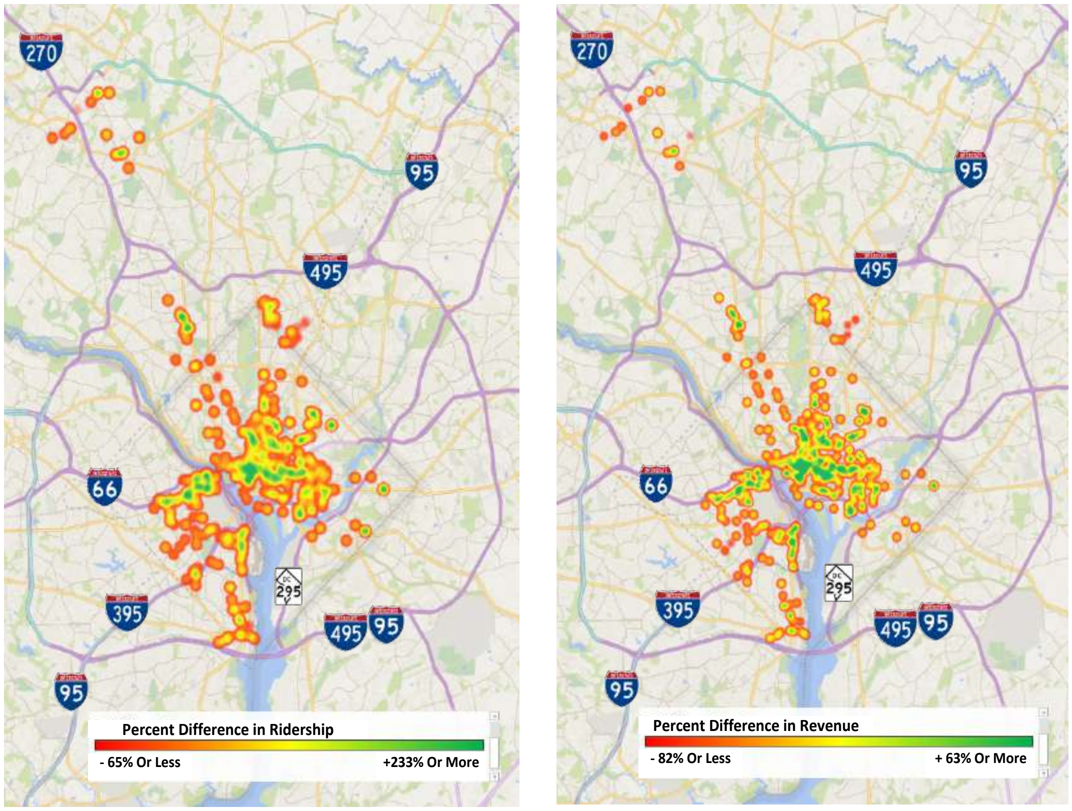
Station	Before STF (June 2015 - May 2016)			After STF (June 2016 - May 2017)			
	24-hour Pass	3-Day Pass	Total Casual	24-hour Pass	3-Day Pass	Single Trip	Total Casual
Jefferson Dr & 14th St SW	$157,272	$10,540	$167,812	$90,968	$7,021	$31,564	$129,553
Lincoln Memorial	$141,872	$8,755	$150,627	$58,344	$5,287	$29,418	$93,049
Smithsonian-National Mall / Jefferson Dr & 12th St	$113,368	$7,735	$121,103	$67,960	$5,287	$23,052	$96,299
4th & C St SW	$48,440	$5,253	$53,693	$28,392	$3,060	$9,222	$40,674
New York Ave & 15th St NW	$48,800	$4,182	$52,982	$29,616	$3,043	$9,664	$42,323
Massachusetts Ave & DuPont Circle NW	$35,880	$7,157	$43,037	$23,016	$4,930	$8,450	$36,396
Ohio Dr & West Basin Dr SW / MLK & FDR Memorials	$41,272	$1,343	$42,615	$24,040	$1,037	$10,026	$35,103
Constitution Ave & 2nd St NW/DOL	$38,216	$4,148	$42,364	$26,160	$3,468	$10,352	$39,980
Jefferson Memorial	$33,272	$1,734	$35,006	$22,904	$1,530	$12,030	$36,464
19th St & Constitution Ave NW	$33,072	$1,921	$34,993	$14,184	$1,122	$5,688	$20,994
Columbus Circle / Union Station	$26,800	$4,828	$31,628	$17,096	$3,315	$7,498	$27,909
10th St & Constitution Ave NW	$28,392	$2,414	$30,806	$18,704	$1,275	$6,584	$26,563
17th & G St NW	$28,760	$1,938	$30,698	$20,576	$1,649	$6,322	$28,547
14th & D St NW / Ronald Reagan Building	$26,344	$2,805	$29,149	$20,864	$2,227	$6,470	$29,561
Thomas Circle	$22,272	$6,069	$28,341	$12,968	$3,485	$5,498	$21,951
USDA / 12th & Independence Ave SW	$25,032	$2,414	$27,446	$16,400	$1,156	$5,006	$22,562

Table 4.3: Revenues from casual fare products at the top 20 stations

21st St & Constitution Ave NW	$24,504	$2,329	$26,833	$9,960	$1,190	$4,808	$15,958
Georgetown Harbor / 30th St NW	$23,912	$1,581	$25,493	$14,120	$884	$7,332	$22,336
7th & F St NW / National Portrait Gallery	$22,200	$2,448	$24,648	$12,904	$1,547	$6,542	$20,993
Washington & Independence Ave SW/HHS	$20,904	$2,176	$23,080	$12,104	$1,156	$4,786	$18,046
Totals	**$940,584**	**$81,770**	**$1,022,354**	**$541,280**	**$53,669**	**$210,312**	**$805,261**
Percent change after STF				**-42%**	**-34%**	N/A	**-21%**

4.6.3 Comparisons at All 330 Common Stations

The comparison of metrics at the top 20 stations indicates that ridership and usage have increased after the launch of STF. The top 20 station statistics reflected in Tables 4.2 and 4.3 are indicative of the pattern at all 330 common stations. Figure 4.3 illustrates heat-maps of changes in ridership and revenue after the launch of STF. Table 4.4 presents a summary of various metrics at the 330 common stations.



(a) Change in Ridership (b) Change in Revenue

Figure 4.3 Heat map of changes in ridership and revenue after the introduction of STF

Table 4.4: Summary of station-level changes in casual user ridership and revenues

Metric		12-month Period			Stations with Increase after STF Launch	
		Before STF	After STF	% Change	Number	Percent
20 Stations with the highest ridership						
Casual Users	Starting trips	212,004	213,315	0.6%	9	45.0%
	Starting trip-hours	118,602	120,887	1.9%	10	50.0%
	Revenue ($)	$1,022,354	$805,261	-21.2%	2	10.0%
Registered Users	Starting trips	187,926	181,285	-3.5%	4	20.0%
	Starting trip-hours	42,017	41,341	-1.6%	5	25.0%
330 Stations that existed throughout the 24-month analysis period						
Casual Users	Starting trips	607,621	727,691	19.8%	282	85.5%
	Starting trip-hours	322,445.7	445,438.5	38.1%	266	80.6%
	Revenue ($)	$2,205,559	$1,850,467	-16.1%	70	21.2%
Registered Users	Starting trips	2,541,227	2,610,443	2.7%	142	43.0%
	Starting trip-hours	487,500.6	442,827.5	-9.2%	117	35.5%
Revenue recognized from registered members is not attributable to any particular station.						

After the introduction of STF, trips starting at the top 20 stations have grown by less than 1% and total trip hours increased by nearly 2% (Table 5). In contrast, for all 330 common stations casual trips increased by nearly 20% and trip duration increased by 38%. Of the 330 stations, 282 (or 85%) stations recorded growth in trips and 266 (or 81%) recorded growth in trip durations. It is interesting to note here that the usage (both in terms of trips and trip-hours) by casual users increased at nearly twice as many stations as is the case for registered users. Despite such large increases in usage at common stations, it can be seen that the total revenue at 330 stations declined by 16% (over 21% decline at the top 20 stations). These observations led to the following research questions:

4.7 Hypotheses Testing

A number of hypotheses tests were conducted to statistically verify if STF had caused the differences outlined above. Hypotheses tests were conducted on mean values of response variables, namely, number of trips, trip duration and normalized revenue, and the growth rates of ridership and revenue. Because of its simplicity and time-tested dependability in establishing statistical significance, paired z-test is determined to be the most appropriate hypothesis test for comparing the response variables 'before' and 'after' the introduction of STF. The generalized formulation of hypotheses tested using z-scores is shown below.

Null Hypothesis, H_0:

$$(\mu_{r,p})_A - (\mu_{r,p})_B = 0;$$

Alternate Hypotheses, H_a:

$(\mu_{r,p})_A > (\mu_{r,p})_B$ (One-tailed)

$(\mu_{r,p})_A < (\mu_{r,p})_B$ (One-tailed); or

$(\mu_{r,p})_A - (\mu_{r,p})_B \neq 0$; (Two-tailed)

Where:

$(\mu_{r,p})_A$ is the mean of response variable *r* for the comparison pair *p* - after the launch of STF; and

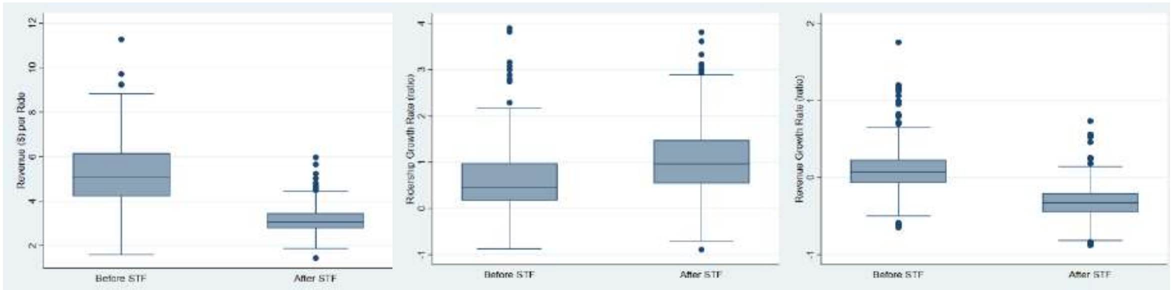
$(\mu_{r,p})_B$ is the mean of response variable *r* for the comparison pair *p* - before the launch of STF

Response variable set, *r* represents the mean ridership (number of casual users); mean normalized revenue ($ per casual ride); mean growth rate in ridership; and mean growth rate in normalized revenue

Pair-level *p* represents the paired levels of independent variables at which comparisons are made. (a) 330 individual stations (319 in the case of growth rate comparisons); (b) station and weekend/weekday (two-way interaction); (c) station and month (two-way interaction); and (d) station, month, and weekday/weekend (three-way interaction).

4.7.1 Tests for Normality

Z-test is applicable only to normally distributed variables. Therefore, to confirm if the response variables are normally distributed, mean values of ridership, normalized revenue ($ per trip) and growth rates of revenue and ridership were tested for Normality using descriptive (box plots) and theory-driven methods (quantile-quantile or Q-Q plots). Box plots (Figure 4.4) show that whiskers are evenly spread out around the boxes, and the median values are generally in the middle of the box – both of which are indicative of a Normal distribution of the variables. Box plots also indicate a sharp decline in revenue for casual ride and the associated growth rates (Figure 4.4 (a) and (c)), a noticeable increase in ridership growth (Figure 4.4 (b)).



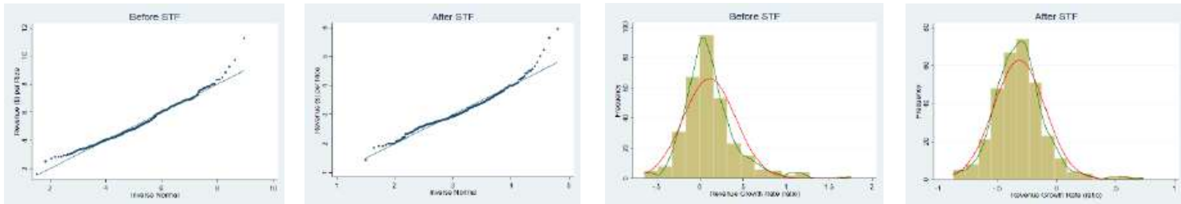
(a) Revenue per casual ride (n=330)

(b) Calendar month growth rates of casual user ridership (n=319)

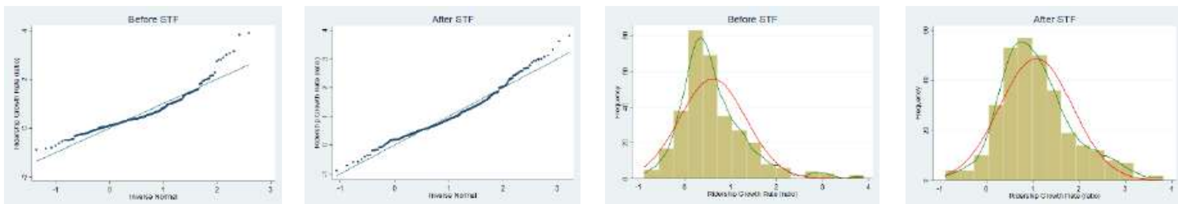
(c) Calendar month growth rate of revenue per casual user (n=319)

Figure 4.4: Box-plots for revenue and growth rates of ridership and revenue before and after STF

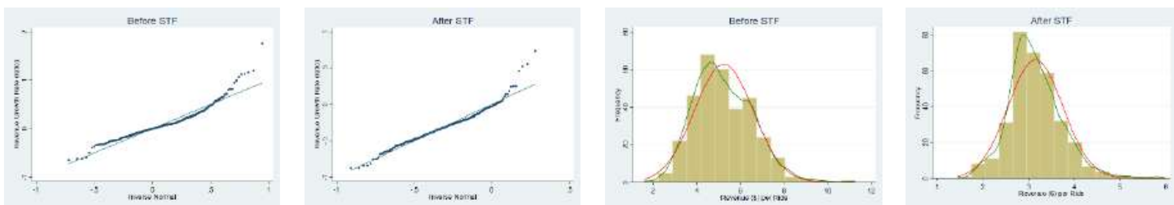
Q-Q plots and comparative histograms illustrating the distribution of response variables for all stations in the analysis are shown in Figure 4.5. Linearity of Q-Q plots and the histograms' approximation of Gaussian curve indicate that three response variables are normally distributed.



(a) Revenue per casual ride (n=330)



(b) Calendar month growth rates of casual user ridership (n=319)



(c) Calendar month growth rate of revenue per casual user (n=319)

Normal Kernel

Figure 4.5: Q-Q plots and comparitive histograms with normal and kernel densities

The data preparation for hypotheses testing included the following steps:

1. Arranging 'before' and 'after' revenue, casual trips and trip-hours data aggregated by all possible combinations of station, month, and weekday/weekend.
2. Maintaining aggregation of paired observations of response variables by station, month, and whether the trip occurred on a weekday or a weekend. This grouping is chosen to verify if calendar month or weekday status has any impact on the

increase/decrease because it has been widely established in the literature that bikeshare ridership is dependent on these variables.

3. Normalizing station-level revenue per casual trip (as opposed to total revenue) to smooth wide variations in total revenue among stations
4. Removing data points on days with precipitations as precipitation has its own impact on bikeshare ridership. However, no attempt was made to control for temperature such as eliminating data points on extremely cold or hot days.
5. Computing background growth rates using available data for the 5-months prior to the launch of STF so as to compare these rates to the growth rates after the launch of STF. Such comparison would establish whether or not the background growth itself has changed due to the launch of STF, there by confirming or negating the impact of STF on trips and revenue by casual users.

4.7.2 Pairwise Comparisons

A series of pairwise comparisons were made to verify the following two primary one-tailed alternative hypotheses:

Hypothesis 1: Casual user revenues <u>decreased</u> significantly after the launch of STF product. i.e., $\left(\mu_{r,p}\right)_A < \left(\mu_{r,p}\right)_B$

Hypothesis 2: Casual user ridership <u>increased</u> significantly after the launch of STF product, i.e. $\left(\mu_{r,p}\right)_A > \left(\mu_{r,p}\right)_B$

Presented in Table 4.5 are the results of z-tests at various levels of aggregation for hypothesis 1. The table shows that the mean values of revenue per ride 12-months before and 12-months after STF for each combination of 330 stations, 12 months and 2 weekday/weekend possibilities are \$5.05 and \$3.11, respectively. These mean values indicate that before the launch of STF, on average casual users paid \$5.05 per trip. This amount declined to \$3.11 per trip after the STF launch. The total possible number of paired observations for these combinations would be 7,920 (330 stations, 12 months and 2 weekend/weekday designations). However, Table 4.5 shows only 6,635 paired observations indicating missing data for some combinations. Statistics presented in the table show that the decline in mean revenue is statistically significant at 5% level of significance as indicated by a z-score of 59.9 and a p-value of near zero. Likewise, pairwise comparisons of mean values of revenues aggregated at station and month; and station and weekday/weekend combinations indicate statistically significant decline in revenues after STF launch.

Table 4.5: Pairwise comparisons of revenue per casual ride

Pair-level (p)	N	Observation pair: Mean revenue (\$) per casual ride		z-test		
		12-months Before STF μ_B	12-months After STF μ_A	H_a (Alternative hypothesis)	z-score	P-value of Type II error
Station, Month and Weekday/Weekend	6,635	5.046	3.113	$\mu_B > \mu_A$	59.96	**0.00**
Station and Month	3512	5.131	3.127	$\mu_B > \mu_A$	49.91	**0.00**
Station and Weekday/Weekend	655	5.214	3.147	$\mu_B > \mu_A$	33.16	**0.00**
Station	330	5.236	3.147	$\mu_B > \mu_A$	25.63	**0.00**
Low p-values (bold emphasis indicates significance at α = 5%) indicate that null hypotheses may be rejected.						

Table 4.6 presents analysis for change in casual ridership (trips) in a month before and after the launch of STF. As the table shows, average number of trips for each combination of 330 stations, 12 months and 2 weekend/weekday possibilities before and after STF are 90.5 and 101.1, respectively. The difference is indicative of an increase in ridership after STF launch. The z-score (-2.545) and p-value (0.005) denote statistical significance to this increase. Similarly, pairwise comparisons aggregated at all possible combinations of station and month indicate a statistical significance to the ridership increase at each station by month. The p-value of 0.276 for the difference in average trips at the station level (151.7 vs. 169.4) indicates that there is a relatively weaker evidence of station-level aggregate increase in trips after the launch of STF. Pairwise comparison for casual user ridership was not examined for dataset aggregated by station and weekday/weekend because the casual user ridership in a month was considered in the analysis. A closer examination of the data indicated that station-level aggregation might have been skewed by a few outliers that saw dramatic reductions in ridership. However, for consistency, no attempt was made to remove those outliers. For example, in the CaBi service area the March 2017 was unusually colder when compared to March 2016. This resulted in dramatic drop in ridership in March 2017 over March 2016 (Venigalla et al 2018).

Table 4.6: Pairwise comparisons of casual user ridership

Pair-level (p)	N	Observation pair: Mean monthly casual user ridership (trips)		z-test		
		12-months Before STF μ_B	12-months After STF μ_A	H_a (Alternative hypothesis)	z-score	P-value of Type II error
Station, Month and Weekday/Weekend	6,635	90.54	101.09	μ_B<μ_A	-2.54	**0.005**
Station and Month	3,512	171.05	190.98	μ_B<μ_A	-1.82	**0.034**
Station	330	151.70	169.37	μ_B<μ_A	-0.59	0.276
Low p-values (bold emphasis indicates significance at α = 5%) indicate that null hypotheses may be rejected.						

Thus, the common stations have experienced generally significant increase in ridership and decisively significant decline in revenue after the launch of STF. However, it is not known if the launch of STF itself caused these changes or if the changes were due to the continuation of a trend that was in existence from months prior to the launch. Additional pairwise z-tests were performed to verify if the growth trends in revenues and ridership have significantly changed after STF.

Presented in Table 4.7 and 4.8 are the pairwise comparisons of revenue and ridership growth rates for 5-months before and after the launch of STF, respectively. In Table 4.7, the mean revenue growth rate of 0.162 (column labeled μ_B) indicates that before the launch of STF an average growth rate in casual user revenue of 16.2% was recorded for each combination of 319 stations, five calendar months and two weekday or weekend designates. Its counterpart after STF (column labeled μ_A) registered about 29% decline in revenues after the launch of STF. That is, trends in revenue growth changed from positive growth to negative growth after STF launch. On the other hand, as Table 4.8 shows, mean year-over-year growth rates of the casual user ridership for comparable calendar months have accelerated after the introduction of STF from about 66% to about 119% (station level). The pattern is similar for other levels of aggregation. Thus, the statistical measures presented in Tables 4.7 and 4.8 establish statistical significance to the decline in revenue growth and increase in ridership growth after the launch of STF.

Table 4.7: Pairwise comparisons of growth rates of casual user revenue

Pair-level (p)	N	Observation pair: Mean growth rates of casual user revenue (ratio)		z-test		
		12-months Before STF μ_B	12-months After STF μ_A	H_a (Alternative hypothesis)	z-score	P-value of Type II error
Station, Month and Weekday/Weekend	2407	0.162	-0.287	$\mu_B > \mu_A$	18.79	**0.00**
Station and Month	1319	0.171	-0.289	$\mu_B > \mu_A$	15.94	**0.00**
Station and Weekday/Weekend	622	0.168	-0.308	$\mu_B > \mu_A$	15.34	**0.00**
Station	319[@]	0.165	-0.314	$\mu_B > \mu_A$	12.66	**0.00**

[@] Only 319 of the 330 stations which existed during January – May 2015 are used in growth rate analysis
Low p-values (bold emphasis indicates significance at α = 5%) indicate that null hypotheses may be rejected.

Table 4.8: Pairwise comparisons of growth rates of casual user ridership

Pair-level (p)	N	Observation pair: Mean growth rates of casual user ridership (ratio)		z-test		
		12-months Before STF μ_B	12-months After STF μ_A	H_a (Alternative hypothesis)	z-score	P-value of Type II error
Station, Month and Weekday/Weekend	2407	0.662	1.194	$\mu_B < \mu_A$	-8.82	**0.00**
Station and Month	1319	0.734	1.262	$\mu_B < \mu_A$	-6.99	**0.00**
Station and Weekday/Weekend	622	0.617	1.288	$\mu_B < \mu_A$	-7.91	**0.00**
Station	319[&]	0.648	1.332	$\mu_B < \mu_A$	-5.82	**0.00**

[&] Only 319 of the 330 stations which existed during January – May 2015 are used in growth rate analysis
Low p-values (bold emphasis indicates significance at α = 5%) indicate that null hypotheses may be rejected.

Since trip duration and ridership tend to be highly correlated, pairwise comparisons were not performed on trips duration as response variable.

4.8 Conclusions, Recommendations and Discussion

This research examined the impact of the launch of a single-trip fare (STF) product on Capital Bikeshare ridership and revenue by analyzing large amounts of system wide data. The analysis presented in this paper employs ‘big data’ on individual bikeshare trips and revenue transactions at station-level. The revenue and ridership datasets combined contain over 22 million data records. The unique characteristics of the point of sale system at Capital Bikeshare are leveraged for designing and executing a controlled experiment. The experiment allowed revenues to be sourced to individual stations, which further allowed comparing station-level revenues and ridership before and after the launch of STF.

Statistical tests were performed on casual user revenue and casual user ridership for 12-month period before and after the introduction of STF at the 330 common stations. The results showed a decrease in casual user revenue per ride and an increase in monthly casual user ridership after the introduction of the STF. Furthermore, calendar-month growth rates for ridership and revenue were compared for periods before and after the launch of the new fare product for a five-month period at hundreds of common stations. The study has established statistical evidence that the launch of STF has significantly decreased revenues and increased ridership at CaBi. Additionally, trends in revenue growth changed from positive growth to negative growth after the launch of STF. However, it should be noted that it is not practical to identify and control for all possible variables that could have caused the decline. This study also demonstrates that the disaggregate analysis conducted at the station level has superior accuracy and helps in better understanding of the data than the community-level analysis performed by Kaviti et al (2018).

It is possible that the results and findings may be unique to Capital Bikeshare. However, the controlled nature of the experiment and the analysis shed light on the fundamental nature of the impact of change in fare structure on revenues and ridership. Bikeshare providers who are considering making changes to fare product line and their pricing could benefit from the findings of this study. In cases where changes have already been made, the methods used in this research may be employed to evaluate the impact of those changes on ridership and revenue at those systems. For example, following CaBi's lead, Metro Bike (Los Angeles) in 2017, and Divvy (Chicago) and Citi Bike (New York) in 2018 have introduced single-trip fare products ($3/trip at Divvy and Citi Bike; and $3.50/trip at Metro Bike). The methods discussed in this paper are flexible enough to study the impact of STF on ridership and revenue at these systems.

Most importantly, this paper fills a notable gap in literature related to the impact of introducing new fare options on bikeshare ridership and revenue. It should be noted that this study only examined the impact of pricing change on usage and did not investigate the user behavioral factors that may have influenced the changes in usage. Studies focused on examining inter-relationship between pricing and user sensitivity to pricing such as developing price elasticities, logit models etc., can further advance this research.

5 PROFILES AND PRICING PREFERENCES OF BIKESHARING MEMBERS AND CASUAL USERS

5.1 Introduction

Public bikesharing improves urban mobility, solves the first mile/last mile problem and acts as a substitute for public transit in denser cities (Martin & Shaheen, 2014). For analyzing bikeshare demand and to get a sense of who will use it and at what scale, the Institute for Transport Development and Policy recommends creating profiles of current and potential bikeshare users (ITDP & Gauthier 2013). In this context, bikeshare user surveys play an important role in bikeshare policy-making, planning and operations. National Association of City Transportation Officials (NACTO) even provides a number of bikeshare intercept survey templates to analyze travel behavior of the riders, barriers to bikeshare, demographics, economic impacts, pricing, and perceptions of bikeshare (NACTO, 2018). In broader terms, these user surveys would provide critical input to help fine-tune the system to maximize operational efficiencies, usage and financial returns, enhance environmental stewardship and societal benefits.

The two most prominent types of bikeshare users are casual users and registered members (or simply members). Casual users are short-term users who typically purchase a variety of fare products that range from a single-trip to a short-term membership that would be in effect for several days (up to a month) from the date of purchase. On the other hand, members purchase long term passes that range from one month to a year and register with the system operator with such details as email address and contact information. Casual users are typically not required to register with any identifying information, which makes it harder to obtain information pertaining to casual users.

Subscriptions from members provide a steady stream of revenue to the bikesharing programs. Therefore, many bikesharing providers place an emphasis on catering to the preferences of members. On the other hand, casual users of bikeshare programs in North America generate the largest source of revenue through membership and usage fees ranging from 44% to 67% of the programs total revenue for the year 2012 (Shaheen et al., 2014). The market share split of trips and revenues between members and casual users varies by system. For example, for the year 2016 registered members and casual users of Washington DC's Capital Bikeshare (CaBi) account for about 72% and 28% of trips, respectively (Venigalla et al., 2018). While the casual users have a relatively smaller share of the total trips taken, they represent a vast majority of long trips that bring in disproportionately higher usage revenue (for usage over a specified duration, which is usually 30 min) to the bikeshare systems. Casual users also account for about 71% of the total revenue at CaBi for the year 2016 (Venigalla et al., 2018). However, in terms of market share of revenue, New York city's Citi Bike, which reported that casual users generate only 27% of its total revenue for the year 2016 (Citi Bike, 2018) is completely opposite of Capital Bikeshare. As evidenced by these market share splits, casual user profiles and preferences have a substantial role to play in policy-making, planning and operational management at public bikesharing systems. Therefore, it is critical to gain insights into the profiles of casual users as well as members.

Many bikeshare providers routinely conduct surveys to profile their users and study their travel behavior and preferences. This may be due to the availability of email addresses and contact information of members enables the bikeshare providers to reach members easily. For example, Capital Bikeshare conducts biennial survey of registered members. However, the periodic surveys conducted by CaBi till 2016 did not include casual users. Therefore, the demographic information, travel behavior and preferences of casual users of CaBi remained largely unknown (Capital Bikeshare 2018, DC Capital Bikeshare Development Plan, 2015). The lack of information on casual users is not a unique phenomenon to Capital Bikeshare. To date, there were only two studies conducted so far in North America that collected information on casual users: the first study was by Buehler (2012) in the Washington, DC area and the second was by Shaheen, Christensen and Viegas de Lima (2015) in San Francisco Bay area. Additionally, though numerous user survey-based studies have examined motivations and barriers to bikeshare system, socio-economic and demographic characteristics of bikeshare members, and impact of bikeshare on automobile usage etc., similar information on casual users is sporadic. Furthermore, literature search comes up nearly empty on studies related to pricing preferences of the bikeshare users, be it members or casual users.

The primary goal of this research, therefore, is to help fill the knowledge gap related to profiles and preferences of both types of bikeshare users via an intercept survey. As its first objective, this study aims at providing detailed insights on users of the Capital Bikeshare (CaBi), the public bikesharing system in the Washington DC metro region, by portraying similarities and differences between casual users and members.

Secondly, the study examines the pricing preferences of both casual users and members of the CaBi system. Specifically, this study answers the following research questions.

1. How, and in what way the casual user is different or similar from the registered member?
2. What are the pricing preferences of the bikeshare users?

5.2 State of the Art in Profiling the Bikeshare User

This section summarizes the survey of literature related to studies that are based on bikeshare user surveys and reinforces the motivation for this study.

5.2.1 User Demographics

Empirical studies based on user surveys indicate that bikeshare users tend to be young (Fuller et al., 2011; Buck et al., 2013), professional, and the vast majority of them are white (Lazo 2015). Since 2011, the respondents of periodic Capital Bikeshare surveys have remained mostly of white race and have increasingly dominated by male and affluent demographics. The 2011 CaBi member survey reported that 55% of the respondents were male, which continued to increase in subsequent years with 57% and 58% of respondents being male in 2012 and 2016, respectively. The 2016 CaBi member survey reported that about 52% of the CaBi members are in households that make $100,000 or more annually. In the 2011 survey, only 39% of respondents were in that bracket and in 2012 it was up to 45%. The survey does not include casual users and nor did it address user sensitivity to bikeshare pricing (Capital Bikeshare, 2018).

A few studies analyzed the bikeshare usage levels for the under-represented groups. McNeil, Dill, MacArthur, and Broach et al. (2017) drew their findings from a survey (n = 1,092) intended to reach lower-income and people of color who have engaged in bikeshare either through membership or equity-focused discount program (target users) in New York, Chicago and Philadelphia. The results suggested that once target users become members with the help of discount membership, they may use bikeshare as often as white, high-income users. The findings also revealed that target users are more likely to increase their use if the fees for longer trips were lower. The results also suggest that changing the pricing structure may motivate more bike usage among low-income people and people of color. Murphy and Usher (2012) conducted a survey (n = 360) to analyze socio-economic characteristics of bikeshare users in Dublin, Ireland. The results showed that vast majority of Dublin bike users were male (78%), 58.8% of whom were between 25-36 years of age and about 17.2% of the survey respondents earn less than 30,000 euros/year. Bachand-Marleau, Lee, and El-Geneidy (2012) conducted a survey (n = 1,432) in Montreal to determine the factors that influenced frequency of bikeshare use. The results showed persons who earn less than $40,000 per year are 32% and are less likely to use bikeshare than other income groups. The results also showed that women have about 0.6 times the odds of using the bikeshare. Ogilvie and Goodman (2012) examined bike usage levels by gender and income of the London bikeshare system. The study revealed that registered individuals are more likely to be male, live in low deprivation areas and high cycling prevalence. The results also showed females made 1.63 fewer trips per month than males. Additionally, studies consistently indicate more efforts are necessary to accommodate and attract older adults, females, people of color, and lower-income residents (Buck et al., 2013; Fishman, 2016; Howland et al., 2017; McNeil et al., 2018).

Wang, Akar and Chen (2018) studied station-level bikeshare use focusing on whether and how the effects of land-use and built environment vary across five age cohorts: younger Millennials (born 1995 to 2000), mid Millennials (1989 to 1994), older Millennials (born 1979 to 1988), Generation Xers (born 1965 to 1978), and Baby Boomers (born 1946 to 1964). The study developed zero-inflated negative binominal models to estimate hourly trip productions at stations for these age groups using New York's Citi Bike system data. Consistent with the literature, the study results suggested that weather related variables, land-use and built environment characteristics have significant effects on the overall bike sharing usage.

5.2.2 Survey-Based System Impact Studies

A few studies that are based on user surveys analyzed the impact of bikeshare system or bicyclists on automobile usage. Fishman et al. (2014a) used ridership and mode substitution data from bikeshare programs to analyze the impact of changes to automobile use due to the bikeshare programs. The study compared the reduction in car use with the vehicle-kilometers travelled for fleet distribution and maintenance of the bikeshare system. The results indicated an overall reduction in motor vehicle use due to bikeshare in Melbourne, Minneapolis, Washington, DC and increase in motor vehicle use in London's bikeshare program. Hatfield and Boufas (2016) conducted an online survey (n = 1,525) for bicycle users in Australia to estimate the percentage of replacement of car use by cycling for transport. The study found that 50% of the recent trips reduced car-use and approximately 1/3rd of the trips eliminated a 100%-car trip. Reduced car use was less likely for commuting trips, females, and respondents under 55, and was more likely for those who use bicycling to avoid parking.

5.2.3 Motivations and Barriers to using Bikesharing

Surveys were also conducted to study major motivations and barriers to using the bikeshare programs. Braun et al. (2016) developed a travel mode choice model using survey data (n = 765) in Spain to find out the motivations for bikeshare use. The results suggested that bicycle commuting has positive connection with access to bikeshare station and negative association with access to public transport stops. The study also concluded that bikeshare availability is more significant at work location than at home end and the presence of bike lanes has minimal effect on bicycle commuting. Fishman et al. (2014b) examined the survey results (n = 875) of members and non-members of two bikeshare systems in Australia. The study found that the conveniences associated with car usage and the inconveniences of docking station are key barriers to bikeshare membership. The findings indicated that expanding docking station locations, efficient bicycle routing, and integrating bikeshare programs with public transport may increase the bikeshare membership. Godavarthy and Taleqani (2017) studied on understanding users' desire to use bikeshare program in harsh winters (n = 654). The users conveyed their readiness to use bikeshare in the wintertime when the bike paths and sidewalks could be cleared of snow. Also, the expected bikeshare ridership during the winter season was found between 10 and 30% of peak summer ridership. Zhang (2016) studied the impact of expansion of bicycle sharing system in China using operational usage data of different years following system expansion. The results showed that expanding the system attracts first time users and extends the ability to reach new areas for existing users.

5.2.4 Surveys on Emerging Technologies and Operating Models

Being one of the hotbeds of transformation in the realm of urban transportation systems, bikesharing has been attracting innovative technologies and operational mode transitions in its own right. For example, current bikeshare operation models include the information technology based 3rd generation systems with docking stations and the smart-phone assisted 4th generation systems with dockless bikes (often a combination of both 3rd and 4th generation systems). Also, battery-operated electric bicycles (e-bikes) have been gaining popularity due to their ease of use (Velib, 2018). User surveys are integral part of taking measurements and evaluating the acceptance and performance as well as studying the policy implications of these innovative shifts in bikesharing technology and operating models. Campbell et al. (2016) conducted a survey (n = 1,188) in Beijing to analyze the factors influencing the use of e-bikes. The results indicate that e-bikeshare is more tolerant of trip distance, high temperatures, and poor air quality compared to traditional bikeshare system. The findings also demonstrate that e-bikeshare is an appealing alternative to short and medium distance bus trips. Within two years since its advent in 2016, dockless bikesharing has become very popular in certain parts of the world (e.g. China) and only recently gaining traction in North America. Due to its relative infancy compared to the decade long (2007-2017) existence of 3rd generation bikesharing, much work is needed in understanding the characteristics of the users of dockless bikes.

5.2.5 Profiles of Casual Users

Shaheen et al. (2014) conducted expert interviews and two kinds of surveys with bikesharing users: an online survey for bikeshare members in Montreal, Toronto, Salt Lake City, Minneapolis-Saint Paul, and Mexico City, and a second survey on-street survey that was designed for anyone, including casual users in Boston, Salt Lake City, and San Antonio. The casual user survey, which was an experimental method in this study, contained very few casual users. The study found that most respondents were members in Boston, while the majority was 24-hour pass holders in San Antonio (only one annual member responded in Salt Lake City)

Shaheen et al. (2015) conducted an intercept survey (n = 170) to understand socio-economic and demographic characteristics of casual users of Bay Area Bike Share (BABS). The study observed that surveys that developed casual user profiles of North American bikeshare systems are limited. Key findings of the study also indicated that casual users are similar to annual members in terms of race, income, and educational attainment. The survey results showed majority of the bikeshare users have a bachelor's degree (annual: 87%, casual: 82%), an annual household income of $50,000 or more (annual: 89%, casual: 71%), and are Caucasian (annual: 75%, casual: 70%). Buehler (2011) conducted an intercept survey (n = 340) to study the profile of casual users of the CaBi system. The analysis revealed that the average CaBi user is a well-educated, Caucasian female between the ages of 25 and 34 and a domestic tourist. The gender and racial elements of the casual user differ from the profiles of a typical CaBi annual member. Buck et al. (2013) extended this study to compare demographic and socio-economic characteristics of CaBi users with that of the area cyclists. Data for this study originated from the MWCOG 2007–2008 regional household travel survey of area cyclists, the 2011 Capital Bikeshare Casual User Survey, and the 2011 Capital Bikeshare Member Survey. The MWCOG survey was conducted before the inception of CaBi and provided a profile of cyclists in the area. The results suggested that CaBi short term users are more likely to be female and young who have lower household income and use bicycle for utilitarian purpose compared to the area cyclists. The study also concluded that new segments of society are motivated to cycle through the implementation of bikeshare programs. This study did not compare the similarities and differences between various CaBi users.

5.2.6 Pricing Preferences

A limited research was focused on studying the impact of pricing on the bikeshare ridership and on user perception of bikeshare pricing. Judrak (2013) examined the time-specific cost structure of the public bikesharing system of Boston and Washington, DC. The study found that registered members exhibit higher cost sensitivity around the 30 and 60-minute pricing boundaries compared to the casual users. Based on the results, providing ample racks (or docks) in central location, proper spacing of bikeshare stations to maximize coverage within the cost-free time limit, and dynamic pricing of the public bikeshare system based on the current traffic conditions were recommended in this study. Goodman and Cheshire (2014) examined how the profile of income-deprived and women users changed in the first three years in London Bicycle Sharing System (LBSS). The introduction of casual use has encouraged women to use the system and the percentage of income-deprived users doubled as the LBSS expanded its system to poorer areas. However, the study found that these positive developments have been partially offset by the 50% increase in the then prevailing prices, which made a single bikeshare trip more expensive than a single bus trip. This study clearly shows that prices should be accommodative enough to make the system more equitable to all the users. Ahillen et al. (2015) compared the policies and ridership trends of the Washington, DC's Capital Bikeshare and Brisbane's Citycycle. The findings show CaBi had few changes in its pricing policy since its launch in 2010. However, Brisbane CityCycle reduced the daily subscription fees from $11 to $2, introduced weekly subscriptions and provided free helmets at each of the stations. The results showed that providing helmets, reducing subscription fees, and adding flexible subscriptions to users may have contributed to a 50% increase in Citycycle ridership in just six months. Kaviti et al. (2018) studied the impact of introducing single-trip fare (STF) for $2 on CaBi ridership and revenue. The study observed that introducing this new fare option increased the first-time casual users and casual users' monthly ridership by 79% and 41% respectively.

5.2.7 Summary

User surveys play a key role in understanding the usage, travel behavior, and preferences of bikeshare users, thereby improving the system. Even though casual users account for large percentages of usage and revenue at all major bikeshare systems in North America, little is known about the casual users and how they compare to members.

Also, research on pricing preferences of bikeshare users (casual users and members) is sporadic. This study fills the gap by conducting an intercept survey at various CaBi locations and examining the ways in which casual users are different or similar from registered members. Furthermore, preferred pricing models of the bikeshare users were also examined in this research.

5.3 Methodology

The objectives of the study are met by conducting an intercept survey of CaBi system users – both casual users and members and analyzing that survey data. To distinguish prior CaBi member surveys from the current survey, in this research paper the current intercept survey is referred to as the '2017 User Survey' and the earlier surveys are referred to as 'Member Survey' for the given year. The study methodology includes the following sequential steps:

1. Design, plan and execute a user survey to elicit responses on the demographics, travel behavior and preferences of casual users as well as registered members
2. Verify and validate the current survey data with established data sources
3. Model survey data using logistic regression methods to draw inferences on the profiles and preferences of casual users and members

5.3.1 Survey Design and Execution

The first step in the methodology was to design a survey instrument that meets the study objectives. A detailed 5-page, 26-question survey instrument was designed in consultation with various CaBi stakeholders. Each of the survey questions and the associated user responses are worded in such a way that the differences and similarities between casual users and registered members could be captured. Questions collected information on user demographics such as age, gender, and household income of the person. Also, the survey questions capture user sensitivity to price and service (as revealed by relative preference between service as indicated by number of bikeshare stations and price), top three trip-purposes and pricing model preferences. Other questions include the CaBi trips made by the respondent in the prior month and the major driving factors to use CaBi. Most importantly, to facilitate validation of the 2017 CaBi User Survey data, several questions used in the 2016 CaBi Member survey were also included in the survey instrument. It should be pointed out that the overall objectives of the survey and the questions included in the instrument were much broader than the narrowly focused objectives of this study. For example, included in the survey instrument are questions related to monadic price testing that were aimed at capturing price elasticities of different fare product purchasers, which is beyond the scope of this paper.

A sample size of 600 was targeted. Due to resource constraints, no scientific sampling methods were adopted. The sample selection, though not scientific, observed the following simple rules:

- The survey should be conducted during the non-winter months (March through October).
- Coverage should be geographically diverse and include all demographic groups.

- At each survey location, as many users as possible should be intercepted at each location.
- Final sample must have proportional representation of casual and registered users and underrepresented groups should be adequately represented.

The survey plan included distribution of printed survey forms at various intercept locations. The locations were chosen to cover all jurisdictions with high CaBi ridership. Figure 5.1 shows various locations of the intercept survey (shown in red) with respect to all CaBi stations (shown in blue) system at the time of the survey. The survey respondents were given an option to fill a paper survey at the intercepted location, mail in the form using a self-addressed stamped envelope or take the survey online. Additionally, simultaneous social media and email campaigns were also conducted. The response rates for the intercepted users and mail-in surveys were above 70% and 14%, respectively. Researchers at George Mason University (GMU) conducted the survey in September and October 2017 and a total of 622 users responded.

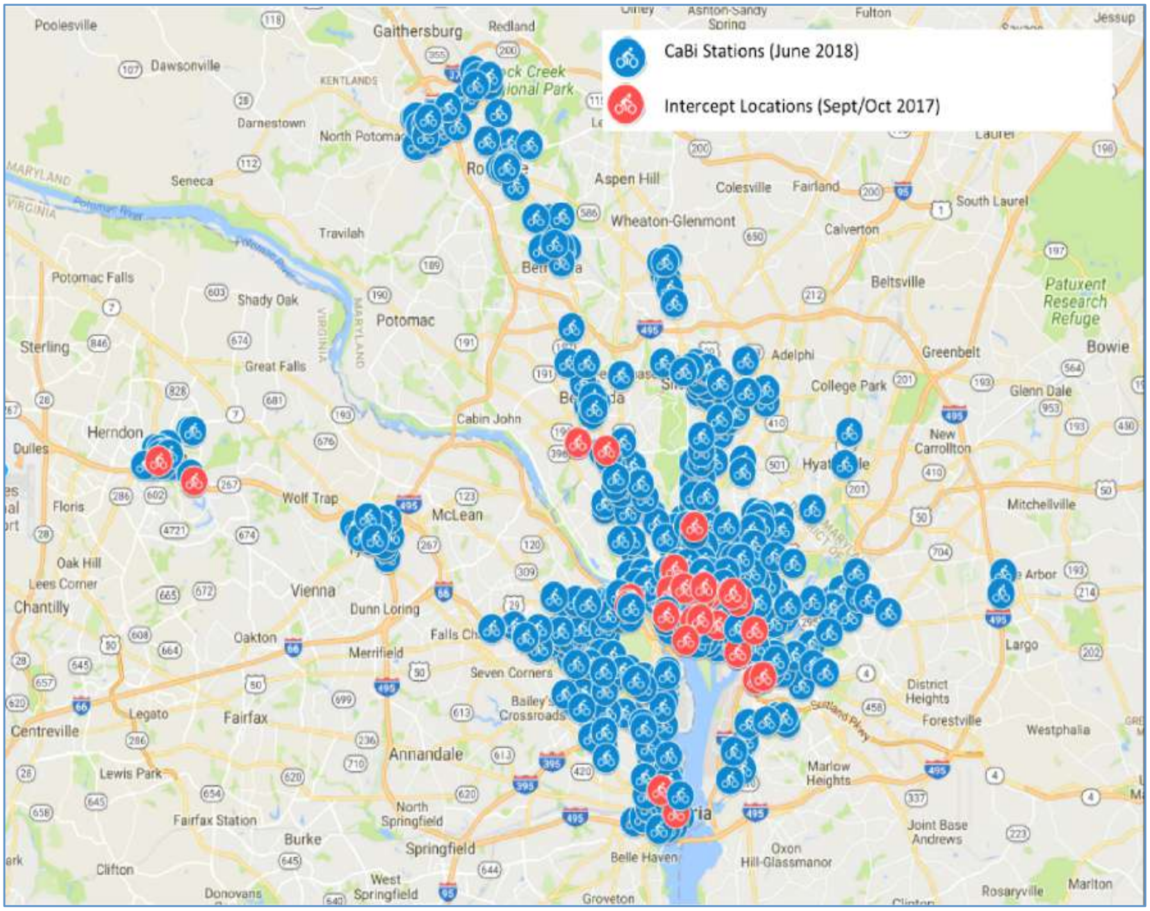


Figure 5.1: Intercept locations for CaBi pricing survey

5.3.2 Verifying and Validating Survey Data

Due to the sheer size of its sample (n = 5,498) of the most recent CaBi member survey for 2016, which represents approximately 18% of the then CaBi member base, the 2016 CaBi Member Survey is considered a good reference data set for validating the current survey data. This validation was done by means of goodness of fit assessments using Pearson's chi-square tests between member responses for identical questions in the

2017 CaBi User Survey and the member responses in the 2016 CaBi Member Survey. The goodness of fit tests would indicate whether or not the responses by members between the two surveys have similar distributions.

5.3.3 Developing Profiles and Understanding Preferences using Logistic Regression

The purpose of this step is to develop insights about the demographic profiles and preferences of casual users and how they compare to members. Chi-square tests were also performed on the 2017 CaBi User Survey data for drawing inferences on similarities and differences of profiles and preferences of casual users and members. Logistic regression models were developed to analyze if there are any statistically significant differences in demographics and other characteristics between the registered members and casual users and among the casual membership pricing options (single-trip fare, 24-hour pass).

5.4 Goodness of Fit Tests

The 2016 CaBi Member Survey sample (n = 5,498) may be regarded as a fairly accurate representation of the CaBi members as the sample size is large and represents about 18% of the then total members. In order to establish the validity of current survey sample for use in various policy, planning and operational analyses considerations, responses by CaBi members for identical questions in the 2017 CaBi User Survey and the 2016 CaBi Member Survey were compared and contrasted using Pearson's chi-squared (χ^2) tests. The results of these goodness-of-fit tests and interpretation of statistics are shown in Table 5.1.

Table 5.1: Goodness of Fit tests

			2016 Member Survey (%), *(n = 5,498)*	2017 User Survey- [Registered Members Only] (%); *(n = 317)*	χ^2	p-value
					Inference(s) based on p-value	
Gender					1.728	0.189
Male			58	67	*The two samples may be regarded as not different*	
Female			42	33		
Age					1.096	0.778
under 35			51	55	*The two samples are very similar in terms of age distribution.*	
35-44			23	24		
45-54			15	14		
54 and over			11	7		
Ethnicity					1.781	0.619
White			80	77	*Ethnic composition of registered members is similar for both samples.*	
Asian			7	6		
Hispanic			7	5		
African-American			4	8		
Income (Census category, group #, $ range)					1.767	0.94
Low	1	<35,000	6	10	*High p-value indicates income distributions of registered members in both samples are almost identical.*	
Medium	2	$35,000 - $49,999	9	7		
	3	$50,000 - $74,999	18	17		
	4	$75,000 - $99,999	15	16		
High	5	$100,000 - $149,999	22	21		
	6	$150,000 - $199,999	13	15		
	7	$200,000 or more	17	14		
Motivators (multiple responses allowed)					7.914	0.637
Get around more easily, faster			89	85	*Factors that motivated the members for using bikeshare in both samples are similar.*	
Like to bike, fun way to travel			69	70		
Save money on transportation			53	59		
Exercise, fitness			56	59		

Table 5.1: Goodness of Fit tests

Access to other form of transportation	54	40		
Concern about environment	36	39		
New travel option/one-way travel option	57	36		
Access to another bike/backup bike	30	29		
Health concern	12	16		
Employer benefit	12	11		
Discounted or free membership	14	10		
Top trip types or trip purpose (Multiple responses permitted)			2.26	0.812
Work or School	70	82	*Top trip types for which the members used bikeshare in both samples are very similar.*	
Personal appointment	42	40		
Social	55	55		
Restaurant	33	27		
Exercise	22	21		
Shopping	40	33		
Alternative mode of transportation to bikeshare			1.57	0.814
Walk	39	31	*Alternative mode of transportation used by members if CaBi is not available in both samples is almost identical.*	
Metrorail	21	22		
Uber, Lyft or taxi	16	17		
Bus	14	16		
Personal bike or vehicle	8	11		
Mode of transportation to CaBi station			0.32	0.572
Walk	89	84	*Mode of transportation used by members to pick up CaBi bikes in both samples is similar.*	
Metrorail	8	10		

p-value ranges used in drawing above inferences

$0 \le p \le 0.05$ two survey samples are different	$0.65 < p \le 0.80$ two samples are very similar
$0.05 < p \le 0.20$ two samples cannot not be different	$0.80 < p \le 0.90$ two samples are nearly identical
$0.20 < p \le 0.50$ two samples are comparable	$0.90 < p \le 1.00$ two samples are identical
$0.50 < p \le 0.65$ two samples are similar	

The 2016 Member Survey had lesser share of males (58%) than the 67% males sampled in the 2017 User Survey. Despite this notable difference, based on the p-value (0.19) it may be surmised that the two samples are ‘not dissimilar’ with regards to gender. As also seen in Table 1, age distribution of respondents in both surveys is very similar. A majority of the survey respondents (51% and 55%) from both surveys are men under the age of 35 years. There is no statistically significant difference in race and income between the 2016 Member Survey and the 2017 User Survey. A big majority of members in both surveys use CaBi for commuting purpose (70% in the 2016 survey and 82% in the 2017 survey) followed by social trips (55% in both surveys) and personal appointment (42% and 40%). About 80% and 77% of respondents reported their ethnicity as “White” in the 2016 and 2017 surveys, respectively. The rationale for income group classification shown in Table 1 was based on household income range as specified by U.S. Census Bureau (Table 5.2). A simple majority of the members in both surveys (52% and 50% in the 2016 and 2017 surveys, respectively) fall under high-income category. On the other hand, approximately, 6% of the 2016 survey and 10% of the 2017 survey respondents constitute low-income users (annual household income < $35,000).

Table 5.2: Income group classification by U.S. Census Bureau

Household Income Range	Households in Millions	Percent of Total	Income Group
<$35,000	38.1	30.17%	Low
$35,000-$99,999	53.3	42.20%	Medium
$100,000+	34.9	27.63%	High

Also, with regards to motivations for using bikesharing service, identical distribution can be seen between the two samples. A majority of the users from both surveys indicated that they use bikeshare because it helps them get around more easily and faster (89% in the 2016 survey and 85% in the 2017 survey). About 70% from both surveys like to bike, and 30% use bikesharing to access another bike. About 53% of the member survey and 59% of the registered survey members utilize bikesharing to save money on transportation. Other notable driving factors for bikesharing include saving money, exercise/fitness and access to other modes of transportation. Distribution of members' top three trip purposes found to be very similar for both samples. In both samples a vast majority of the members use bikeshare for commuting purpose (70% in the 2016 survey, 82% in the 2017 survey). About 55% and 21% of the respondents indicated that they use bikesharing for social activity and exercise purpose in the 2016 and 2017, respectively.

Samples of the 2016 Member Survey and the 2017 User Survey are found to be almost identical with respect to alternative transportation mode that would have been chosen by members if bikeshare were not available to them. A plurality (39% in the 2016 survey and 31% in the 2017 survey) of the users would have walked if bikeshare were not available to them. About 21% and 22% indicated that they would have used metro rail and bus, respectively, as their alternative mode of transportation. Similar distribution was observed between the two survey samples when the survey participants were asked about their preferred mode of transportation to the bikeshare station. Most of the members reported that they would walk to get to the nearest CaBi station (89% in the 2016 survey and 84% in the 2017 survey). About 8% of the Member Survey and 10% of the CaBi User Survey participants responded that they used metro rail in order to reach the CaBi.

In summary, the chi-Square goodness of fit analysis showed that none of the responses in the 2017 User Survey to seven identical questions in the 2016 Member Survey showed a significant difference in the two samples. Furthermore, the comparison analysis indicated that based on the responses to identical questions, the two-member surveys ranged from ‘not dissimilar’ (for gender) to ‘almost identical’ (for income). Thus, the major takeaway from Table 1 is that the member distribution in the 2017 User Survey (n = 317) is similar or identical to the member distribution in the 2016 Member Survey (n = 5,498). By extension, the 2017 User Survey (current survey) sample is a good representative of the CaBi member population. Given that the 2017 User Survey also contains responses from casual users (n = 305), it may also be surmised that the 2017 User Survey sample includes a fair and accurate approximation of CaBi’s casual user population.

5.5 Differentiating Between Casual Users and Members

To identify similarities and differences between casual users and members, additional Chi-square goodness of fits were conducted on the 2017 User Survey data. Table 5.3 presents the results of this analysis for several different questions on the survey and the responses to those questions given by casual users and members. Members were predominantly male (67%), while gender distribution was similar across casual users (51% male and 49% female). Similar age distribution was observed between members and casual users. Majority of the survey respondents (55% and 61% for members and casual users respectively) were under 35 years old. The percentage of bikeshare usage by 54 and older years is the lowest (7% members, 10% casual users) among all age groups.

Table 5.3: Similarities and differences between casual users and members

	User type (2017 User Survey)		χ^2	p-value
	Registered Members (%) *(n = 317)*	Casual users (%) *(n = 305)*	*Observation(s) / inference(s) based on p-values*	
Gender			5.29	**0.021**
Male	67	51	*Members are predominantly male and casual users are evenly split between gender groups.*	
Female	33	49		
Age			2.92	0.405
Under 35	55	61	*No significant difference in age between the casual users and members*	
35-44	24	15		
45-54	14	14		
54 and over	7	10		
Ethnicity			7.44	0.059
White	77	59	*Fairly strong evidence of significant differences in ethnicity between casual users and members. A larger proportion of casual users are of Asian, Hispanic or African-American groups than members.*	
Asian	6	12		
Hispanic	5	12		
African-American	8	10		
Income			8.42	**0.015**
Low: <35,000	10	24	*The income profiles of casual users and members is significantly different. Larger portion of casual users fall under low-income (<$35,000) category.*	
Medium: $35,000 - $100,000	40	41		
High: >$100,000	50	35		
Frequency of cycling (in past month)			89.13	**0.000**
1-5 trips	19	85	*Casual users make significantly fewer number of trips than members. A majority of the members (58%) make more than 10 trips per week.*	
6-10 trips	23	8		
>10 trips	58	7		
Motivators (multiple answers allowed)			22.75	**0.004**
Get around more easily, faster	85	74	*The motivations for using bikeshare are significantly different between casual users and members.*	
Like to bike, fun way to travel	70	54		
Save money on transportation	59	33		
Exercise, fitness	59	37		
Access to other form of	40	11		

Table 5.3: Similarities and differences between casual users and members

	User type (2017 User Survey)		χ^2	p-value
	Registered Members (%) *(n = 317)*	Casual users (%) *(n = 305)*	*Observation(s) / inference(s) based on p-values*	
transportation				
Concern about environment	39	17		
New travel option/one-way travel option	36	12		
Access to another bike/backup bike	29	7		
Health concern	16	11		
Top trip types (multiple answers allowed)			79.58	**0.000**
Work or School	82	30	*Casual users use bikeshare for different trip purposes than members.*	
Personal appointment	40	15		
Social/ entertainment/ visiting	55	46		
Restaurant, meal	27	14		
Exercise, recreation	21	36		
Shopping or errands	33	14		
Touring / sightseeing	10	57		
Alternative mode of transportation			10.02	**0.040**
Walk	31	50	*Alternative modes of travel to the bikesharing trips taken by casual users and members are different. A majority of casual users would have walked. Members would have used five different modes with double-digit patronage.*	
Metrorail	22	15		
Uber, Lyft or taxi	17	18		
Bus	16	9		
Personal bike or vehicle	11	5		
Mode of transportation to CaBi station			4.61	0.099
Walk	84	78	*Modes of transportation to bikeshare stations are similar for both casual users and members.*	
Metrorail	10	7		
Others	6	15		
Mobile App Usage			9.66	**0.022**
Yes. I use Mobile App	37	21	*Members use mobile app a lot more than casual users.*	
No. I am aware of the app but won't use it.	29	25		
No. I am NOT aware of the app but will check it out.	21	37		
No. I am NOT aware of the app and have no plan to check it out.	13	17		
Effect of mobile app on CaBi usage			5.35	0.069
I am likely to use Bikeshare a lot more	13	23	*Majority of the members and casual users feel that mobile app does not affect their bikeshare usage.*	
I am likely to use it somewhat more	11	16		
It does not affect my usage	76	61		
Preferred Duration of Trip Before Re-Docking			28.43	**0.00**

Table 5.3: Similarities and differences between casual users and members

	User type (2017 User Survey)		χ^2	p-value
	Registered Members (%) *(n = 317)*	Casual users (%) *(n = 305)*	*Observation(s) / inference(s) based on p-values*	
30 min	47	21	*Members prefer shorter durations for trips. A plurality (36%) of casual users prefers a 60-min duration for the trip before user fee is assessed.*	
40 min	37	29		
60 min	16	36		
90 min	0	14		
Service Sensitivity			6.25	**0.044**
A lot more important	51	39	*Sensitivity on service is different between casual users and members.*	
Somewhat more important	31	26		
Equally important	16	30		
Residency			84.48	**0.000**
D.C. Area resident	96	34	*Members are predominantly residents of the DC area, nearly 2/3rd of casual users are not residents of the DC area*	
Not from DC Area / Visitor	4	66		
All statistically significant ($p<0.05$) values are emphasized in bold.				

A statistically significant difference in ethnicity of members and casual users can be seen in Table 5.3. Most of the members have identified themselves as "White" (77% registered members, 59% casual users). About 8% of the members and 10% of the casual users were African-American. Other major race / ethnic groups among members include Asians (6% members, 12% casual users) and Hispanics (5% members, 12% casual users). Significant differences were also observed for income groups between members and casual users. Nearly a quarter of the casual users and 10% of the members have household income less than \$35,000 (low-income group). About one third of the casual users and only 17% of the members earn less than \$50,000. About 32% of the casual users and a third of the members reported incomes between \$50,000-\$99,999 (medium-income group). Half of the member survey respondents and 35% of the casual users reported their annual household income greater than \$100,000 (high-income group).

Notable differences could be seen in the frequency of usage between member and casual users. Majority of the members (58%) reported to have made greater than 10 bikeshare trips in the prior month whereas most of the casual users (85%) made less than 5 trips in the past month. Considerable differences could also be seen in motivations for CaBi use and top trip purposes between member and casual users. Majority of the users utilize CaBi as a mode of transportation because it helps them get around more easily and faster (85% members, 74% casual users). About 59% of the members and more than 33% of the casual users indicated that they use CaBi for fitness purpose. Also, 59% of the members and more than 37% of the casual users use CaBi to save money on transportation. Approximately 40% of the casual users' bike because it is eco-friendly mode of transportation and about 54% of the members use bikeshare to access any other form of transportation. In case of top trip purposes, most of the members use CaBi for commuting purposes (82%) and casual users' bike mainly for sightseeing or touring (57%). Apart from commuting purpose, majority of the members use bikeshare for entertainment (55%) or personal appointment (40%).

There are statistically significant differences between members and casual users for choosing alternative mode of transportation if CaBi were not available to them. Majority of the casual users (50%) and 31% of the member survey respondents indicated that they would walk instead of using bikeshare. About 22% of the members and 15% of the casual users among the survey respondents noted that they would use Metrorail or bus. Approximately 17% of the bikeshare members indicated that they would use Uber or Lyft or Taxi. The preferred mode of transportation to the CaBi station is similar to both members and casual users. Most of the respondents denoted that they got to the bikeshare station by walk (84% members, 78% casual users). About 10% of the members and 7% of the casual users used metro rail to get to the nearest CaBi station.

Members and casual users indicated that they use the CaBi app differently. About 37% of the members and 21% of the casual users use the CaBi mobile app. There is no evidence that the CaBi App has any effect on bikeshare usage for both user groups as indicated by the majority of users. However, a minority of users (13% of members and 23% of casual users) reported that they are likely to use bikeshare a lot more due to the mobile app. This finding may have some immediate implications on the acceptance of bikesharing using dockless bikes in the DC area.

Survey respondents were asked about the importance of stations compared to the price (shown as service sensitivity in Table 5.3). With regards to service sensitivity members and casual users differed considerably from each other. About 51% of the members and 39% of the casual user respondents feel that the number of stations is more important compared to the price. Also, 16% of the members and 30% of the casual users responded that price is equally important compared to the availability of number of stations. This trend indicates that members are more sensitive to station density than casual users. The CaBi users should pay the usage fee if they cross the 30-minute time limit. Differences between members and casual users are statistically significant for the preferred duration of the trip prior to the assessment of usage fee. Nearly half (47%) of the members felt that a 30-minute duration is enough to complete the trip. However, approximately 79% of the casual users' experience that they need more time than 30-min to finish the trip, which indicates casual users need more time to complete the trip than registered members. Notable differences can be seen between the residency of the two groups. About 96% of the members live in the D.C. area while 66% of the casual users are visiting D.C. area on vacation or business trip.

5.6 Pricing Preferences

In addition to the basic demographic and other characteristics of users, the survey also captures the preferred bikeshare pricing options and pricing models of the CaBi users.

5.6.1 Fare Product Usage

Composition of various fare products used by respondents in the 2017 User Survey is illustrated in Figure 5.2. Annual members represented 49% of the survey sample followed by single-trip fare and 24-hour pass of about 25% and 16% respectively. Combined total of casual users (49%) is slightly less than the 51% representation by registered members in the survey data.

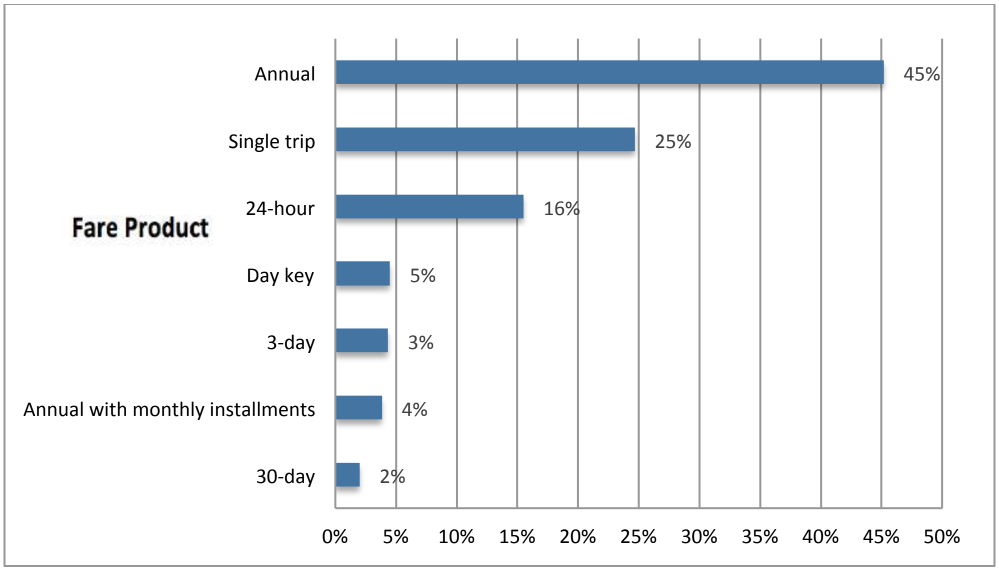


Figure 5.2: Fare product used by survey respondents

5.6.2 Preferred Bikeshare Pricing Options

Survey respondents were asked to choose all the pricing options they would prefer to be available irrespective of the pricing option they were using at the time of survey. As can be seen in Figure 5.3, single-trip fare and annual membership-paid once pricing options were chosen by 22% and 19%, respectively. About 15% and 12% of the survey respondents expressed preference to have the option of purchasing 24-hour pass and 3-day pass to be available, respectively. The least favorable pricing options among the respondents were monthly membership and 'day-key'.

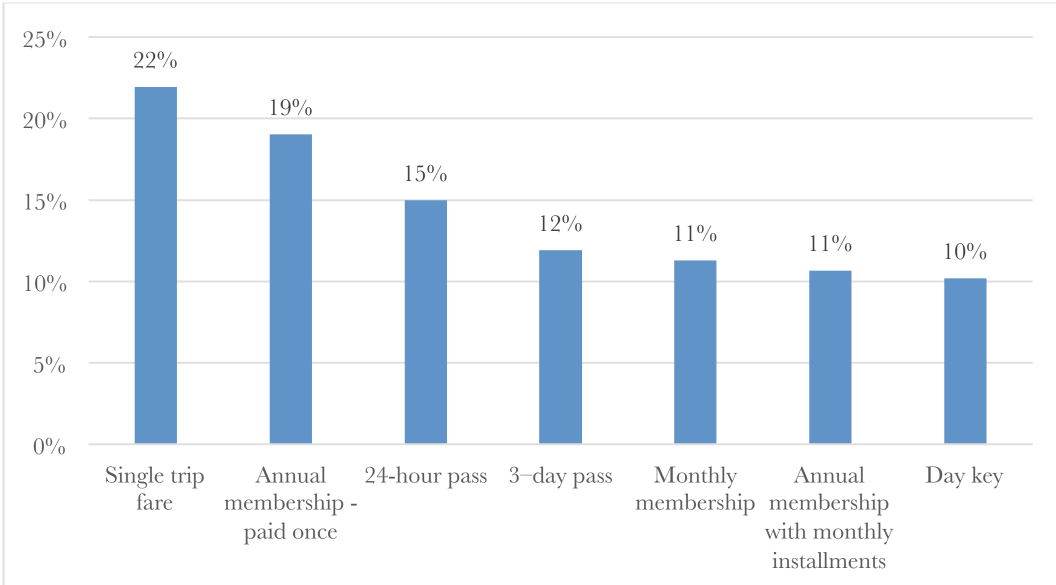


Figure 5.3: Preferred bikeshare pricing options

5.6.3 Preferred Pricing Models

When the respondents were asked to choose the pricing model that best suits them, a plurality (38%) of the respondents chose a combination of single-trip, 24-hour pass, and annual membership with monthly installments as the favorable pricing option (Option 1). About 22% of the respondents chose bulk single-trip passes with discount and expiry date, 24-hour pass, and annual membership with monthly installments (Option-3). A question about bulk single-trip passes were added as an option though it is not presently available in the CaBi system. The survey analysis showed slightly less than a quarter are interested in having bulk single-trip passes as an added option. Preferred pricing models of the bikeshare users is illustrated in Figure 5.4.

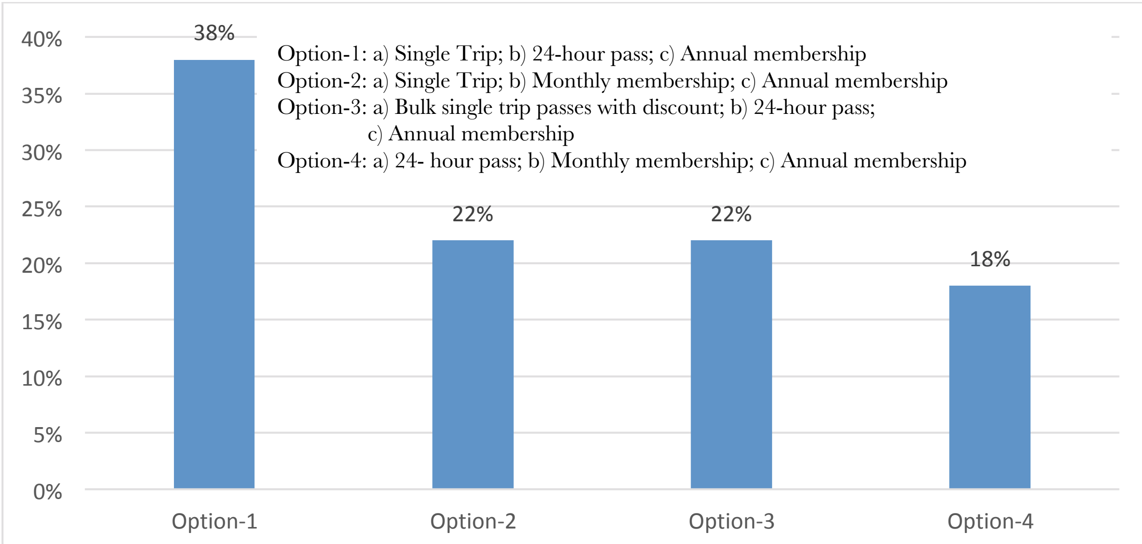


Figure 5.4: Preferred pricing models

5.6.4 Comparing Profiles of Under-Represented Groups

The member profiles of bikeshare users for under-represented groups from a very limited number of studies with information on casual users are summarized in Table 5.4. Comparatively, all three studies show that women tend to be more casual riders than members. Also, more low-income people use bikeshare on a short-term basis than members. In general, these studies indicate that members are more likely to be male and affluent compared to the casual users. Studies by Buehler (2011) and Venigalla et al. (2018) provide an important chronological observation on Capital Bikeshare usage by under-represented groups. The results of Buehler's study, which was based on an intercept survey conducted in 2011 shortly after the launch of CaBi, showed that the percentage of Black and Hispanic users among members and casual users was very low. The current study, which is an extension of the study Venigalla et al. (2018) is based on a 2017 survey, showed that all users of Black and Hispanic races more than doubled between 2011 and 2017. However, more data are needed to verify if these increases are indicative of a representative trend. Also, it is important to point out that these profiles are derived from three different surveys at two different bikeshare systems (Washington DC and San Francisco) in three different years. Therefore, caution is warranted in making any generalized inferences based on comparisons of these aggregate summaries of the surveys.

Table 5.4: Casual user and member profiles for under-represented groups from different surveys

Study and City (cities)	*n*	Casual users				Members			
		% Women	% Black	% Hispanic	% Low Income (<35k)	% Women	% Black	% Hispanic	% Low Income (<35k)
Venigalla et al. (2018); Washington DC	622	49%	10%	12%	24%	33%	8%	5%	10%
Shaheen et al. (2015); San Francisco	170	35%	1%	12%	15%	28%	1%	4%	5%
Buehler (2011); Washington DC	340	52%	5%	4%	-	33%	2%	3%	-

5.7 Logistic Regression and Odds Ratio Analyses

A logistic regression model estimates the log-odds of the probability of an event that is explained by a linear combination of one or more independent variables, which may be interval, ratio, ordinal or nominal variables. For this study, logistic regression analyses were conducted to model the following:

- Significant differences in demographics and other dissimilarities between the registered members and casual users
- Fare-product preference of casual users between single-trip fare and 24-hour pass

The generalized form of the models developed is given as follows:

$$\text{logit}\ (Y) = \ln\left(\frac{\pi}{1-\pi}\right) = \alpha + \sum_{i=1}^{n} \beta_i X_i$$

$$\pi = Probability\ (Y, the\ outcome\ of\ interest) = \frac{exp^{(\alpha+\sum_{i=1}^{n}\beta_i X_i)}}{1+exp^{(\alpha+\sum_{i=1}^{n}\beta_i X_i)}}$$

Where:

α = intercept

$\beta_{1 \ldots n}$ = slope parameters (*1 to n)*

$X_{1 \ldots n}$ = a set of predictors (*1 to n*)

The values of α and β are estimated using the maximum likelihood method.

The regression coefficients (β_i) of independent variables represent the estimated increase in the log odds of the outcome per unit increase in the value of the explanatory variable. The odds ratio (*OR*) in logistic regression modeling represents the odds that an outcome will occur given a particular feature, compared to the odds of the outcome occurring in the absence of that feature. The odds ratio can also be used to determine whether a particular attribute affects the outcome, and to compare the magnitude of various factors for that outcome (Szumilas, 2010). For example, in the current study odds ratios are used to compare the relative odds of purchasing a particular membership type given exposure to set of socio-economic, demographics and other characteristics.

Two logistic regression models were developed to determine which explanatory variables are determinants of user type (Model 1: Formative model for user type); and fare product choice (between single-trip fare and 24-hour pass) by casual users (Model 2: Casual user fare product choice model). Even though casual users have the option of purchasing three fare products, the survey data contained very few 3-day pass purchasers. For this reason, the response variable for Model 2 was modeled as a binary choice between single-trip fare and 24-hour pass. Both models were built with and tested for a set of seven explanatory variables ($X_{1 \text{ to } 7}$), namely: Trips (*T*), Gender (*G*), Age (*A*), Income (*I*), Residency (*R*), Service Sensitivity (*S*), and Race (*C*). Descriptive statistics for all variables in both models are listed in Table 5.5.

Table 5.5: Descriptive statistics for variables in logistic regression models

(a) Response variables

	Model 1: Formative Model for User Type			Model 2: Casual User Fare Product Choice Model		
Response Variable, Y	User type			Fare product choice of casual user		
	Values / Levels of Y	N	**%**	Values / Levels of Y	N	**%**
	1=Registered Member	329	68.12	1=single-trip fare	102	60.36
	0=Casual user	154	31.88	0=24-hour pass	67	39.64

(b) Explanatory variables

			Model 1 (Formative Model for User Type)		Model 2 (Casual User Fare Product Choice)	
Explanatory Variable, X_i	Description	Values / Levels	N	%	N	%
Trips, T	Number of trips in past month	Number of bikeshare trips	483	100	169	100
Gender, G	Gender of the user	1=Male	293	60.66	88	52.07
		0=Female	190	39.34	81	47.93
Age, A	Age range of the user (years)	21-24	59	12.22	32	18.93
		25-34	223	46.17	76	44.97
		35-44	105	21.74	27	15.98
		45-54	59	12.22	17	10.06
		55-64	32	6.63	15	8.88
		>65	5	1.04	2	1.18
Income, I	Group	Income range ($)				
	Low	0=<$35,000	70	14.49	34	20.12
	Medium/High	1=≥$35,000	413	85.51	135	79.88
Residency, R	Residency status	1=DC area resident	329	68.12	61	36.09
		0= Non-resident	154	31.88	108	63.91
Service Sensitivity, S	User's importance on number of stations relative to price (1-5 scale)	1=A lot more important	230	47.62	60	35.50
		2=Somewhat more important	140	28.99	53	31.36
		3=Equally important	94	19.46	45	26.63
		4=Somewhat less important	15	3.11	8	4.73
		5=A lot less important	4	0.83	3	1.78
Race, C	Race/Ethnicity of the user	1=White	349	72.26	101	59.76
		0=Other race	134	27.74	68	40.24

5.7.1 Model 1: Formative Model for User Type

Model 1 is developed to identify the determinants of user type ($Y = 1$ for members and $Y = 0$ for casual users) within the set of seven explicatory variables. The parameter estimates of Model 1, along with brief statements of inference are shown in Table 5.6. As seen in the table, the number of trips made in the prior month is a reliable predictor of bikeshare membership. The analysis showed that each additional increase in the number of monthly trips leads to about 18% increase in the odds of the bikeshare user being a registered member. Gender and age distribution between members and casual users do not appear to influence membership. Due to low survey samples for users of '*Black'*, '*Hispanic'*, '*Asian'* and '*Other'* race/ethnicity, users identified themselves in these categories were grouped as '*Other race*'. The OR analysis shows that White users have 2.4 times greater odds of being a registered member than those in the '*other race*' category. Also, at 10% level-of-significance, members are 2.4 times more likely to belong to higher income brackets (incomes above $35,000/year) than casual users.

The degree of sensitivity to service was also found to be a significant predictor of whether the CaBi user is member or casual user. Respondents were asked the degree to which the number of stations is important compared to price, using a 1-5 scale from "*A lot more important*" to "*A lot less important*". Compared to casual users, members were found to more sensitive to service than price. Respondents who indicated that they reside in the D.C. area have about 19-times greater odds of being a member, which confirms intuition.

Table 5.6: Formative model for user type (Model 1)

Fare option	Odds Ratio (OR)	Std. Err.	z	p>|z|	Inference
Constant	0.012	0.010	-5.36	0	
Trips, T	1.177	0.028	6.77	**0.00**	*Members make more bike trips than casual users. A typical member is likely to take 18% more trips than a casual user.*
Gender, G	1.006	0.305	-0.02	0.98	*No significant difference. i.e. gender is not a determinant of user type*
Race, C	2.362	0.811	2.50	**0.01**	*Members are nearly 2 times more likely to be of White ethnicity than other races.*
Age, A	1.017	0.015	1.15	0.25	*No significant difference*
Income, I	2.352	1.186	1.70	0.09	*At α=10%, members are 2.4 times more likely to be in higher income groups than casual users.*
Service sensitivity, S	0.703	0.107	-2.31	**0.02**	*Members are less price sensitive compared to casual users (as indicated by odds ratio that is less than parity).*
Residency, R	19.359	7.226	7.94	**0.00**	*Members are 19 times more likely to be D.C. area resident than non-resident.*
Values of Y and X_i *Y (binary): 1 Member; 0 is casual user* *T (interval): Number of trips in the prior month* *G (binary): 1 is male, 0 is female* *C (binary): 1 is White, 0 other race* *I (binary): 1 is Medium or high income (>$35,000); 0 is Low income (<$35,000)* *S (ordinal scale): 1(lot more important) to 5 (lot less important)* *R (binary): 1 is DC area, 0 is non-resident*				*Interpretation of OR values:* *OR = 1 Variable does not affect odds of the outcome* *OR > 1 Variable is associated with higher odds of the outcome* *OR < 1 Variable is associated with lower odds of the outcome. In case of binary variable, odds are in favor of outcome variable where Y=0* *Bold emphasis indicates statistical significance at α=5%*	

5.7.2 Model 2: Casual User Fare Product Choice Model

single-trip fare (STF) and 24-hour pass constituted 25% and 16% of the total survey sample. Model-2 is developed to determine the influence of explanatory variables in the choice between single-trip fare ($Y = 1$) and 24-hour pass ($Y = 0$). Other casual fare products were ignored in the model due to their low sample size (day key pass, 3-day pass constituted of less than 5% of the survey sample). The model parameters are shown in Table 5.7. Gender, age, and income distribution do not appear to influence casual fare product choice. However, 24-hour pass holders are more likely to be 'White' than STF purchasers. In terms of service sensitivity and number of trips made in the prior month, STF purchasers and 24-hour pass holders are not different. D.C. residents have higher odds of being a STF user than a 24-hour pass user. In contrast, non-residents are likely to prefer 24-hour pass, which allows them to take multiple trips with the same purchase.

Table 5.7: Determinants of casual user fare product choice (Model 2)

Fare option	**Odds Ratio (OR)**	**Std. Err.**	z	$p>\lvert z\rvert$	**Inference**
Constant	1.307	0.892	0.39	0.694	
Trips, *T*	1.033	0.042	0.80	0.425	*No significant difference. i.e. the choice of fare product is not determined by number of trips the user makes.*
Gender, *G*	1.219	0.408	0.59	0.554	*No significant difference. i.e. both males and females make similar choices in purchasing STF or 24-hour pass.*
Race, *C*	0.439	0.162	-2.24	**0.025**	*24-hour pass purchasers are more likely to be "White".*
Age, *A*	0.997	0.015	-0.21	0.834	*No significant difference.*
Income, *I*	1.763	0.787	1.27	0.204	*p-value, though low, indicates that income may have less influence on casual user preference between STF and 24-hour pass.*
Service sensitivity, *S*	0.939	0.160	-0.37	0.714	*Service preferences of user of STF and 24-hour pass are comparable.*
Residency, *R*	2.209	0.832	2.11	**0.035**	*STF users are nearly 22 times more likely to be D.C. area residents than non-residents. Contrarily, visitors are more likely to purchase 24-hour pass than pay for each trip separately.*

Values of Y and X_i

- *Y (binary): 1 is single-trip user; 0 is user with 24-hour pass*
- *T (interval): number of trips in the prior month*
- *G (binary): 1 is male, 0 is female*
- *C (binary): 1 is White, 0 other race*
- *I (binary): 1 is Medium or high income (>$35,000); 0 is Low income (<$35,000)*
- *S (ordinal scale): 1(lot more important) to 5 (lot less important)*
- *R (binary): 1 is DC area resident, 0 is non-resident*

Interpretation of OR values:

OR = 1 Variable does not affect odds of the outcome

OR > 1 Variable is associated with higher odds of the outcome

OR < 1 Variable is associated with lower odds of the outcome. In case of binary variable, odds are in favor of outcome variable where Y=0

Bold emphasis indicates statistical significance at α=5%

5.8 Conclusions and Recommendations

This research compared and contrasted the profiles of casual users and members of Capital Bikeshare (CaBi), the third largest bikeshare program in United States by conducting an intercept survey at various CaBi stations. The survey data was validated by verifying its consistency with a member survey of much larger sample size (n = 5,498) via chi-squared goodness of fit tests. Additional Pearson's chi-squared test results showed that gender and income distributions are different for members and casual users. It was observed that members were predominantly male (67%), while gender distribution was similar across casual users (51% male and 49% female). Similar age distribution was observed between members and casual users. Significant difference was observed in terms of ethnicity between members and casual users. Majority of the members in the survey have identified themselves as "White". Notable differences could be seen in the trip purposes and alternative mode of transportation between members and casual users. Most of the members use bikeshare for commuting purposes (82%) and casual users' bike mainly for sightseeing or touring (57%). Half of the casual users and 31% of the member survey respondents indicated that they would walk instead of using bikeshare. Less percentage of casual users use the mobile app and a majority of them indicated that they require more time (>30 minutes) to complete the trip before re-docking compared to members. Participants report STF and annual membership paid at once as their preferred pricing options and a combination of STF, 24-hour pass, and annual membership with monthly installments as their favorable pricing model. Buck et al. (2013) study results suggested that CaBi casual users were more likely to be female. However, the results of this study, which are based on the 2017 CaBi User Survey, showed that the odds of CaBi casual users being male are slightly higher.

Logistic regression models were developed to determine which explanatory variables are determinants of user type and fare product choice by casual users (single-trip fare vs. 24-hour pass). The findings indicated that members are more likely to be white, earn more and reside in the D.C. area compared to the casual users. Casual users make less bikeshare trips and are less sensitive to the service (station density) compared to members. Regression results among the casual users demonstrate that single-trip fare users are less likely to be white and more likely to be D.C. residents compared to the 24-hour pass users. Gender, age, and income distribution do not appear to influence casual fare product choice.

5.8.1 Discussion

This study sheds light on various crucial elements that are useful in policy-making, planning and operational management for bikeshare. Some examples use for the findings of this study include the following:

1. Determining financial support for users belonging to economically disadvantaged groups
2. Monitoring the bikeshare usage over time, across geographies and among different types of users
3. Identifying incentives to help increase membership
4. Identifying target demographics for marketing campaigns
5. Evaluating pricing models

However, several of these findings may be unique to the CaBi system because of its unique structure and the user-base. Therefore, caution must be exercised when extrapolating the study findings to other bikeshare systems. Further research is needed to study the price sensitivities and price elasticities of the bikeshare users. Even though the results of this study are not transferable, the methods discussed in this research are transferable.

6 DYNAMIC ESTIMATES OF PRICE ELASTICITIES FOR PUBLIC BIKESHARE SYSTEMS

6.1 Introduction

Numerous potential benefits of bikesharing include increased mobility, cost savings from modal shifts, reduction in traffic congestion and fuel use, increased use of public transit, increased health benefits, and greater environmental awareness (Shaheen et al., 2010). Pricing is one of the major factors that affects ridership and revenue of the bikeshare systems. Various factors such as bikeshare expenses, revenue generated, and socio-demographic characteristics are considered in determining the optimal prices of the bikeshare fare products. A few studies revealed reducing bikeshare subscription fees and providing flexible subscriptions to users would increase the bikeshare ridership (Ahillen et al., 2015; Fishman, 2016).

Factors that affect price sensitivity of a transportation mode include user characteristics, trip type, geography, type of price change, time period and mode type (Litman, 2004). The simplest way to measure price sensitivity is by developing elasticities, defined as the percent change in price with one percent change in demand. Price elasticities have many applications in transportation policy and planning. Elasticities are used to predict the impact of changes to transit fares on ridership; develop models to predict how changes in transit service will affect vehicle traffic volumes; and they can help evaluate the impacts of new transit services, road tolls, and parking fees

(Litman, 2004). Several studies focused on analyzing price and service elasticities of transit systems like metro rail and bus services (Dargay and Hanly, 2002; Litman, 2004; Matas, 2004; Cats et al., 2014; Schimek, 2015). A few studies had evaluated the influence of price changes of vanpool and carsharing services (Concas et al., 2005; Schwiterman and Bieszczat, 2017). However, research on assessing price and service sensitivities of the bikeshare users is negligible.

User surveys play a critical role in taking measurements on users' sensitivities to price and service. Several bikeshare user surveys have indicated that bikeshare members are largely influenced by the service elements of the system, such as station density. For example, surveys of registered members of Capital Bikeshare (CaBi), indicated that majority of members reported that they would ride even more if the system had more bikes and docks available (Capital Bikeshare 2016). CaBi is the public bikeshare system in the metro Whashington DC area, which spreads across several jurisdictions in DC and its Northern Virginia and Maryland suburbs. The 2016 CaBi registered member survey also reported that most of the members use bikeshare to get to work and saved an average of $631 on travel costs in a year. However, none of the periodic CaBi member survey reports (2011, 2014 and 2016) and numerous survey reports of users at other bikeshare programs discussed the user sensitivity to bikeshare pricing (Venigalla et al. 2018). Numerous studies analyzed the effect of price change on metro rail, bus, vanpool, and carsharing services. However, to date no studies were conducted on model sensitivities of bikeshare users to price and service. Furthermore, research on price elasticities of bikeshare fare products that could be used in policy calculations to project the change in bikeshare ridership and revenue is also scant. This research fills these gaps through analysis of an intercept survey of bikeshare users conducted at several CaBi locations. The main objective of the research is to examine bikeshare users' sensitivity to changes in price and preferences on service. Additionally, price elasticities of bikeshare fare products were developed. Specifically, this study addresses the following research questions:

1. Which variables influence the price and service sensitivities of the bikeshare users?
2. What are the price elasticities for different bikeshare fare options available?

In this study, price elasticity is defined as the percent change in price with one percent change in demand for the considered fare. Ordered logit regression models were developed to determine the influence of socio-economics, demographics and other characteristics on the price and service sensitivities of the bikeshare users. Furthermore, pivot-elasticity curves for various fare products pivoted at the prevailing prices were generated using monadic price testing

6.2 Prior Research

Several studies derived fare elasticities of metro rail and bus services. Cats et al. (2014) evaluated fare-free public transport (FFPT) policy in Estonia based on public transport demand model. The study revealed that passenger demand increases only by 1.2% after the introduction of FFPT. This seemingly small difference could be due to the previous price level, public transport share, and analysis of the short-term impact of this policy. Schimek (2015) estimates fare and service elasticities with panel data for 198 U.S. transit agencies from 1991 to 2012. The dynamic model estimated short-run (less than two years) and long-run (more than five years) elasticities as -0.34 and -0.66 respectively. The results showed that transit demand in large areas was less sensitive to fare and much more sensitive to service compared to small areas. The study also concluded that where fares are initially low, an increase in fare would lead to a greater decline in ridership than in places where fares are high even initially.

A similar study conducted by Dargay and Hanly (2002) indicated that the long-run elasticities are about twice the short-run elasticities. The study examined the fare elasticities for local bus services in England using dynamic econometric model. The analysis revealed that demand was more price-sensitive at higher fare levels and most likely values of the fare elasticity are -0.4 in the short run and -0.9 in the long-run. The per capita bus kilometers were considered as the measure of service quality. The estimated service elasticities are almost similar to the fare elasticities in magnitude and opposite in sign. Matas (2004) showed that the introduction of an integrated fare system and improvement in bus and underground networks increased the public transport use. The introduction of a travel card system has increased underground trips and bus trips by 15% and 7% respectively. Pham & Linsalata (1991) conducted a special survey to obtain ridership data 24 months before and 24 months after each fare change for 52 transit systems. The data collected for the study included monthly ridership, vehicle miles and hours, basic adult fare, and total 'farebox' revenues during peak and off-peak periods of the transit systems. The results showed a 10% increase in bus fares would result in a 4%

decrease in ridership. The study also ascertained transit riders in small cities are more responsive to fare increases than those in large cities and peak-hour commuters are less responsive to fare changes than off-peak hour commuters. Elasticities for off-peak transit travel are higher than peak period elasticities as the peak period travel consists mainly of commute trips (Litman, 2004).

Limited research was performed to assess the influence of price change on vanpool and carsharing services. Concas et al. (2005) studied the effects of fare subsidies on the demand for vanpool services using logistic regression modeling technique. The study used employer and employee data from the survey done in year 1999 as part of the commute trip reduction program in the Puget Sound region (Washington). The results showed 10% increase in vanpool price was associated with a 7.3% decrease in its demand and the probability of choosing a vanpool doubles if subsidies are provided to the employees. The study also presented that individuals become less responsive to price change as the distance increases beyond 60 miles. Schwiterman and Bieszczat (2017) explored the changing prices and taxation level for carsharing between 2011 and 2016 in the United States. The study noted that significant fall in prices made carsharing more affordable to lower-income consumers. The study concluded that tax increases had offset almost a third of the price decline, which negatively affected the operating margins. Empirical studies based on user surveys indicated that bikeshare users are more likely to be male and young who have higher household income (Fuller et al., 2011; Murphy and Usher, 2012; Bachand-Marleau, Lee, and El-Geneidy, 2012; Ogilvie and Goodman, 2012).

Various studies discussed elements affecting bikeshare ridership but did not include pricing as one of the factors. Fishman (2016) reviewed recent bicycle infrastructure and finds out that convenience is the major factor that increases bicycle usage and the introduction of mandatory helmet legislation decreases the bicycle ridership. Judrak (2013) examined the time-specific cost structure of the public bikesharing system of Boston and Washington, DC. The study found that registered (annual or monthly pass) users exhibit higher cost sensitivity around the 30 and 60-minute pricing boundaries compared to the casual (short-term) users. Based on the results, providing ample racks in central location, proper spacing of bikeshare stations to maximize coverage within the cost-free time limit, and dynamic pricing of the public bikeshare system based on the current traffic conditions were recommended in this study. Ahillen et al. (2015) compared the policies and ridership trends of the Washington, DC's Capital Bikeshare and Brisbane's CityCycle. The findings showed that CaBi had few changes in its pricing policy since its launch in 2010. However, CityCycle reduced the daily subscription fees from \$11 to \$2, introduced weekly subscriptions and provided free helmets at each of the stations. The results indicated providing helmets, reducing subscription fees, and adding flexible subscriptions to users may have contributed to a 50% increase in CityCycle ridership in just six months. Goodman and Cheshire (2014) examined how the profile of income-deprived and women users changed in the first three years in London bicycle sharing system. The introduction of casual use fare products has encouraged women to use the system and the percentage of income-deprived users doubled as the bikeshare expanded its system to poorer areas. Kaviti et al. (2018) studied the impact of introducing single-trip fare (STF) for $2 on CaBi ridership and revenue. The results showed that introducing this new fare option increased the first-time casual users and casual users' monthly ridership by 79% and 41% respectively. In a doctoral dissertation work, Kaviti (2018) presented comprehensive profiles of CaBi users, their price preferences and studied the impact of STF on ridership and revenue. A study report by Venigalla et al. (2018) documented the development of price elasticities for Capital Bikeshare using monadic price testing. The report confined its scope to price elasticity of the single-trip fare product. The research work presented in this paper is based on an expanded scope of price elasticity modeling work performed by Venigalla et al. (2018). In summary, though several studies and surveys were conducted to analyze the fare and service elasticities of transit system like metro rail and buses, very limited research work was found in literature that evaluated price sensitivity of users towards metro-rail, bus and carsharing services. At the same time, no modeling studies examined the price and services sensitivities of bikeshare users. Only the study by Venigalla et al. (2018) developed price elasticities of bikeshare fare product. Though numerous studies have been conducted to profile bikeshare users and understand their behavior, very few surveys examined price sensitivity of users. This research will study the fare and service sensitivities of various membership options available in the public bikesharing system by analyzing the survey conducted at CaBi locations.

6.3 Methodology

The study methodology includes the following sequential steps:

1. Design, plan and execute a user survey to elicit responses on the demographics and other preferences of the bikeshare users.
2. Model survey data using ordered logistic modeling techniques to draw inferences on the price and service sensitivities of casual users and members.
3. Estimate the price elasticities of popular fare products of CaBi system using monadic price testing approach.

6.3.1 Survey Design and Execution

A detailed 5-page, 26-question survey instrument was designed in consultation with CaBi stakeholders. Key elements of the survey that were used in this study include questions on user sensitivity towards bikeshare service and pricing of different fare products. The overall scope of the survey, which was much broader than what was used in this study, included capturing profiles of casual users as well as registered members. In addition to information on price and service sensitivity, questions collected data on user demographics such as age, gender, and household income of the person. The survey locations were chosen to cover all the jurisdictions and to include various demographic groups. Also, the survey execution ensured that the final sample has proportional representation of casual and registered users and underrepresented groups. The survey respondents were given an option to fill a paper survey at the intercepted location, mail in the form using a self-addressed stamped envelope or take the survey online. Additionally, simultaneous social media and email campaigns were also conducted. The response rate of the intercepted users is above 70% and mail-in surveys is 14%. Researchers at George Mason University (GMU) conducted the survey in September and October 2017 and a total of 622 users responded. More details about the survey are presented in Venigalla et al. (2018).

6.3.2 Monadic Price Testing (MPT)

Monadic design is one of the most commonly used and the least biased among the techniques used in consumer pricing research (Lyon, 2002). The monadic experiment consists of sample of consumers who are randomly assigned to dissimilar price groups with one of the several possible prices presented in each of these groups (Bakken, 2012). In a monadic design, no respondent ever knows that other prices are being tested or the price is the object of the research (Lyon, 2002). One of the objectives of using monadic design for some questions in the intercept survey was to create pivot-price elasticities of demand curves for various pricing options available at CaBi. The survey form included a few questions that were designed based on the monadic design. The questions were intended for studying the sensitivity of CaBi users to price changes for various fare products. Each of the respondents was asked about her/her preferences to two new prices of a product he/she is currently using. One of the two new prices tested is above the current price and the other is below the current price. The questions are thus framed, "Currently the XYZ product (i.e. the fare product such as single-trip fare) costs $X1 (X1 = current or pivot price). If it costs $X2, how would it affect your bikeshare usage?" The question-set for a hypothetical decrease and increase in price by the same amount ($0.50), and the options given to the respondent (ordered in a logical hierarchy or ordinal scale) is shown below:

Q#. Currently the single-trip fare costs $2.00 per trip. If it costs $1.50, how would it affect your bikeshare usage?

a) Likely to use it a lot more

b) Likely to use it somewhat more

c) Does not affect my choice for commuting

Q#. Currently the single-trip fare costs $2.00 per trip. If it costs $2.50, how would it affect your bikeshare usage?

a) Likely to use it a lot less

b) Likely to use it somewhat less

c) Does not affect my choice for commuting

A completely different version of the same survey form polled the same question-set for an altered price pair with a larger difference from the pivot price (current price). Phrasing of the questions was slightly different for monthly and annual membership fares as the membership fares are not on 'per trip' basis. Different versions of the survey form were distributed randomly to the respondents. The matrix of prices tested in each version of the survey is listed in Table 6.1.

Table 6.1: Monadic pricing options

Pricing Option	Current or Pivot Price	Suggested New Price	
		Survey Version-1	Survey Version-2
single-Trip	$2	$1.50	$1.00
		$2.50	$3.00
Monthly membership	$28	$25	$23
		$31	$33
Annual	$85	$93	$97

membership		\$77	\$73

6.3.3 Ordered Logit Regression Model

An ordered logit model is typically used when there are more than two ordinal responses are possible for the outcome variable. The model is routinely applied in various fields including sociology, political science, economics, and psychology (Long and Freese, 2014). Various accident research studies used this approach to examine the effects of geodemographic characteristics on the severity of injuries sustained by vehicle occupants (Srinivasan, 2002; Wang & Kockelman, 2005; Quddus, 2015), to evaluate factors contributing to bicycle-vehicle conflicts (Stipancic et al., 2016) and pedestrian injury severity (Kwigizile, Sando, & Chimba, 2011). Ordered logit methodology was also used to determine the influence of service quality on demand of buses (Rojo et al., 2012; Efthymiou et al., 2017) and bikeshare usage (Faghih-Imani & Eluru, 2016). However, to date this model was not applied to determine the price sensitivity of transit or bikeshare systems.

Ordered logit modeling technique was employed to analyze the price and service sensitivities of bikeshare users as the response variables and user characteristics as explanatory variables. Both response variables were measured on ordinal scale as they have more than two categories and the values of the answers have a valid sequential order. The generalized form of the two ordered logit models developed for this study with *J* alternatives and *(J-1)* intercepts is given as follows:

$$y_i^* = x_i\beta + \varepsilon_i \tag{6.1}$$

Predicted probability for the ordinal regression model is given as

$$Pr(y = m|x_i) = F(\tau_m - x\beta) - F(\tau_{m-1} - x\beta)\ for\ m = 1\ to\ J \tag{6.2}$$

$$x\beta = \sum \beta_i x_i$$

(6.3)

$$F\ is\ the\ cumulative\ distribution\ function\ for\ \varepsilon = var(\varepsilon) = \frac{\pi^2}{3}$$

Where:

y = response variable (price and service sensitivity).

x = vector of independent variables varies between the chosen response variables. (Trips (*T*), Gender (*G*), Age (*A*), Income (*I*), and Race (*R*) for price sensitivity models; and Fare option (*F*), Trips (*T*), Gender (*G*), Age (*A*), Income (*I*), and Race (*R*) for service sensitivity models)

β = vector of regression coefficients.

ε = error term.

6.4 Analysis Results

6.4.1 Ordered Logistic Regression Analysis

The ordered logit models were developed using "*ologit*" (proportional odds model) function in statistical software Stata. Ordered logit regression assumes that the relationship between each pair of outcome groups is the same, which is referred to as the parallel regression assumption (or also as proportional odds assumption). Only one set of coefficients exists, as the relationship between all pairs of groups is same. The Wald test developed by Brant (1990) was used to test the parallel regression assumption by employing ‘brant’ function in Stata. The advantage of the ‘brant’ function is that it tests the proportional odds assumption for each variable individually. Several models were developed to determine which variables explain the price and service sensitivity of the bikeshare users. Registered members (or simply members) are those who have purchased monthly or annual membership whereas casual users are those who have purchased STF, daily or 3-day membership. The analysis to test the price sensitivity included one casual user (STF) and one-member fare product (annual membership), both of which had adequate representation in the survey sample. Ordered logit regression technique is also employed to test the service sensitivity of all the CaBi users.

6.4.2 Price Sensitivity

Survey questions were designed to test the price sensitivity of the STF, annual and monthly membership fare options. In this study, only STF and annual membership option have been analyzed due to the low sample size of monthly membership (n = 12). As mentioned in Table-1, two versions of the survey were designed to perform the monadic price testing. Furthermore, ordered logistic regression was performed only for Version-1 of the survey form due to the limited sample availability for STF (n = 16) and annual membership (n = 45) in Version-2. The following four models were developed to account for price change (increase and decrease from current price) for STF and annual membership.

- Model-1: STF reduced to $1.50

- Model-2: STF increased to \$2.50
- Model-3: Annual membership reduced by \$8
- Model-4: Annual membership increased by \$8

Survey respondents were given three options to choose from based on the increase or decrease from the current price. Ordered logit regression method is used to analyze the price sensitivity of bikeshare users as the response variable has three possible outcomes depending on the price change.

- $Y = 1$ - Likely to use bikeshare a lot more/less (High price sensitive)
- $Y = 2$ - Likely to use bikeshare somewhat more/less (Medium price sensitive)
- $Y = 3$ - Does not affect my usage (Not price sensitive)

All four models were built and tested for a set of five explanatory variables namely Trips (*T*), Gender (*G*), Age (*A*), Income (*I*), and Race (*R*). Descriptive statistics for study sample are summarized in Table 6.2. The results of the parallel test showed that all variables in Model-1 (STF reduced to \$1.50) & Model-2 (STF increased to \$2.50) satisfy the proportional odds assumption. However, 'gender' variable was found to violate the parallel regression assumption in Model-3 (Annual membership reduced by \$8) and Model-4 (Annual membership increased by \$8). Therefore, 'gender' variable was removed from these models to satisfy the proportional odds assumption. Income ranges included in the survey forms were regrouped into low (<\$35,000), medium (\$35,000 to \$100,000), and high (>\$100,000) categories according to the U.S. Census Bureau (U.S.

Census Bureau, 2017). The weighted average values of the income were used as the income variables in the models.

Table 6.2: Descriptive statistics for study sample

(a) Response variable

Response Variable, *Y*		Price Sensitivity							
		Model-1: STF reduced to $1.50		Model-2: STF increased to $2.50		Model-3: Annual membership reduced by $8		Model-4: Annual membership increased by $8	
Price sensitivity of the bikeshare user (1 to 3 scale)	Values / Levels of *Y*	N	%	N	%	N	%	N	%
	1=High price Sensitive	26	31.33	14	16.87	35	18.13	39	20.21
	2=Medium price Sensitive	24	28.92	29	34.94	27	13.99	35	18.13
	3=Not price sensitive	33	39.76	40	48.19	131	67.88	119	61.66

(b) Explanatory variables

Variable	Description	Values / Levels	Model-1 & Model-2		Model-3 & Model-4	
			N	%	N	%
Trips, *T*	Number of trips in past month	Number of trips	83	100	193	100
Gender, *G*	Gender of the user	1=Male	43	51.81	143	74.09
		0=Female	40	48.19	50	25.91
Age, *A*	Age range of the user (years)	21-24	19	22.89	11	5.70
		25-34	38	45.78	96	49.74
		35-44	13	15.66	50	25.91
		45-54	8	9.64	22	11.40
		55-64	5	6.02	13	6.74
		>65	-	-	1	0.52
Income, *I*	Group	Income range ($)				
	Low	<$35,000	15	18.06	19	9.84
	Medium	$35,000 to $100,000	38	45.78	72	37.31
	High	≥$100,000	30	36.15	102	52.86
Race, *R*	Race/Ethnicity of the user	1=White	45	54.22	150	77.72
		0=Other race	38	45.78	43	22.28

Regression results for price sensitivity are shown in Table 6.3. The likelihood ratio for all the models has a p-value less than 0.05 (at 95% confidence level) meaning that all the models are statistically significant, as compared to the null model with no predictors. Model 1 and Model 2 represent regression results when the STF is decreased or increased by half-a-dollar, respectively. The response variable decreases with increase in price sensitivity of the bikeshare users. All the coefficient estimates with positive sign implies decrease in the price sensitivity levels with the increase in value of the explanatory variables. Race is found to be statistically significant at 95% confidence level for Model 1 and Model 2. The positive sign of the coefficient in the race signifies White users are less sensitive to STF price change compared to other races. Model 3 and Model 4 represents regression results when the annual membership is decreased or increased by $8 respectively. Income is the only variable found to be significant in Model-3. Higher income groups were found to be less responsive to the price change. Household income and race were found to be statistically significant in Model-4, which indicates that higher income groups and White users are less sensitive to price compared to other income groups and other ethnicities respectively.

Table 6.3: Regression results for price sensitivity

	Coef.	Std. Err.	z	P>|z|	Inference
Model 1: STF reduced to $1.50					
Trips, *T*	-0.055	0.037	-1.50	0.135	*Number of weekly trips and gender of the bikeshare user have no significant impact for reduction in price for STF product.*
Gender, *G*	0.235	0.439	0.54	0.592	
Age, *A*	0.018	0.232	0.79	0.428	*Age and income of the bikeshare user do not influence the bikeshare usage by lowering the price by $0.50*
Income, *I*	-0.003	0.004	-0.60	0.547	
Race, *R*	1.086	0.442	2.45	**0.014**	*White users are less reactive to change in price than users of 'other' races.*
Y=1|*Y*=2	0.014	0.748			
Y=2|*Y*=3	1.321	0.763			
Model 2: STF increased to $2.50					
Trips, *T*	-0.014	0.038	-0.37	0.712	• *Influence of number of trips, gender and age of the bikeshare on usage is not statistically significant if the STF price is increased by $0.50 to $2.50* • *At α=10%, lower income groups are more susceptible to price change to $2.50.* • *White users are 1.7 log-odd times less sensitive to price than other race groups.*
Gender, *G*	-0.224	0.468	-0.48	0.632	
Age, *A*	-0.009	0.026	-0.34	0.736	
Income, *I*	0.008	0.005	1.71	0.087	
Race, *R*	1.688	0.484	3.49	**0.00**	
Y=1|*Y*=2	-0.706	0.833			
Y=2|*Y*=3	1.345	0.838			
Model 3: Annual membership reduced by $8.00					
Trips, *T*	0.028	0.007	0.37	0.709	• *Trips made and age of the bikeshare user have no significant impact for increase in annual membership price.* • *Higher income groups were found to be in higher levels (medium or not sensitive) of price sensitivity.* • *Race appears to have no influence on price sensitivity if the price is lowered by $8.*
Age, *A*	0.006	0.020	0.27	0.784	
Income, *I*	0.011	0.004	3.19	**0.001**	
Race, *R*	0.156	0.378	0.41	0.680	
Y=1|*Y*=2	0.046	0.725			
Y=2|*Y*=3	0.868	0.728			
Model 4: Annual membership increased by $8.00					
Trips, *T*	0.007	0.007	1.01	0.313	• *Trips made and age of the bikeshare user is insignificant to $8 increase in price for annual membership.* • *Lower income groups are more responsive to price increase by $8.* • *White are less sensitive to $8 increase in annual membership price.*
Age, *A*	-0.002	0.019	-0.12	0.908	
Income, *I*	0.015	0.003	4.29	**0.00**	
Race, *R*	0.984	0.356	2.77	**0.006**	
Y=1|*Y*=2	0.901	0.710			
Y=2|*Y*=3	1.986	0.723			
Notes:					

Table 6.3: Regression results for price sensitivity

- *Negative sign for coefficient of any explanatory variable indicates that higher value of that variable, lower the price sensitivity*
- *Bold emphasis indicates statistical significance at α=5%.*
- *Y = 1, 2, and 3 are the cut points (intercepts) of the model. Y = 1 - Likely to use bikeshare a lot more/less; Y = 2 - Likely to use bikeshare somewhat more/less; and Y = 3 - Does not affect my usage*

Predicted probabilities are the probability values of different models when all the predictors are at their mean value. The results, as shown in Table 6.4, suggest that the bikeshare users purchasing STF are more sensitive to fare changes than those who purchase annual membership. Approximately 39% and 47% of STF users does not have any influence of bike share usage with price decrease or increase respectively by half-a-dollar from the current pricing. Majority of the annual members are found to be unresponsive to price change. About 16% of the annual members are highly sensitive to the change in price.

Table 6.4: Predicted probabilities

Model	High price sensitive	Medium price sensitive	Not price sensitive
STF reduced to $1.50	0.299	0.313	0.388
STF increased to $2.50	0.127	0.403	0.470
Annual membership reduced by $8.00	0.160	0.142	0.698
Annual membership increased by $8.00	0.160	0.200	0.640

Marginal effects expressed as a percent for all the models are presented in Table 6.5. These effects show that each unit increase in the explanatory variable increases/decreases the probability of selecting the level of price sensitivity while all other variables are held constant. Marginal effects of the explanatory variables must sum to zero, which means that the lower probability of users who are not price sensitive (Y = 3) equals the sum of increased probability of persons who are price sensitive (Y = 1 and Y = 2). For a variable with a positive coefficient, an increase in the magnitude of the variable is associated with an increased chance of people not being price sensitive. The marginal effects indicate that users of races/ethnicities other than White users are more sensitive to price for the STF option. The effects indicate that about 25% and 38% of White users are not sensitive to STF fare decrease or increase respectively. Other explanatory variables have a minimal or no influence on the price sensitivities for STF. Trips, age and income of the bikeshare user have minimal or no influence on response to the price change for annual membership. The results also indicate that 21% of the White users are not sensitive to increase in annual membership price.

Table 6.5: Marginal effects for price sensitivity

	High price sensitive	Medium price sensitive	Not price sensitive	Inference
Model 1: STF reduced to $1.50				
Trips, *T*	0.011	0.001	-0.012	*Trips, gender, age and income of the bikeshare user have minimal or no influence on response to the reduction in price of STF product. However, about 25% of White users were not sensitive to $0.50 decrease in STF price.*
Gender, *G*	-0.046	-0.005	0.052	
Age, *A*	-0.004	0	0.004	
Income, *I*	0	0	0	
Race, *R*	-0.223	-0.022	0.245	
Model 2: STF increased to $2.50				
Trips, *T*	0.002	0.001	-0.003	*Trips, gender, age and income of the bikeshare user have minimal or no influence on response to the increase in price of STF product. 38% of White users were found to be unresponsive to this price change.*
Gender, *G*	0.027	0.017	-0.044	
Age, *A*	0.001	0	-0.001	
Income, *I*	0	0	0	
Race, *R*	-0.207	-0.173	0.380	
Model 3: Annual membership reduced by $8.00				
Trips, *T*	0	0	0	*All the explanatory variables have minimal or no influence on the sensitivity to $8 reduction in price of annual membership.*
Age, *A*	-0.001	0	0.001	
Income, *I*	-0.001	-0.001	0.002	
Race, *R*	-0.022	-0.009	0.031	
Model 4: Annual membership increased by $8.00				
Trips, *T*	-0.001	0	0.001	*Trips, age and income of the users have minimal or no influence on response to the increase in price of annual membership by $8. However, about 21% of White users were not sensitive to increase in price.*
Age, *A*	0	0	0	
Income, *I*	-0.002	-0.001	0.003	
Race, *R*	-0.154	-0.054	0.208	

6.4.3 Service Sensitivity

Survey was also designed to take measurements on the service sensitivity of all the bikeshare users. Ordered logit regression method is used to analyze the service sensitivity as the response variable has five possible outcomes. Bikeshare user importance on number of stations relative to price is given as follows.

Y = 1 – A lot more important

Y = 2 – Somewhat more important

Y = 3 – Equally important

$Y = 4$ – Somewhat less important

$Y = 5$ – A lot less important

The service sensitivity model was developed and tested for set of six explanatory variables namely Fare option (*F*), Trips (*T*), Gender (*G*), Age (*A*), Income (*I*), and Race (*R*). Descriptive statistics for study sample are shown in Table 6.6. All the variables included were found to fulfill the parallel regression assumption.

Table 6.6: Descriptive statistics for study sample

(a) Response variable

Response Variable, *Y*	Service Sensitivity		
User's importance on number of stations relative to price (1-5 scale)	Values / Levels of *Y*	N	%
	1=A lot more important	230	47.62
	2=Somewhat more important	140	28.99
	3=Equally important	94	19.46
	4=Somewhat less important	15	3.11
	5=A lot less important	4	0.83

(b) Explanatory variables

	Description	Values / Levels	N	%
Fare option, *F*	Fare option used by CaBi	1=Registered Member	329	68.12
		0=Casual user	154	31.88
Trips, *T*	Number of trips in past month		483	100
Gender, *G*	Gender of the user	1=Male	293	60.66
		0=Female	190	39.34
Age, *A*	Age range of the user (years)	21-24	59	12.22
		25-34	223	46.17
		35-44	105	21.74
		45-54	59	12.22
		55-64	32	6.63
		>65	5	1.04
Income, *I*	Group	Income range ($)		
	Low	0=<$35,000	70	14.49
	Medium/High	1=≥$35,000	413	85.51
Race, *R*	Race/Ethnicity of the user	1=White	349	72.26
		0=Other race	134	27.74

Regression results for service sensitivity are summarized in Table 6.7. The likelihood ratio has a p-value less than 0.05 (at 95% confidence level) meaning that all the models are statistically significant, as compared to the null model with no predictors. Registered members are found to be more sensitive to the service compared to casual users. Gender, race, and age of the bikeshare user does not influence the importance of number of stations. However, medium or high-income groups are found to be more sensitive to the service. As the number of bike trips increases, service sensitivity of the bikeshare users increases.

Table 6.7: Regression results for service sensitivity

<table>
<tr><th></th><th>Coef.</th><th>Std. Err.</th><th>z</th><th>P>|z|</th><th>Inference</th></tr>
<tr><td>Fare option, F</td><td>-0.427</td><td>0.215</td><td>-1.99</td><td>0.047</td><td rowspan="6">Casual users are more responsive to price than registered members.
As the number of trips increases, bikeshare users are more sensitive to service.
No significant difference, i.e. service sensitivity is not influenced by the age and gender of the CaBi user.
Higher income is more sensitive to service than the low-income bikeshare users.
Race of the bikeshare user does not influence the service sensitivity.</td></tr>
<tr><td>Trips, T</td><td>-0.012</td><td>0.006</td><td>-1.99</td><td>0.047</td></tr>
<tr><td>Gender, G</td><td>-0.098</td><td>0.184</td><td>-0.53</td><td>0.594</td></tr>
<tr><td>Age, A</td><td>-0.113</td><td>0.081</td><td>-1.38</td><td>0.166</td></tr>
<tr><td>Income, I</td><td>-0.532</td><td>0.269</td><td>-1.98</td><td>0.048</td></tr>
<tr><td>Race, R</td><td>0.135</td><td>0.205</td><td>0.66</td><td>0.509</td></tr>
<tr><td>Y=1|Y=2</td><td>-1.235</td><td>0.299</td><td colspan="3" rowspan="4"><u>Bold emphasis indicates statistical significance at</u>
α=5%</td></tr>
<tr><td>Y=2|Y=3</td><td>0.11</td><td>0.293</td></tr>
<tr><td>Y=3|Y=4</td><td>2.175</td><td>0.35</td></tr>
<tr><td>Y=4|Y=5</td><td>3.773</td><td>0.565</td></tr>
<tr><td colspan="6">Y = 1 to 5 are the cut points (intercepts) of the model. Y = 3: Equally important
Y = 1: A lot more important Y = 4: Somewhat less important
Y = 2: Somewhat more important Y = 5: A lot less important</td></tr>
</table>

Marginal effects expressed as a percent for service sensitivity is presented in Table 6.8. Trips, gender, age, and race of the bikeshare user have minimal or no marginal effects on the service sensitivity. About 10% of registered members feel that number of stations is lot more important compared to casual users. Also, approximately 13% of medium/high income group bikeshare users are extremely sensitive to the service.

Table 6.8: Marginal effects for service sensitivity

	Y=1	Y=2	Y=3	Y=4	Y=5	Inference
Fare option, *F*	0.104	-0.027	-0.06	-0.013	-0.003	*About 10% of registered members feel that service is lot more important compared to price.*
Trips, *T*	0.003	0	-0.003	0	0	*Trips, gender, and age of the bikeshare users have minimal marginal effects on service sensitivity.*
Gender, *G*	0.023	-0.006	-0.013	-0.003	0	
Age, *A*	0.002	0	-0.002	0	0	
Income, *I*	0.127	-0.023	-0.078	-0.019	-0.005	*About 13% of higher income bikeshare users are the most sensitive to the service.*
Race, *R*	-0.032	0.009	0.018	0.004	0.001	*Race has minimal marginal effects on service sensitivity.*

Bikeshare user importance on number of stations relative to price:
Y = 1: A lot more important — *Y = 4: Somewhat less important*
Y = 2: Somewhat more important — *Y = 5: A lot less important*
Y = 3: Equally important

Figure 6.1 illustrates the predicted probabilities of service sensitivities when all the predictors are at their mean value. About 47% of the bikeshare users perceive that number of stations is a lot more important compared to the price. Approximately 19% of the bikeshare users regard service and price are equally important. Less than 1% of the bikeshare users feel that service is lot less important compared to price.

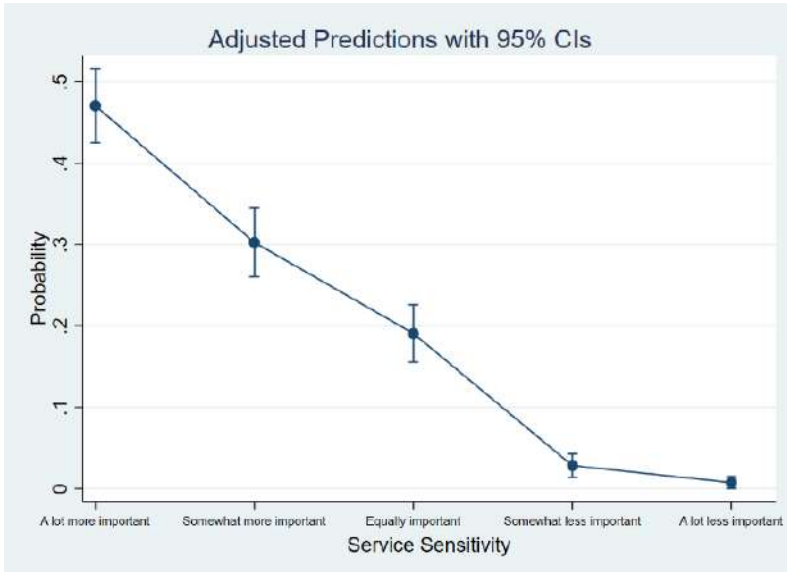


Figure 6.1: Predicted probabilities for service sensitivity

Thus, the ordered logit modeling results show that fare product type (or fare option), number of weekly trips and income of the user are influential on users' sensitivity to service. On the other hand, variation in service sensitivity is not responsive to gender, age, and race variables.

6.4.4 Price Elasticity Analysis

A frequently used rule-of-thumb, known as the Simpson-Curtin rule, suggests that an average fare elasticity has a value of -0.3 meaning that each 3% price increase reduces ridership by 1% (Curtin, 1968). This method can be used for rough estimates and cannot be used for detailed modeling techniques. Development of price elasticities using monadic price testing approach would be more scientific and obviate the need for the use of rules of thumb. The monadic experiment included in the survey data was used to create a demand curve for different pricing options pivoted to current price of the fare product. Price elasticity of demand for calculating price sensitivity is given as follows.

$$Price\ elasticity\ of\ demand\ (PED) = \frac{\%\ change\ in\ price}{\%\ change\ in\ demand} = \frac{\Delta P/P_1}{\Delta D/D_1} \tag{4}$$

where P_1 is the current price, P_2 is the new price, D_1 is the current demand, and D_2 is the new demand

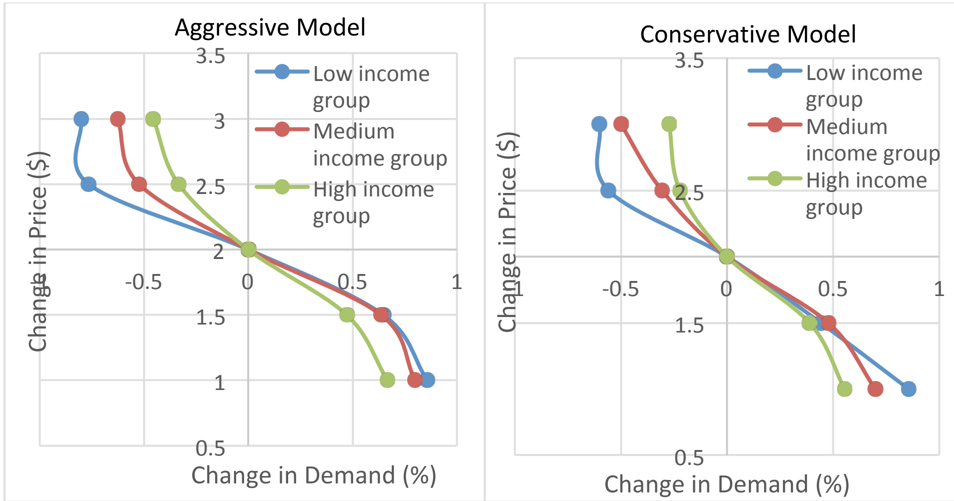
Two sets of assumptions were made to derive two different sets of price elasticities: 'aggressive' and 'conservative'. In the aggressive case, 100% of the users choosing $Y = 1$ (high price sensitive) or $Y = 2$ (medium price sensitive) would be considered as likely to use the product more based on price decrease (alternatively, use less in case of price increase). In the conservative case 100% of the users choosing $Y = 1$ and 50% of the users choosing $Y = 2$ would likely use the product more more/less based on price decrease increase, respectively, than they are currently using. Aggressive and conservative price elasticity models were developed only for STF and annual membership options. Due to very low sample sizes, price elasticities for other fare products were not developed. Ordered logit modeling discussed earlier revealed that race and income are influential on price sensitivity (Table 6.3). Therefore, price elasticities developed were categorized by income and race. However, elasticities were also developed for other categories including gender, trip purpose and membership type.

6.4.4.1 Income-based elasticities

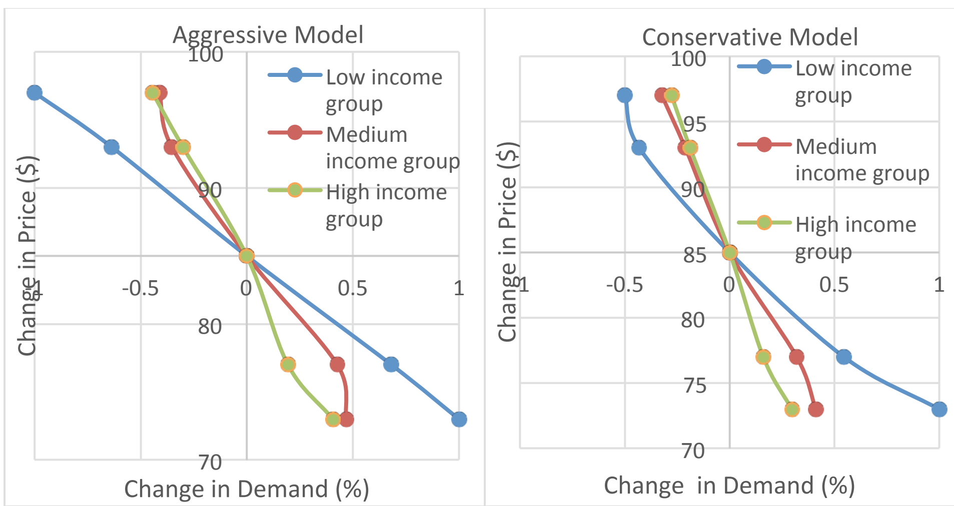
Data are grouped into the following income groups, as defined by the US Census Bureau for developing price elasticities (U.S. Census Bureau, 2017).

- Low-income group (income less than \$35,000)
- Medium income group (income \$35,000 to \$99,999)
- High-income group (income greater than \$100,000)

Figure 6.2 illustrates income-based price elasticity curves for single-trip fare and annual membership. Aggressive and conservative models show that for all income groups the demand is sensitive to price for STF and annual membership. As would be expected, low-income groups are more sensitive to price than the middle and high-income groups, which confirms intuition. Low-income group's price sensitivity ranges from +85.7% to -80.0% for a \$1 decrease or \$1 increase in STF, respectively (aggressive model). The same range for high-income group is +66.7% to -45.5%. In aggressive model, high-income group price sensitivity ranges from +40.7% to -44.4% for a \$12 decrease or \$12 increase respectively from current price for annual membership. The same range for low-income group is +/- 100%.



(a) STF

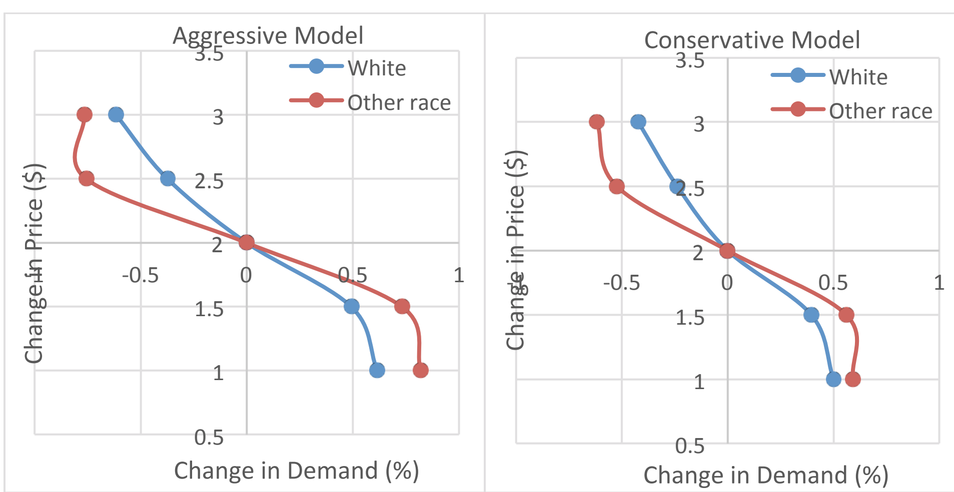


(b) Annual membership

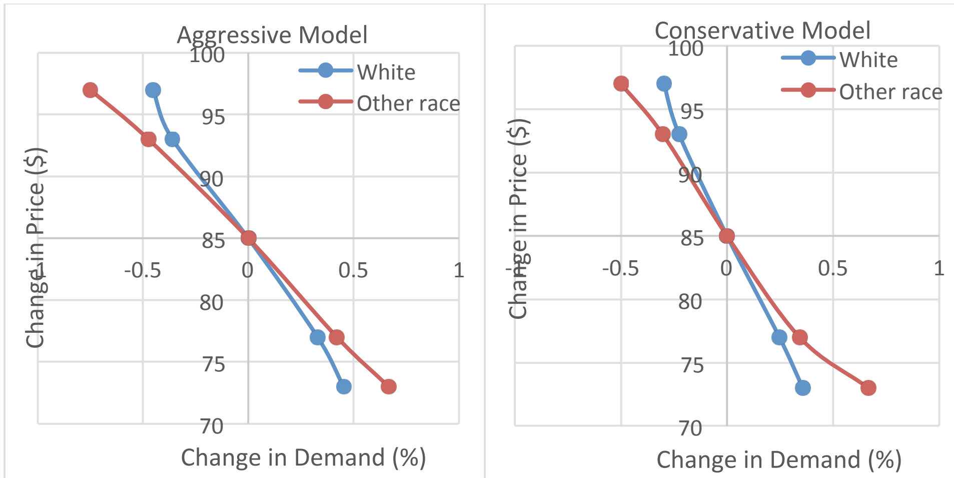
Figure 6.2: Income-based pivot-price elasticity curves

6.4.4.2 Elasticities by race

Majority of the bikeshare users are predominantly White. For sample size adequacy considerations, all non-White users were grouped as 'other race'. Therefore, price elasticity curves are not generated for all the races separately. White users were found to be less price sensitive compared to other ethnicities for both STF and annual membership options. Price sensitivity of White users ranges from +61.5% to a negative 61.5% for a \$1 decrease or \$1 increase in STF, respectively, for aggressive model. Other races were found to be about 10-20% more price sensitive than White for both the models for STF option. "Other race" price sensitivity ranges from +66.67% to -75% for a \$12 decrease or \$12 increase in annual membership respectively for aggressive model. White users were found to be 20% less price sensitive than 'other race' for the annual membership option. Figure 6.3 shows the price elasticity curves based on race for STF and annual membership options.



(a) STF



(b) Annual membership

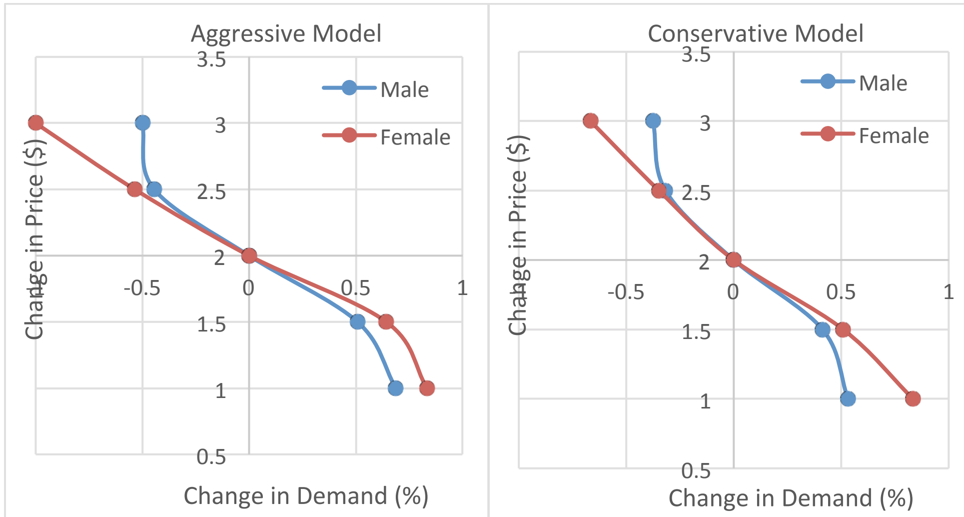
Figure 6.3: Race-based pivot-price elasticity curves

6.4.4.3 Elasticities by other categories

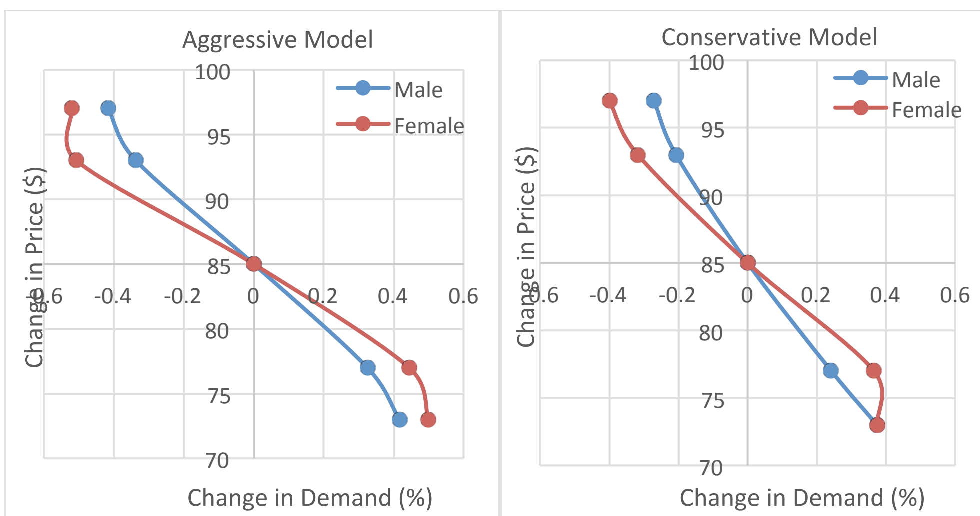
The ordered logit analysis indicated that only income and race have an influence on price sensitivities of users. However, several transit pricing research studies developed elasticity models categorized by user's gender and trip purpose. Consistent with this practice, elasticity curves were also developed for gender and trip purpose. Furthermore, aggregate elasticities for STF and annual membership were also developed.

6.4.4.4 Gender-based elasticities

Females are found to be more price sensitive compared to males for STF and annual membership. The percentage change in demand is moderate even when the annual membership is subject to higher variation in price. Female group price sensitivity ranges from +83.3% to -66.66% for a 50% decrease or 50% increase in STF price respectively for conservative model. Male group price sensitivity is about 30% less than the female group in case of the conservative approach for STF. Price sensitivity ranges from +41.66% to -41.66% for a $12 decrease or $12 increase in annual membership for aggressive model. Females are found to be 10% more price sensitive than males for annual membership. Price elasticity curves based on gender for STF and annual membership is illustrated in Figure 6.4.



(a) STF

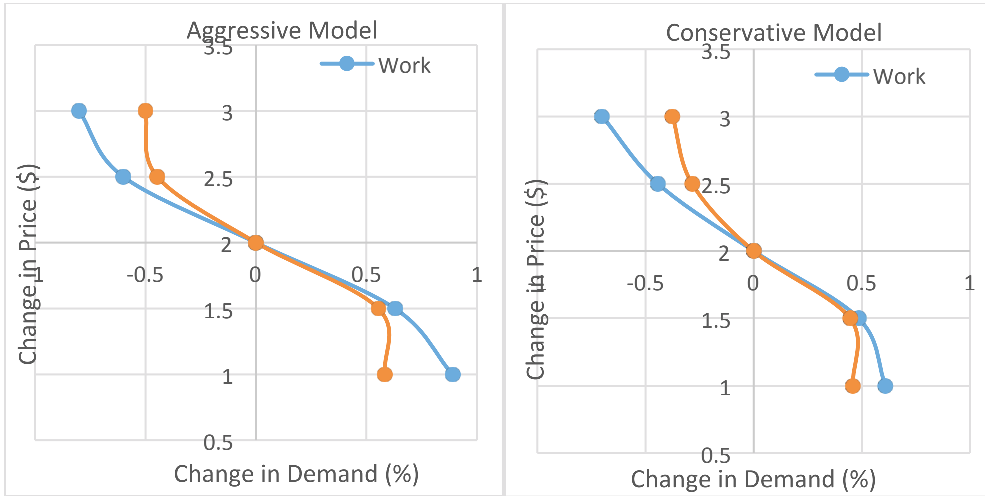


(b) Annual membership

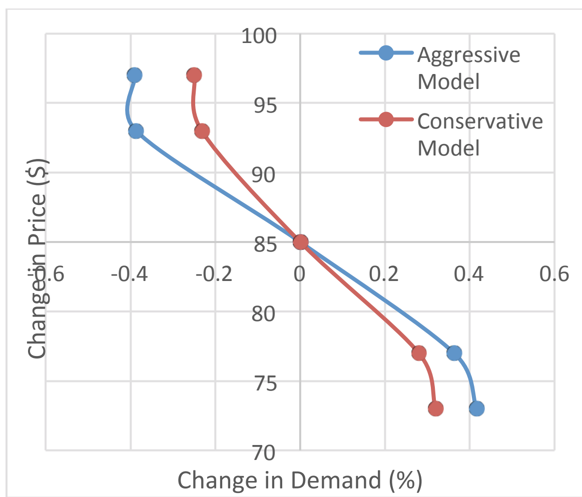
Figure 6.4: Gender-based pivot-price elasticity curves

6.4.4.5 Elasticities based on trip purpose

Price elasticity is compared for both work and sightseeing trips for STF. Work trips are more price sensitive compared to touring/sightseeing trips for STF. All the annual membership survey respondents reported that they used bikeshare for commuting (work) purpose. Therefore, only work trips exists in annual membership fare option. Percentage change in demand is moderate for work trips even when the annual membership is subject to higher variation in price. For aggressive model, commuting trips price sensitivity ranges from +88.89% to -80.0% for a $1 decrease or $1 increase in STF, respectively. Sightseeing trips are 30% less price sensitive to work trips for STF option. The commuting trips price sensitivity ranges from +31.94% to -25.0% for a $12 decrease or $12 increase in annual membership in case of conservative approach. Figure 6.5 illustrates the price elasticity curves based on trip purpose. These results are similar to the price elasticities research conducted for transit systems which indicates that shopping trips are less sensitive to the change in fare than work trips (Cervaro, 1990; Pham & Linsalata, 1991; Litman, 2004).



(a) STF

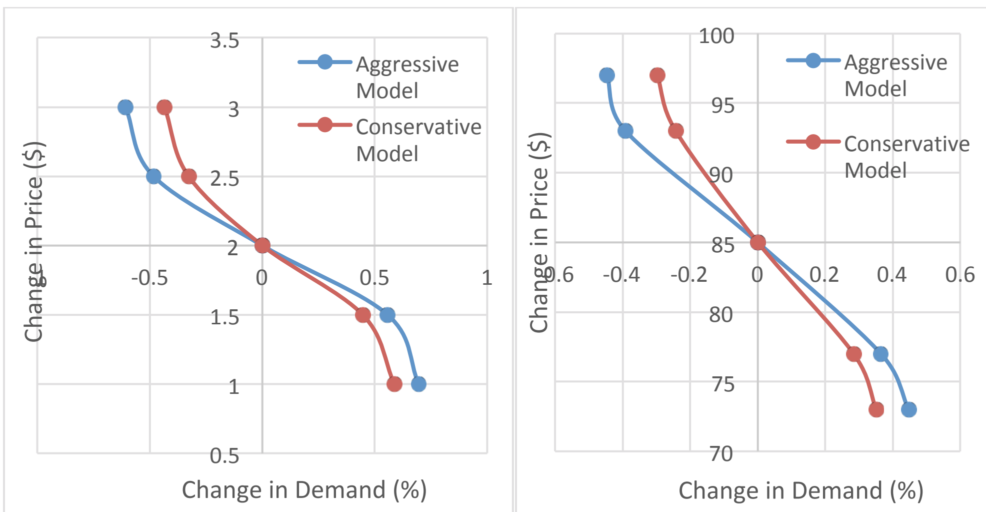


(b) Annual membership

Figure 6.5: Pivot-price elasticities based on trip purpose

6.4.4.6 Elasticities based on membership type

Price elasticity curves are compared for STF and annual membership options as seen in Figure 6.6. STF pricing option is found to be more price sensitive than the annual membership. For aggressive model, STF price sensitivity ranges from +69.56% to -60.87% for a 50% decrease or 50% increase in STF price respectively. Annual membership price sensitivity ranges from +31.94% to -25.0% for a $12 decrease or $12 increase from the current price for aggressive approach. The results of the membership price sensitivity are similar to those obtained in the ordered logistic regression analysis.



(a) STF (b) Annual membership

Figure 6.6: Price elasticity based on membership type

6.4.4.7 Summary of price elasticity analysis

Price elasticities for different fare options tested in this survey for various categories including income, race, trip purpose and gender are summarized in Table 6.9. The negative sign indicates drop in the bikeshare demand due to the increase in price of the chosen fare product. It can be concluded that high-income, White and males are less sensitive to change in fares for STF and annual membership. Sightseeing or touring trips are less sensitive to price than commuting (work) trips.

Table 6.9: Summary of price elasticities

(a) STF

STF (Pivot: $2.0)		Aggressive Model				Conservative Model			
		$1.0	$1.5	$2.5	$3.0	$1.0	$1.5	$2.5	$3.0
Income	Low	85.7%	64.7%	-76.5%	-80.0%	85.7%	44.1%	-55.9%	-60.0%
	Medium	80.0%	63.6%	-52.3%	-62.5%	70.0%	47.7%	-30.7%	-50.0%
	High	66.7%	47.2%	-33.3%	-45.5%	55.6%	38.9%	-22.2%	-27.3%
Race	White	61.5%	49.3%	-37.3%	-61.5%	50.0%	39.6%	-23.9%	-42.3%
	Other	81.8%	73.2%	-75.6%	-76.5%	59.1%	56.1%	-52.4%	-61.8%
Trip purpose	Work	88.9%	62.9%	-60.0%	-80.0%	61.1%	48.6%	-44.3%	-70.0%
	Touring	58.3%	55.4%	-44.6%	-50.0%	45.8%	44.6%	-28.5%	-37.5%
Gender	Male	68.8%	50.8%	-44.4%	-50.0%	53.1%	41.3%	-31.7%	-37.5%
	Female	83.3%	64.3%	-53.6%	-100%	83.3%	50.9%	-34.8%	-66.7%
STF Aggregate		69.6%	55.7%	-48.4%	-60.9%	58.7%	44.7%	-32.8%	-43.5%
Illustrative interpretation: Low income group price elasticity for $1.0 as new single-trip fare +85.7% using an aggressive assumption. It indicates that at $1.0, there would be an 85.7% increase of single-trip rides purchased by low income users. Similarly, if the single-trip fare were to be raised to $3.0 (from the current price of $2.0), there would be an 80%, 62.5% and 45.5% drop in trips made by low, medium, and high-income groups, respectively.									

(b) Annual membership

Annual membership (Pivot: $85)		Aggressive Model				Conservative Model			
		$73	$77	$93	$97	$73	$77	$93	$97
Income	Low	100%	68.2%	-63.6%	-100%	100%	54.5%	-43.2%	-50.0%
	Medium	47.1%	42.7%	-35.3%	-41.2%	41.2%	32.0%	-21.2%	-32.4%
	High	40.7%	19.4%	-30.1%	-44.4%	29.6%	16.0%	-18.9%	-27.8%
Race	White	45.2%	32.9%	-36.0%	-45.2%	35.7%	24.7%	-22.6%	-29.8%
	Other	66.7%	42.1%	-47.4%	-75.0%	66.7%	34.2%	-30.3%	-50.0%
Trip purpose	Work	41.7%	36.3%	-38.7%	-39.0%	31.9%	28.0%	-23.2%	-25.0%
Gender	Male	41.7%	32.5%	-33.8%	-41.7%	37.5%	24.2%	-20.7%	-27.1%
	Female	50.0%	44.4%	-50.8%	-52.0%	37.5%	36.5%	-31.7%	-40.0%
Aggregate for annual membership		44.7%	36.5%	-39.2%	-44.7%	35.1%	28.4%	-24.3%	-29.8%
Note: Only work trips exist in annual membership. Low income group price elasticity for annual membership reduced to $73 is +100% using an aggressive assumption. It indicates that at $73, there would be a 100% increase of using bikeshare by low income users.									

6.4.4.8 Example applications of elasticities

A potential use for the elasticities is presented in this section by developing revenue and ridership projections of single-trip fare and annual memberships for the monadic prices tested in the survey (as shown in Table 6.1). The illustration assumes the ridership changes are only due to change in price for both products.

For the 12-month period after the introduction of single-trip fare in June 2016, 368,634 single-trips ($2 each) were purchased at CaBi kiosks booking $737,268 as revenue (data obtained from DDOT). These numbers were considered as the based case for projections. It was assumed that the income distribution of the users of these single-trips is the same as the income groups represented by the CaBi user survey (low-income: 18.64%, medium-income: 41.53% and high-income: 31.83%). Additionally, it was also assumed that there would be no organic growth (or decline) in demand from the levels recorded in the 12-month period after the implementation of STF. Income-based elasticities shown in Table 6.9 were applied to estimate annual ridership and revenues resulting from each monadic price tested in the survey.

The projections shown in Table 6.10 indicate that using the aggressive assumptions, STF ridership could increase by as much as 75% (for STF $1.00) or decrease by as much as 59% (for STF $3.00). The corresponding projected revenue, however, could decrease by 12% and 38.5%, respectively. Using the conservative model, ridership may increase by 67% with a corresponding decrease of 16% in revenue when

STF is set at $1.00. Both aggressive and conservative models suggest that when STF is set at $1.50, ridership could increase by 57% and 43% with a corresponding increase in revenue of 18% and 7%, respectively. Thus, $1.50 may be regarded as an optimal price for STF from the current pricing at $2 for the same fare option.

Table 6.10: Ridership and revenue projections from changes to STF based on income

STF	Estimated split[1]	Low Income	Medium Income	High Income	Trips	Percent change	Revenue	Percent change
		18.64%	41.53%	39.83%				
$2.00 Current	Number of trips	68,728	153,077	146,829	368,634[2]	Base case	$737,268	Base case
New fare	Aggressive Model							
$1.00	Change in demand	85.7%	80.0%	66.7%				
$1.50		64.7%	63.6%	47.2%				
$2.50		-76.5%	-52.3%	-33.3%				
$3.00		-80.0%	-62.5%	-45.5%				
$1.00	Estimated trips	127,638	275,538	244,715	647,891	75.8%	$647,891	-12.1%
$1.50		113,200	250,489	216,165	579,854	57.3%	$869,780	18.0%
$2.50		16,171	73,059	97,886	187,117	-49.2%	$467,792	-36.6%
$3.00		13,746	57,404	80,088	151,238	-59.0%	$453,714	-38.5%
New fare	Conservative Model							
$1.00	Change in demand	85.7%	70.0%	55.6%				
$1.50		44.1%	47.7%	38.9%				
$2.50		-55.9%	-30.7%	-22.2%				
$3.00		-60.0%	-50.0%	-27.3%				
$1.00	Estimated trips	127,638	260,231	228,400	616,269	67.2%	$616,269	-16.4%
$1.50		99,050	226,136	203,929	529,115	43.5%	$793,672	7.7%
$2.50		30,321	106,110	114,200	250,632	-32.0%	$626,579	-15.0%
$3.00		27,491	76,538	106,785	210,814	-42.8%	$632,443	-14.2%

Sources: [1] Intercept Survey; [2] DDOT

Ridership and revenue projections resulting from changes to annual membership based on income-based elasticities were made using the same methodology as shown in Table 6.11. For the same 12-month period June 2016 through May 2017, there were about 25,461 annual memberships, which resulted in total revenue of $2,164,185. Aggressive and conservative models suggest that when annual membership is reduced by $12, ridership can increase by 49% and 40% with a corresponding increase of revenue of 28% and 21%, respectively. Thus, $73.00 may be regarded as the ideal price for annual membership.

Table 6.11: Ridership and revenue projections from changes to annual membership based on income

Annual	Estimated Split[1] ➔	Low Income	Medium Income	High Income	Number of purchases	Percent change	Revenue	change
		9.39%	37.55%	53.06%				
$85.00 Current	Number of subscriptions	2,390	9,561	13,510	25,461[2]	Base case	$2,164,185	Base case
New fare	Aggressive Model							
$73.00	Change in demand	100%	47.06%	40.74%				
$77.00		68.18%	42.67%	19.42%				
$93.00		-63.64%	-35.29%	-30.10%				
$97.00		-100%	-41.18%	-44.44%				
$73.00	Estimated subscriptions	4,780	14,060	19,014	37,854	48.68%	$2,763,378	27.69%
$77.00		4,020	13,640	16,133	33,793	32.73%	$2,602,083	20.23%
$93.00		869	6,186	9,444	16,499	-35.20%	$1,534,448	-29.10%
$97.00		0	5,624	7,506	13,130	-48.43%	$1,273,566	-41.15%
New fare	Conservative Model							
$73.00	Change in demand	100%	41.18%	29.63%				
$77.00		54.55%	32.00%	16.02%				
$93.00		-43.18%	-21.18%	-18.93%				
$97.00		-50.00%	-32.35%	-27.78%				
$73.00	Estimated subscriptions	4,780	13,498	17,513	35,791	40.57%	$2,612,742	20.73%
$77.00		3,694	12,620	15,674	31,988	25.64%	$2,463,110	13.81%
$93.00		1,358	7,536	10,952	19,847	-22.05%	$1,845,725	-14.72%
$97.00		1,195	6,468	9,757	17,420	-31.58%	$1,689,732	-21.92%
Sources: [1] Intercept Survey; [2] DDOT								

6.5 Conclusions

This research examined bikeshare users' sensitivity to changes in price and their preferences on service by conducting an intercept survey of Capital Bikeshare (CaBi) users. Monadic design was used in the wording of relevant survey questions. The survey data was used to obtain demand curves or price elasticities that could be used in policy calculations to project the change in bikeshare ridership and revenue. Ordered logit regression method was used to analyze the price and service sensitivity of bikeshare users. For all four prices tested, the bikeshare user's race was found to have a statistically significant influence on price sensitivity. For three of the four models, household income was found to be statistically significant determinant of the user's price sensitivity. The results showed that higher household income groups and White users are less sensitive to price compared to other income groups and other races/ethnicities respectively. Predicted probabilities showed that approximately 39% and 47% of STF users are not sensitive to price decrease or increase, respectively, by half-a-dollar. Nearly 2/3rd (or 64% and above) of the annual members were found to be not impacted by a $8-change in membership price.

The service sensitivity, as indicated by the importance placed on number of stations compared to price, of all the bikeshare users was also tested using ordered logit modeling. Registered members were found to be more sensitive to the service compared to casual users. Gender, race, and age of the bikeshare user does not have any influence on the importance of number of stations. Service sensitivity of the bikeshare users was found to increase as the income and number of bike trips increases.

Ordered logit modeling results also revealed that race and income of the bikeshare users are influential on price sensitivity. Therefore, development of price elasticities based on income and race would be appropriate. The demand curves showed that low-income groups are more sensitive to price than the middle and high-income groups.

White users were found to be approximately 20% less price sensitive than other races for STF and annual membership. Consistent with literature on price elasticities for transit fares, elasticity curves were also developed for other categories including gender, trip purpose and membership type. The study reveals that females are about 30% and 10% more price sensitive than males for STF and annual membership respectively. Also, sightseeing trips are 30% less price sensitive than work trips for STF option. These results are similar to the price elasticities research conducted for transit systems which indicated that shopping trips and high-income groups are less sensitive to the change in transit fares (Cervaro, 1990; Pham & Linsalata, 1991; Litman, 2004).

The most significant among many contributions made by this study is the methodological innovation in the application of monadic price testing, which is a widely used technique in consumer pricing research, in bikeshare research. Furthermore, innovative application of ordered logistic regression method enabled to better understand bikeshare user sensitivities to price and service. This research fills a significant gap in literature on research related to bikeshare pricing.

Judrak (2013) found that registered members exhibit higher cost sensitivity compared to the casual users. However, this study proves that persons purchasing STF (casual users) are about 40% more price sensitive than those who purchased annual membership (registered members). An illustrative application of income-based elasticities indicated that reducing the STF to $1.50 (from $2.00 per trip) and annual membership to $73.00 (from $85 per year) were found to improve both ridership and revenue of the CaBi system. Further studies are needed to investigate the optimal pricing of the other fare products available at various the bikeshare systems.

It is expected that the contributions from this study would provide insights and guidance on evaluating future pricing policy changes at various bikeshare systems. For example, effective July 2018 Metro Bike (bikeshare system in Los Angeles) reduced its single-trip fare from $3.50 per trip to $1.75 (Sotero, 2018). It is not known if this price reduction was based on the results of any structured study such as this one. However, the Metro board would have benefitted from the results and methods used in this study in evaluating their policy decision to reduce STF by half. Additionally, a structured study of the impact the STF product price reduction at Metro, similar to the price impact studies by Venigalla et al. (2018), Kaviti et al. (2018), and Kaviti (2018) and this study would be not only of academic interest but is also of immense value for policy makers at various bikeshare systems.

7 CONCLUSIONS AND FUTURE WORK

The primary goal of this doctoral dissertation work is to study the profiles, preferences, and reactions to price change of bikeshare users. The research examined the effect of introducing new fare product on bikeshare ridership and revenue. The profiles and preferences of registered members and casual users were obtained and studied from the intercept survey conducted at CaBi stations. The research also evaluated price sensitivities and elasticities of bikeshare fare products using monadic design implemented in the survey instrument.

7.1 Impact of Pricing of Fare Products on Ridership and Revenues

As its first objective, this research evaluated the impact of pricing on bikeshare ridership and revenue. To achieve this objective, the introduction of single-trip fare (STF) for $2 by Capital Bikeshare (CaBi) was studied. The analysis showed that introduction of a popular fare product such as single-trip fare (STF) product could result in major changes to revenue and ridership as experienced at Capital Bikeshare. The analyses also showed that the STF product might have caused an increase in the first-time casual users by as much as 79%. The addition of STF product to fare options may also have contributed to the increase in the casual users' monthly ridership by 41%. Statistical tests showed that there is a significant increase in daily ridership levels after the introduction of the STF. However, the tests also showed a significant decrease in the daily revenue for riders with 24-hour pass and 3-day pass after the introduction of STF showing that a shift towards the use of single-trip fare ($2/trip) instead of the 24-hour pass (for $8) or the 3-day pass (for $17). Year-over-year calendar monthly growth rates of new casual users were significantly higher after the introduction of STF. Results of analysis of variance showed that jurisdiction and season variables play a statistically significant role in the percentage change in revenue and ridership. Regression analyses indicate daily ridership to have a positive correlation with temperature and a negative correlation with precipitation.

Furthermore, casual user revenues before and after the introduction of STF were compared at the station-level, while controlling for seasonal and weather factors. The analysis employed big data analytics on individual bikeshare trips and revenue transactions at station-level. Statistical tests were performed on casual user revenue and casual user ridership for 12-month period before and after the introduction of STF at the 330 common stations. The results showed a decrease in casual user revenue per ride and an increase in monthly casual user ridership after the introduction of the STF. Furthermore, calendar-month growth rates for ridership and revenue were compared for periods before and after the launch of the new fare product for a five-month period at hundreds of common stations. The study has established statistical evidence that the launch of STF has significantly decreased revenues and increased ridership at CaBi. Additionally, trends in revenue growth changed from positive growth to negative growth after the launch of STF.

7.2 Impact of Transit Disruptions on Bikeshare Ridership

Due to the concurrency of STF launch with SafeTrack (also known as metro works), it may be surmised that the introduction of STF has created an opportunity for commuters to try CaBi as an alternative travel mode at an affordable price during the metro maintenance work. There is a statistically significant increase in the daily ridership for both registered and casual users of CaBi near Metro stations that affected by transit service disruptions during SafeTrack. The percentage increase in casual riders at these Metro stations was greater than that of registered users. It is possible that people may have taken the casual passes only for the SafeTrack duration instead of the monthly or annual membership. However, after the SafeTrack periods, the rise in CaBi ridership at the affected Metro stations did not sustain as hoped.

7.3 Profiles and Preferences of Bikeshare Users

Even though casual bikeshare users account for a large share of revenue, literature provides very little insights about them. As the second major objective of this research, profiles, and preferences of bikeshare users (registered members and casual users) were obtained by conducting an intercept survey of CaBi users. This research compared the profiles of casual users and members of CaBi. The survey data was validated by verifying its consistency with a member survey of much larger sample size (n = 5,498) via chi-squared goodness of fit tests. Additional Pearson's chi-squared test results showed that gender and income distributions are different for members and casual users. It was observed that members were predominantly male (67%), while gender distribution was similar across casual users (51% male and 49% female). Similar age distribution was observed between members and casual users. Significant difference was observed in terms of ethnicity between members and casual users. Majority of the members in the survey have identified themselves as “White”. Notable differences could be seen in the trip purposes and alternative mode of transportation between members and casual users. Participants report STF and annual membership paid at once as their preferred pricing options and a combination of STF, 24-hour pass, and annual membership with monthly installments as their favorable pricing model.

Logistic regression models were developed to determine which explanatory variables are determinants of user type and fare product choice by casual users (single-trip fare vs. 24-hour pass). The findings indicated that members are more likely to be white, earn more and reside in the D.C. area compared to the casual users. Casual users make less bikeshare trips and are less sensitive to the service (station density) compared to members. Regression results among the casual users demonstrate that single-trip fare users are less likely to be white and more likely to be D.C. residents compared to the 24-hour pass users. Gender, age, and income distribution do not appear to influence casual fare product choice.

7.4 Price Sensitivities Users and Pivot Elasticities of Fare Products

As its third major objective, this research evaluated price sensitivities and elasticities of bikeshare fare products using monadic design implemented in the survey instrument. The survey data was used to obtain demand curves or price elasticities that could be used in policy calculations to project the change in bikeshare ridership and revenue. Ordered logit regression method was used to analyze the price and service sensitivity of bikeshare users. The results revealed that race and income of the bikeshare users are influential on price sensitivity. The service sensitivity, as indicated by the importance placed on number of stations compared to price, was also tested using ordered logit modeling. Registered members were found to be more sensitive to the service compared to casual users. Service sensitivity of the bikeshare users was found to increase as the income and number of bike trips increases.

The pivot elasticity curves showed that low-income groups are more sensitive to price than the middle and high-income groups. White users were found to be approximately 20% less price sensitive than other races for STF and annual membership. The study reveals that females are about 30% and 10% more price sensitive than males for STF and annual membership respectively. Also, the STF users making sightseeing trips using bikeshare are 30% less price sensitive than the STF users making work trips. Casual users purchasing STF are about 40% more price sensitive than those who purchased annual membership (registered members). An illustrative application of income-based elasticities indicated that reducing the STF to \$1.50 (from \$2.00 per trip) and annual membership to \$73.00 (from \$85 per year) were found to improve both ridership and revenue of the CaBi system.

7.5 Major Contributions of this Research Work

The body of research work presented in this dissertation evaluated the impact of introducing a new fare product on bikeshare ridership at community and station level, which is the first ever such evaluation in North America. The study demonstrated that the disaggregate analysis conducted at the bikeshare station level has superior accuracy and helps in better understanding of the data than the community-level analysis. The findings from this research can be useful in the decision-making process related to the introduction of a new fare product at public bikesharing systems.

Literature provides limited understanding on the casual bikeshare users in North America. This research compared and contrasted the profiles of casual users and members of Capital Bikeshare. This study sheds light on various crucial elements that are useful in policy-making, planning and operational management for bikeshare. Some examples use for the findings of this study include monitoring the bikeshare usage over time, across geographies and among different types of users, identifying incentives to help increase membership and evaluating pricing models.

The most significant among many contributions made by this study is the methodological innovation in the application of monadic price testing, which is a widely used technique in consumer pricing research, in bikeshare research. Furthermore, innovative application of ordered logistic regression method enabled to better understand bikeshare user sensitivities to price and service. This study fills a significant gap in literature on research related to bikeshare pricing. Most importantly, this research is the first of its kind that derived price elasticities of the public bikeshare systems based on various factors including income, race, gender, and trip purpose. The findings are consistent with literature on price elasticities for transit fares.

It is expected that the contributions from this study would provide insights and guidance on evaluating future pricing policy changes at various bikeshare systems. For example, effective July 2018 Metro Bike (bikeshare system in Los Angeles) reduced its single-trip fare from $3.50 per trip to $1.75 (Sotero, 2018). It is not known if this price reduction was based on the results of any structured study such as this one. However, the Metro board would have benefitted from the results and methods used in this study in evaluating their policy decision to reduce STF by half.

Several of these conclusions may be unique to Capital Bikeshare system because of its unique structure, geography, and the user-base. Therefore, caution must be exercised when extrapolating the study findings to other cities with bikeshare systems. Bikeshare providers who are considering making changes to fare product line and their pricing could benefit from the findings of this study. However, the methods and procedures used in this research work are transferable to all bikesharing systems in the world, which may be characterized as the most impactful part of this research work.

7.6 Future Work

This research only examined the impact of one fare product, namely $2 per single-trip, on revenue and ridership. More investigation is needed to study the effect of other fare products on ridership and revenue of public bikeshare systems. This study investigated the influence of metro works on bikeshare ridership within quarter and half mile radius of bikeshare stations. However, the study did not explore the system-wide changes in bikeshare ridership due to metro disruptions.

In this research, casual user revenues before and after the introduction of STF were compared at the station-level, while controlling seasonal and weather factors. Even though days with precipitation are excluded from the analysis, no adjustments were made with reference to temperature. Further research can include temperature and special events in the examination while performing the disaggregate analysis at station level.

This dissertation studied the price elasticities and the optimal pricing of STF and annual membership options. Further studies are needed to investigate the optimal pricing of the other fare products available at public bikeshare systems. The survey sample included very limited target users in certain usage and demographic categories. Therefore, no specific investigation was performed to analyze user behavior on the basis of income equity and other popular fare products such as 24-hour pass. Further research can examine the impact of incentives for target (low-income users) demographics to help increase membership.

The time-specific cost structure has been introduced in the public bikeshare systems to control the issue of excessive borrowing times. There is a specific usage fee if the bikeshare users cross a certain time limit (generally 30 minutes). This research proves that CaBi casual users need more time to complete the trip than members. However, it did not study the impact on the bikeshare revenue if there is an extension in the time limit for specific user groups or the influence of introduction of new policy of unlimited trips at higher costs rather than 24-hour pass with time limit.

Dockless bikes have been gaining popularity all over the world. Five dockless bikeshare companies have launched their bikes in Washington, DC at end of 2017. The scope of this dissertation did not include the influence of dockless bikes on Capital Bikeshare system. Further studies can analyze the impact of dockless bikes on ridership and revenue of public bikeshare systems.

Impact of increasing the density of bikeshare stations at central locations is not studied in this dissertation. Additional studies can analyze the effect on bikeshare ridership and revenue by introducing new bikeshare stations or increasing the bike density in central locations. Further research can also analyze the impact of dynamic pricing during peak hours at specific stations to solve the imbalance problem in public bikeshare systems.

The influence of profiles and preferences and reactions to price change of Capital Bikeshare users have only been studied in this dissertation. Further studies can analyze the impact of price changes on ridership and revenue for other public bikeshare systems across the world. Also, other shared transportation services can also use this methodology to study the effect of price change on the demand of the shared transportation systems.

APPENDIX

All the input data files are available at https://tinyurl.com/yck9dv7f

R-code for t-tests, Anova and linear regression

```
t.test(Daily.Ridership.before.STF,Daily.Ridership.afte
r.STF,mu=0,alternative = "less", data=Aggregate data)
t.test(Monthly.Ridership.before.STF,Monthly.Ridership.
after.STF,mu=0,alternative = "less", data=Aggregate
data)
t.test(Monthly.Revenue.before..2.fare,Monthly.Revenue.
after..2.fare,mu=0,alternative="less", data=Aggregate
data)
t.test(New.registered.members.per.month.before.STF,New
.registered.members.per.month.after.STF,mu=0,alteranti
ve="less", data=Aggregate data)
t.test(New.casual.members.per.month.before.STF,New.cas
ual.members.per.month.after.STF,mu=0,alternative =
"less", data=Aggregate data)
RevenueModel<-
aov(Revenue.Percent.Change~County+Month+Membership,dat
a=ANOVA)
summary(RevenueModel)
RidershipModel<-
aov(Ridership.Percent.Change~County+Month+Membership,d
ata=ANOVA)
summary(RidershipModel)
lm(formula = Trips.per.day ~ Avg.Temperature +
Precipitation + Weekday.Weekend +
Before.After + Month, data = DailyRidership)
t.test(Registered.members.one.week.before.SafeTrack.,R
egistered.members.During.SafeTrack,mu=0,alternative =
"less", data=quartermilebuffer)
t.test(Registered.members.one.week.before.SafeTrack.,
Registered.members.one.week.after.SafeTrack.,alternati
ve = "less", data=quartermilebuffer)
```

```
t.test(Registered.members.one.week.before.SafeTrack.,
Registered.members.During.SafeTrack,mu=0,alternative =
"less", data=halfmilebuffer)
t.test(Registered.members.one.week.before.SafeTrack.,
Registered.members.one.week.after.SafeTrack.,alternati
ve = "less", data=halfmilebuffer)
t.test(Casual.Users.one.week.before.SafeTrack.,Casual.
Users.During.SafeTrack,mu=0,alternative = "less",
data=quartermilebuffer)
t.test(Casual.Users.one.week.before.SafeTrack.,Casual.
Users.one.week.after.SafeTrack.,alternative = "less",
data=quartermilebuffer)
t.test(Casual.Users.one.week.before.SafeTrack.,Casual.
Users.During.SafeTrack,mu=0,alternative = "less",
data=halfmilebuffer)
t.test(Casual.Users.one.week.before.SafeTrack.,Casual.
Users.one.week.after.SafeTrack.,alternative = "less",
data=halfmilebuffer)
```

<u>Stata code for z-tests</u>

```
use disaggregateanalysis.dta
. summarize revperride if BeforeAfter==0
. summarize revperride if BeforeAfter==1
. ztest revperride, by(Before) sd1(2.3243) sd2(1.2216)
. summarize ridership if BeforeAfter==0
. summarize ridership if BeforeAfter==1
. ztest ridership, by(Before) sd1(246.8188)
sd2(230.4119)
. summarize revenueperridebystation if BeforeAfter==0
. summarize revenueperridebystation if BeforeAfter==1
. ztest revenueperridebystation, by(BeforeAfter)
sd1(1.3530) sd2(0.6010)
. summarize monthlyridershipbystation if
BeforeAfter==0
. summarize monthlyridershipbystation if
BeforeAfter==1
. ztest monthlyridershipbystation, by(BeforeAfter)
sd1(388.5647) sd2(375.5407)
. summarize revenueperridebymonth if BeforeAfter==0
. summarize revenueperridebymonth if BeforeAfter==1
```

```
. ztest revenueperridebymonth, by(BeforeAfter)
sd1(2.1237) sd2(1.0750)
. summarize monthlyridershipbymonth if BeforeAfter==0
. summarize monthlyridershipbymonth if BeforeAfter==1
. ztest monthlyridershipbymonth, by(BeforeAfter)
sd1(472.4291) sd2(443.3442)
. summarize revenueperridebyweekday if BeforeAfter==0
. summarize revenueperridebyweekday if BeforeAfter==1
. ztest revenueperridebyweekday, by(BeforeAfter)
sd1(1.4186) sd2(0.7291)
. summarize monthlyridershipbyweekday if
BeforeAfter==0
. summarize monthlyridershipbyweekday if
BeforeAfter==1
. ztest monthlyridershipbyweekday, by(BeforeAfter)
sd1(197.0226) sd2(189.4146)
. summarize revenueGR if BeforeAfter==0
. summarize revenueGR if BeforeAfter==1
. ztest revenueGR, by(BeforeAfter) sd1(1.1023)
sd2(0.3919)
. summarize ridershipGR if BeforeAfter==0
. summarize ridershipGR if BeforeAfter==1
. ztest ridershipGR, by(BeforeAfter) sd1(1.8347)
sd2(2.3209)
. summarize revenueGRbystation if BeforeAfter==0
. summarize revenueGRbystation if BeforeAfter==1
. ztest revenueGRbystation, by(BeforeAfter)
sd1(0.6394) sd2(0.2176)
. summarize ridershipGRbystation if BeforeAfter==0
. summarize ridershipGRbystation if BeforeAfter==1
. ztest ridershipGRbystation, by(BeforeAfter)
sd1(0.8536) sd2(1.9158)
. summarize revenueGRbystation if BeforeAfter==0
. summarize revenueGRbystation if BeforeAfter==1
. ztest revenueGRbystation, by(BeforeAfter)
sd1(0.9892) sd2(0.3481)
. summarize revenueGRbyweekday if BeforeAfter==0
. summarize revenueGRbyweekday if BeforeAfter==1
. ztest revenueGRbyweekday, by(BeforeAfter)
sd1(0.7281) sd2(0.2619)
. summarize ridershipGRbyweekday if BeforeAfter==0
. summarize ridershipGRbyweekday if BeforeAfter==1
. ztest ridershipGRbyweekday, by(BeforeAfter)
sd1(0.9655) sd2(1.8811)
```

R-code for Goodness of Fit tests

2016 CaBi member survey Vs 2017 GMU Survey

```
chisq.test(gender.registered,correct=F)
age.registered<-
data.frame(rbind(age.reg$X2016.CaBi.Member.Survey.Repo
rt,age.reg$X2017.GMU.Report.Registered.Members))
chisq.test(age.registered)
incomeregistered<-
data.frame(rbind(income.reg$X2016.CaBi.Member.Survey.R
eport,income.reg$X2017.GMU.Report.Registered.Members))
chisq.test(incomeregistered)
raceregistered<-
data.frame(rbind(race.reg$X2016.CaBi.Member.Survey.Rep
ort,race.reg$X2017.GMU.Report.Registered.Members))
chisq.test(raceregistered)
chisq.test(modeoftransportationregistered,correct=F)
toptriptypes.registered<-
data.frame(rbind(toptriptypes.reg$X2016.CaBi.Member.Su
rvey.Report,toptriptypes.reg$X2017.GMU.Report.Register
ed.Members))
chisq.test(toptriptypes.registered)
motivatorsregistered<-
data.frame(rbind(motivators.reg$X2016.CaBi.Member.Surv
ey.Report,motivators.reg$X2017.GMU.Report.Registered.M
embers))
chisq.test(motivatorsregistered)
alterantivemoderegistered<-
data.frame(rbind(alternativemode.reg$X2017.GMU.Report.
Registered.Members,alternativemode.reg$X2016.CaBi.Memb
er.Survey.Report))
chisq.test(alterantivemoderegistered)
```

2017 GMU survey registered Vs casual users

```
genderx<-
data.frame(rbind(gender$X2017.GMU.Report.Registered.Me
mbers,gender$X2017.GMU.Report.Casual.Members))
chisq.test(genderx,correct=F)
```

```
incomeboth<-
data.frame(rbind(income$X2017.GMU.Report.Registered.Me
mbers,income$X2017.GMU.Report.Casual.Members))
chisq.test(incomeboth)
ageboth<-
data.frame(rbind(age$X2017.GMU.Report.Registered.Membe
rs,age$X2017.GMU.Report.Casual.Members))
chisq.test(ageboth)
raceboth<-
data.frame(rbind(race$X2017.registered,race$X2017.casu
al))
chisq.test(raceboth)
toptriptypesboth<-
data.frame(rbind(toptriptypes$X2017.GMU.Report.Registe
red.Members,toptriptypes$X2017.GMU.Report.Casual.Membe
rs))
chisq.test(toptriptypesboth)
motivatorsboth<-
data.frame(rbind(motivators$X2017.GMU.Report.Registere
d.Members,motivators$X2017.GMU.Report.Casual.Members))
chisq.test(motivatorsboth)
alternativeboth<-
data.frame(rbind(alternativemode$X2017.registered,alte
rnativemode$X2017.casual))
chisq.test(alternativeboth)
modeoftransportationboth<-
data.frame(rbind(modeoftransportation$X2017.registered
,modeoftransportation$X2017.casual))
chisq.test(modeoftransportationboth)
serviceboth<-
data.frame(rbind(service$X2017.registered,service$X201
7.casual))
chisq.test(serviceboth)
mobileboth<-
data.frame(rbind(mobileapp$X2017.registered,mobileapp$
X2017.casual))
chisq.test(mobileboth)
effectofmobileboth<-
data.frame(rbind(effectofmobileapp$X2017.registered,ef
fectofmobileapp$X2017.casual))
chisq.test(effectofmobileboth)
preferreddurationboth<-
data.frame(rbind(preferredduration$X2017.registered,pr
eferredduration$X2017.casual))
chisq.test(preferreddurationboth)
```

```
frequencyofcyclingboth<-
data.frame(rbind(frequencyofcycling$X2017.registered,f
requencyofcycling$X2017.casual))
chisq.test(frequencyofcyclingboth)
```

Stata code for odds ratio

```
use oddsratiodata.dta
logit Fareoption i.Gender i.Location
i.Whitevsotherrace AgeMP HHincomenew CaBitripsinamonth
Servicesensitivity, or
logit Fareoption i.Gender i.Location
i.Whitevsotherrace AgeMP HHincomenew CaBitripsinamonth
Servicesensitivity, or
```

Stata code for ordered logit regression

```
use pricesensitivity.dta
. ologit Singletripincreased i.gender i.race hhincome
cabitripsinamonth age
. margins, atmeans
. ologit Singletripreduced i.gender i.race hhincome
cabitripsinamonth age
. margins, atmeans
. ologit annualincreased i.race hhincome
cabitripsinamonth age
. margins, atmeans
. ologit annualreduced i.race hhincome
cabitripsinamonth age
. margins, atmeans
```

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