ABSTRACT

Title of Dissertation: ESTIMATING THE IMPACTS OF CAPITAL BIKESHARE ON METRORAIL RIDERSHIP IN THE WASHINGTON METROPOLITAN AREA

Ting Ma, Doctor of Philosophy, 2017

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Demographic changes and shared-mobility technology have redefined the urban transportation fabric. Bike share, a public short-term bicycle rental program, has emerged around the world. Many users find bike share to be a convenient, healthy, and smart transportation option that solves first- and last-mile issues. But some are concerned that it may challenge existing rail transit systems and reduce ridership. Hence, it is important to understand the impacts of a bike share program on rail transit ridership.

The Washington metropolitan area lends itself well to studying this topic. Both the bike share and rail transit systems in this area, Capital Bikeshare (CaBi) and Metrorail, are the largest in the United States. According to the Washington Metropolitan Area Transit Authority (WMATA), which operates Metrorail service, CaBi services may challenge Metrorail ridership, especially for the short-distance trips. Based on WMATA's concern, I explore whether CaBi substitutes for Metrorail and reduces its ridership.

An exploratory analysis finds evidence that CaBi can complement Metrorail trips in some cases and substitute for rail in others. To estimate CaBi's impacts more precisely,

three regression models—the Direct Ridership Model (DRM), the Difference-in-Difference (DID) model, and the Station-Specific Dummies (SSD) model—were applied.

The results of the three models consistently demonstrate CaBi's mixed impacts. CaBi may complement some Metrorail trips, but substitute for others, depending on the type and time. More importantly, the SSD results found that CaBi's impacts vary by Metrorail station locations, whether a station is a downtown D.C. core station or a non-core station in peripheral and suburban communities. CaBi reduces core Metrorail station ridership by 4,814.4 per month for the number of AM peak exits and by 4,886.9 per month for the number of PM peak entries, but increases ridership at non-core stations by up to 2,781.2 per month, at a high statistical significance level.

The finding that CaBi can complement Metrorail ridership is contrary to WMATA's concern that a bike share program poses challenges for Metrorail. Policy suggestions are provided to help WMATA maximize the benefits of CaBi's complementary effects.

ESTIMATING THE IMPACTS OF CAPITAL BIKESHARE ON METRORAIL RIDERSHIP IN THE WASHINGTON METROPOLITAN AREA

by

Ting Ma

Dissertation submitted to the Faculty of the Graduate School of the
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Preface

This dissertation is submitted for the degree of Doctor of Philosophy at the University of Maryland, College Park. The research described herein was conducted under the supervision of Professor Gerrit Jan Knaap in the Department of Urban Studies and Planning, University of Maryland, between 2012 and 2017.

This work is to the best of my knowledge original, except where acknowledgments and references are made to previous work. Neither this nor any substantially similar dissertation has been or is being submitted for any other degree, diploma or other qualification at any other university.

An older version of part of this work has been presented in the following publications and conferences:

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Ting Ma
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Dedication

A special feeling of gratitude to my loving parents Zhehe Ma and Nianju Chen who raised, educated and supported me to reach my potential without any questioning. I also dedicate this dissertation to my husband Le An, who has always been by my side through my undergraduate, master and Ph.D. study journeys.

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During my dissertation period, I received feedback, help, and encouragement from many people.

I thank my academic advisor Dr. Gerrit Knaap at the University of Maryland for his excellent guidance through the Ph.D. program and dissertation period. I also appreciate his support and help, as well as that of the National Center for Smart Growth Research and Education (NCSG), which he directs. During my graduate assistant work at NCSG, I had great opportunities to participate several research projects that improved my knowledge and skills in urban planning and urban studies.

I would like to extend my thanks to the amazing faculty members and graduate students working together at NCSG: Chao Liu, Sevgi Erdoğan, Casey Dawkins, Hiro Iseki, Frederick Ducca, Eli Knaap, Jae Jeon, and Yi Niu. In particular, I would like to thank Chao Liu and Sevgi Erdoğan for their support along the way in both my study and life.

In the summer and fall of 2016, I did two internships with the District Department of Transportation. There, I had the opportunity to work on Capital Bikeshare projects, particularly analyzing SafeTrack's impact on Capital Bikeshare ridership. I appreciate the great guidance and mentorship of my supervisors, Amanda Stout and John Thomas, and I thank Kimberly Lucas for her help with Capital Bikeshare data. I also thank Justin Antos at WMATA for helping with Metrorail ridership data.

Disclaimer

The opinions and conclusions expressed or implied in this dissertation are not necessarily those of the University of Maryland, College Park, the National Center for Smart Growth Research and Education, or the District Department of Transportation.

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List of Abbreviations

ACS – American Community Survey
CaBi – Capital Bikeshare
D.C. – District of Columbia
DDOT – District Department of Transportation
FHWA – Federal Highway Administration
FTA – Federal Transit Administration
FRA – Federal Railroad Administration
MTA – Maryland Transit Administration
O-D – Origin-Destination
USDOT – United States Department of Transportation
WMATA – Washington metropolitan area Transit Authority
VRE – Virginia Railway Express
VDOT – Virginia Department of Transportation

Chapter 1: Introduction

1.1 Background

How young people get around has been changing. According to the Federal Highway Administration (FHWA), the millennial generation is "driving less, making fewer trips, and traveling shorter distances" (Federal Highway Administration, 2013). Richard Florida, who has been studying what he calls the creative class, found that the new tech-savvy generation prefers to live in cities, where they can rent an apartment and use public transportation, bike, or walk to work (Florida, 2012). Given the fact that teens are less interested in getting driver's licenses, we can expect the trend toward less driving to continue.

Recent technologies have changed the transportation industry and culture in central cities. Today, besides the traditional bus and rail transit systems, many large cities have car sharing, bike sharing, and ridesourcing programs such as Uber and Lyft. The traditional definition of public transportation has gradually transformed into the concept of *shared mobility*. At the same time, public transportation agencies recognize these emerging shared modes as part of a new urban transportation fabric (Shared-Use Mobility Center, 2016).

Bike share programs have become popular. Bike share is an innovative, publicly-accessible short-term bike rental program. A user can rent a bicycle at one station and return it to any station within the system. Due to its convenience, affordability and health benefits, bike share has become a popular transportation choice around the world, especially in higher-density metropolitan areas, and among young millennials. By the end of 2016, there were approximately two million public use bicycles in systems in approximately 1,175 cities, municipalities or district jurisdictions, in about 63 countries (Meddin, 2017).

Many urban planners and researchers are optimistic about the role of bike share and think it may complement rail trips by providing a solution to the last-mile problem. However, some traditional public transportation systems have seen bike share as a competitor for ridership. For example, the Washington Metropolitan Area Transit Authority (WMATA), which operates the regional Metrorail system serving the Washington metropolitan area, claimed in its *2015 Ridership and Revenue* report that the bike share program is one of the challenges facing Metrorail. WMATA's concern about the bike share program's negative ridership ramifications for Metrorail is legitimate.[1] After all, Metrorail has experienced a continuing ridership decline since 2010, the same time the regional bike share program, Capital Bikeshare, was officially launched. According to WMATA's analysis, the bike share program has captured short-trip riders with cheaper costs and thus led to Metrorail's ridership loss (WMATA, 2015b).

1.2 Research Design

Given this shift, it is urgent to clarify the impact of bike share programs on traditional transportation modes such as rail transit. Surprisingly, most previous empirical studies rely on data from surveys of bike share program members. Very rarely have researchers performed rigorous regression analysis. This research gap is unfortunate. The relationship between bike share program use and rail transit ridership is interesting from a researcher's point of view but also, a deeper understanding of the dynamics between shared mobility

[1] The report was accessed from WMATA website on September 3, 2016. However, the link https://www.wmata.com/about_metro/board_of_directors/board_docs/100815_4BFY2017BudgetRidershipandRevenue.pdf was found broken at the time of writing.

and traditional rail transit will help transit operators more precisely predict ridership, and public transportation agencies more effectively allocate resources and make regulations.

This dissertation is dedicated to applying rigorous scientific methods to estimate the bike share program's impacts on rail transit ridership, using as a case study, the Washington metropolitan area, which has has the largest rail transit and bike share programs in the United States. The Metrorail system began service in the 1970s and the Capital Bikeshare system officially launched in 2010. Both systems have been in operation for some time and have generated sufficient trip data for empirical analysis. Therefore, the Washington metropolitan area lends itself well to exploring the research topic.

This dissertation answers the research question: **What are Capital Bikeshare's impacts on Metrorail ridership in the Washington metropolitan area?** Specifically, does Capital Bikeshare complement Metrorail and increase Metrorail ridership, or does it substitute for Metrorail and decrease ridership?

As mentioned earlier, Metrorail's owner and operator, WMATA, is concerned that CaBi may be a competitor and replace Metrorail trips. If CaBi is acting as a substitute, it would involve two scenarios. First, CaBi docking stations installed near Metrorail stations would reduce the ridership of these stations. Second, per one unit of CaBi trip increase, we would expect to see some decrease in Metrorail ridership. Thus, I hypothesize:

H1: *The existence of a CaBi docking station within a one-quarter mile of a Metrorail station is significantly negatively related to the number of Metrorail trips at that station.*

H2: *One CaBi trip initiated or ending at a Metrorail station area is significantly negatively related to the Metrorail ridership of that station.*

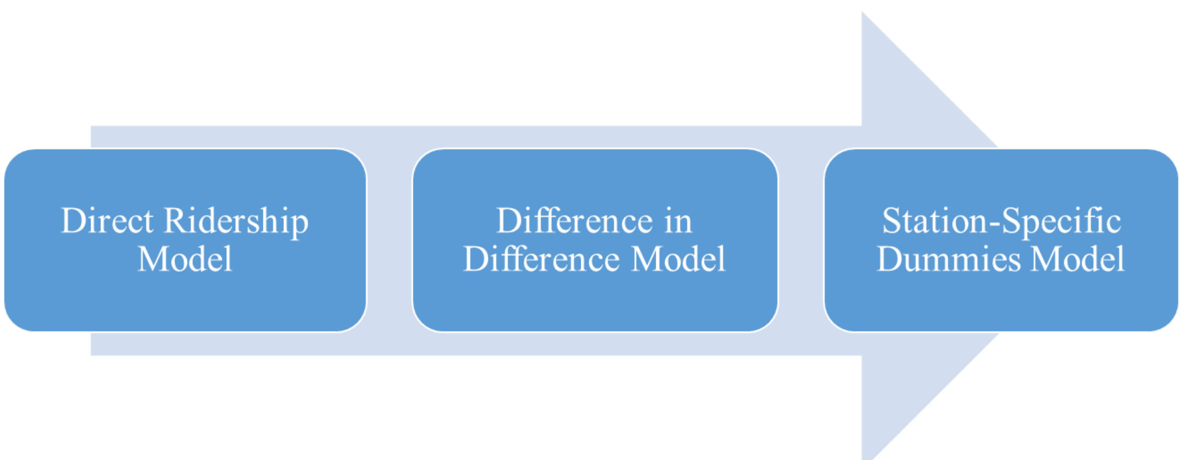
To test these hypotheses, I have designed two sets of quantitative analyses. The first set is the descriptive analysis, which includes temporal analysis and spatial analysis. Temporal analysis helps outline Metrorail ridership and Capital Bikeshare uses over time, while spatial analysis helps identify whether locations of Metrorail and Capital Bikeshare trips are related. Tableau and ArcGIS are the two major software tools used in the descriptive analysis.

In the second set, I offer a slate of regression analysis approaches to quantify CaBi's impacts, specifically, the Direct Ridership Model (DRM), the Difference-in-Difference (DID) model, and the Station Specific Dummies (SSD) analysis, as illustrated in Figure 1. These methods build on each other and each has its advantages and limitations. I start with the Direct Ridership Model, which has been commonly used by transit planners to estimate rail transit ridership based on station area characteristics. Unlike traditional DRM, which includes transit service, socio-demographic, and built environment factors, the DRM for this study is extended to include CaBi trip variables.

The DRM discloses that CaBi may have mixed effects on Metrorail. However, it has two limitations. First, coefficients of CaBi's impacts are too large to explain. Second, the DRM approach relies on the assumption of random assignment, that the Metrorail stations which have CaBi installed nearby is randomly assigned. But this assumtion may not hold. CaBi dock locations are likely to result from a planning process. To overcome this selection bias, I turn to a quasi-experiment technique, the Difference-in-Difference model, to separate Metrorail stations with CaBi nearby from those without CaBi and to estimate their differences before and after the bike share program launch to measure real impacts.

The DID model reveals useful findings, but the average CaBi effects are not statistically significant. Also, the DID results suggest that there may be a relationship between CaBi impacts and Metrorail station locations. One possible solution is to split Metrorail stations into two groups, downtown and suburban, and to estimate CaBi's impacts by location. Therefore, I apply the Station-Specific Dummies (SSD) method to represent Metrorail stations and figure out stations' differences and CaBi's effect for each station. Also, I visualize stations' fixed effects and CaBi impacts using ArcGIS maps and study the spatial patterns.

Figure 1 Research Design—Three Regression Analysis Methods



1.3 Outline of Dissertation

This dissertation has nine chapters. Chapter 1 provides research background, introduces research design, outlines the dissertation structure, and addresses this dissertation's contributions to the existing knowledge on bike share programs' impacts on rail transit.

Chapter 2 provides a comprehensive literature review on bike share programs' history, usage, benefits and other features. This chapter aims to familiarize the readers with bike share programs.

Chapter 3 describes the case study area, the Washington metropolitan area, paying particular attention to its bike-friendly infrastructure system and culture. Also, included in this chapter are sections on Capital Bikeshare and Metrorail. Both sections review program histories, membership mechanisms, trip trends over time, characteristics of users and multi-modal integration policies, accompanied by tables, charts and maps. This chapter aims to provide context and a descriptive analysis of the case study.

Chapter 4 elaborates on the research questions—whether CaBi substitutes for or complements Metrorail trips and whether installing CaBi docking stations within an a-quarter mile of a station increases or decreases ridership. The chapter starts with a price-demand discussion from a microeconomic perspective, and is followed by empirical evidence of CaBi's substitute and complementary effects. Specially, this chapter includes a section on CaBi's performance during WMATA SafeTrack surges as a case study of its substitution impacts. Chapter 4 ends with a literature review of previous studies on bike share programs' impacts on rail transit ridership.

Chapter 5 moves from descriptive analysis to regression analysis. This chapter describes the three regression models that will be applied in later chapters. It also describes the input data and its munging and preparation process. Chapter 5 ends with a discussion of possible coefficients and their interpretations. Since there are four Metrorail ridership measures and four CaBi trip variables, eight scenarios are illustrated as potential regression results.

Chapters 6, 7, and 8 cover the three regression analyses—the Direct Ridership Model, the Difference-in-Difference model, and the Station-Specific Dummies approach. Each chapter starts by describing the methodological approach, including model specifications, equations, and data, followed by regression results reporting and interpretation. These chapters also discuss the limitations of each model. Each chapter ends with a summary section highlighting major findings.

Chapter 9 starts with a summary of analysis findings, addressing CaBi's complementary and/or substitute impacts on Metrorail ridership. Based on that, I suggest specific WMATA policies that make the best use of CaBi's benefits and more general suggestions for public transportation agencies to improve multi-modal integration for better mobility. Finally, the chapter discusses research dimensions that future studies may explore.

1.4 Contribution

This dissertation advances the literature on bike share programs' impacts on rail transit ridership in four ways.

First, the study data is at a high-resolution and high-frequency level. In most previous studies, the authors performed analysis at the system-wide scale. For my dissertation, I reached out to WMATA and the District Department of Transportation (DDOT) for detailed Metrorail and Capital Bikeshare ridership data. The dataset starts from August 2010, before CaBi's launch in October of that year. This dataset allows me to measure CaBi's impacts with a great deal of precision, in both space and time. Therefore, I separate Metrorail ridership into four measures: the number of entries in weekday AM peak (variable *mentryam*), the number of exits in weekday AM peak (variable *mexitam*), the number of entries in weekday PM peak (variable *mentrypm*), and the number of exits in weekday PM peak (variable *mexitpm*). Correspondingly, for Capital Bikeshare, trips are categorized into: the number of trips starting from Metrorail station area in weekday AM peak (variable *cstartam*), the number of trips ending at Metrorail station area in weekday AM peak (variable *cendam*), the number of trips starting from Metrorail station area in weekday PM peak (variable *cstartpm*), and the number of trips ending at Metrorail station area in weekday PM peak (variable *cendpm*). These categories allow precise identification of time and location of CaBi's impacts on Metrorail ridership.

Second, some of this study's research methods are new to the research question and thus provide new perspectives. The Direct Ridership Model is widely-used for estimating rail transit factors' impact. The Difference-in-Difference model allows me to control location and time effects and leads to more accurate estimates of the CaBi program's average impacts. The Station-Specific Dummies model reveals how CaBi's impacts vary by station locations. These three methods complement each other, and together, draw a picture of the relationship of bike share and rail transit ridership that we've never seen before.

Third, besides providing advanced statistical analysis using detailed trip data, I also use advanced data visualization tools, Esri's ArcGIS and Tableau, to map Capital Bikeshare and Metrorail trips. Unlike some other urban studies topics, locations matter in both bike share and rail transit trip analysis and result interpretation. Visualizing spatial patterns using methods such as origin-destination spider diagrams helps link trip numbers and their changes to the location context. From this perspective, visualization is part of the dissertation's analysis content, not an auxiliary.

Finally, this study is timely. Currently, WMATA has been experiencing some transformation. My study includes observations during WMATA's latest maintenance program, SafeTrack, which began in June 2016 and will last one year. During the year, WMATA plans to condense three-years of track maintenance work, which will result in single tracking and line segment shutdowns that reduce Metrorail's service frequency and capacity. However, SafeTrack provides an invaluable opportunity to observe the substitute impacts of Capital Bikeshare, as well as many other transportation alternatives. Including the SafeTrack case study in my dissertation increases its link to ongoing urban planning practice and thus makes my policy implications more relevant and timely.

As a resident of the Washington metropolitan area, I hope my research efforts can help the mobility choices for others who live here.

Chapter 2: Bike Share Programs: A Literature Review

2.1 Background

Where people like to live and work has changed in recent decades. The core American Dream—a big, single-family house with a beautiful lawn and white picket fence in a low-density residence-only suburb has been replaced by a more urbanized "2.0 version." Newer generations are attracted to city downtowns with high-density and mixed-use developments, served with convenient public transportation, and enlivened with first-floor retail and restaurants. According to Robert Fishman, an urban planning historian at the University of Michigan, "in the 1950s, suburbs were the future. The city was then seen as a dingy environment. But today it's these urban neighborhoods that are exciting and diverse and exploding with growth" (Wieckowski, 2010).

The new millennial generation also has a different transportation preference. According to the USDOT, there are 73 million millennials aged 18 to 34 in the United States, and they drive less than their parents. By the end of the 2000s, they drove one-fifth fewer miles than at the beginning of the decade, partly due to the inconvenience of traffic congestion and soaring gasoline prices (DOT, 2015b). Also, between 2001 and 2012, fewer people under 34 got their drivers' licenses. Meanwhile, the number of people who walk or bike has increased. According to a national travel survey, since 1995, the share of walking in all trips has grown from 5% to more than 10%, mainly for social and recreational purposes. In big cities, the share is even higher. For example, in Boston, Washington, D.C., New York, and San Francisco, more than 10% of commuters walk to work (DOT, 2015b). Regarding bicycle use, between 2000 and 2014, bicycle commuting has seen a 62% growth in the United States (The League of American Bicyclists, 2015). The share of bicycle commuting, again, is larger in urban areas. Davis, California has the largest share in the nation, 23.2% of its population cycle to work. D.C. has one of the largest share increases. Between 2005 and 2014, bicycle commuting share increased by 124%. Following this trend, in the future we can expect more non-driving trips in urban areas, with travelers opting for public transportation, biking, walking, carsharing, and ridesourcing services.

Future travel patterns will also be heavily shaped by this young generations' lifestyle. The millennials are the first generation to have access to the internet during their formative years. They are comfortable picking up new technologies to communicate (with Skype), to shop (with Amazon and Ebay), to socialize (with Facebook and Twitter), to visit (with Airbnb), to navigate (with GPS) and to travel (with Zipcar and Uber). Smartphones have become a requisite in daily life to complete various routine activities. One magazine declared the smartphone to be the "most important transportation innovation of the decade" (DOT, 2015b).

In the new era, besides traditional bus and rail transit, we have seen many new transportation modes emerging.[2] Regarding carsharing programs, now we have short-term car rental programs like Zipcar, with easy access/return and smarter Car2Go, as well as rental programs like Enterprise's CarShare and Hertz's 24/7 offered by more old-school car rental companies (Reviews.com, 2015). In total, there are 1.6 million members in 24

[2] As Shaheen, an expert in bikeshare analysis, puts, "now it's not unusual to open your computer or email and find out about two or three new services that have popped up" (Jaffe, 2015a). Almost at the end of this dissertation writing process, I learned about microtransit, a smaller-capacity transit service provided by the private sector. For anyone interested in a more complete picture of the new transportation options, Google "microtransit" to keep yourself up-to-date. Eric Jaffe's article "How the Microtransit Movement Is Changing Urban Mobility" is a good starting point (Jaffe, 2015a).

active carsharing programs in the United States, which has increased by ten times within the past seven years (DOT, 2015b).

Uber and Lyft define another shared transportation mode, ridesourcing services. Ridesourcing allows drivers to convert their personal non-commercial vehicles into temporary taxis and provide service to people who request a ride via a mobile phone application. In the first half of 2015, Uber alone had made more than $3.5 billion dollars in gross bookings (total fares charged to app customers, before the drivers get their payment) (Solomon, 2016).

Bike share programs, which are the focus of my dissertation, are another newly emerging transportation mode in the new sharing economy. A detailed introduction to bike share programs is provided in the next section.

A new concept has been emerging in the U.S.: shared mobility. According to FTA, shared mobility means “Transportation services that are shared among users.” It includes public transit; taxis and limos; bike sharing; carsharing (round-trip, one-way, and personal vehicle sharing); ridesharing (carpooling, vanpooling); ridesourcing; scooter sharing; shuttle services; neighborhood jitneys; and commercial delivery vehicles providing flexible goods movement (Federal Transit Administration, 2016b). As USDOT stated, “over the next 30 years, our legal and regulatory system may be increasingly challenged by emerging forms of business and travel that transcend traditional legal and planning concepts” (DOT, 2015b).

Transportation agencies and experts have recognized this change and given funding support to assist the transformation into a more walkable and bikeable society. Federal funding for pedestrian and bicycle facilities has increased significantly since 1991, reaching $676 million in 2013, or 2% of total federal transportation funding (DOT, 2015b).

Many cities have included multi-modal transportation options as part of their place-making strategies to attract and retain young people and businesses (DOT, 2015b). Specific strategies related to bicycle use include complete streets programs, streetscape projects, greenway and trail planning and design, and bike lane and bike path network planning. Some cities with public transportation traditions are optimistic. For example, Helsinki is comprehensively transforming its public transportation network into a “mobility on demand” system by 2025, so residents will find no reason to own a car (Greenfield, 2014).

2.2 History

So, what is a bike share program and how have they developed in recent years? In this section, I provide an overview of bike share programs, particularly those in the U.S.

Bike share refers to bicycle sharing programs in which owners purchase bicycles and allow short-term rental use by the public. Most bike share programs install a network of bicycle docking stations to provide users convenient access. Users can check out bicycles at docking stations and return them to any station in the network. Bike share might be free to use, but in most cases, users pay a small fee to initiate the rides.

Bike share programs can operate at various levels. Many companies on office campuses provide free bike share programs to employees. Google started its bike share program in 2008 at Googleplex in Mountain View, California. Later in 2010, Google replaced the original bikes with smaller bicycles with 20-inch wheels. Currently, Google has more than 1,000 of these GBikes, free for employees to ride between office buildings. The multi-colored GBikes quickly became popular and famous as part of Google’s company culture. Other IT giants such as LinkedIn and Apple have similar bike share programs. Employees found that bike share programs are not only a transportation alternative but also “a fun, healthy way to relieve work-related stress” and thus improve work productivity (Bikes Make Life Better, 2016).

Many colleges and universities have bike share programs (Zagster, 2016). Princeton University launched its bike share program in 2014. After an expansion in spring 2016, the system now has 60 bikes and nine stations on campus. Occasionally, universities may work with the surrounding municipality to create a bike share program. In May 2016, the University of Maryland, in collaboration with the City of College Park, launched a bike share program, mBike, for students, faculty, staff, residents and visitors. The mBike program offers 120 cruiser bikes, five accessible bikes and 14 docking stations in the city and UMD campus.

Bikeshare programs at the municipal level have received a lot of attention because every resident and visitor can be a program user. Municipal bike share programs usually install facilities in the public right-of-way. In most cases, jurisdiction governments are involved in or lead the planning, funding, administrating, managing, and operating process (Pedestrian & Bicycle Information Center, 2016).

Regarding funding mechanisms, bike share programs can be publicly-owned and contractor operated, privately-owned and operated, or non-profit owned and operated systems (Gaegauf, 2014). In metropolitan areas, several municipalities may collaborate to build a large-scale bike share facility network that provides regional bike share service.

A typical bike share system consists of docking stations and a bicycle fleet. Bike share docking stations have multiple functions. They provide space to store the bicycle fleet and program facilities such as payment machines. They can be installed in street medians, curbside, or even in parking lanes and open space. The National Association of City Transportation Officials (NACTO) created a Bike Share Station Siting Guide to provide guidance on docking station location planning, technologies and design (National Association of City Transportation Officials, 2016). Principles for station sitting include being operationally feasible, and being accessible and convenient for both pedestrians and bicyclists.

Bike share programs have become widespread across the world with successful programs in the North America, South America, Europe and Asia. As of 2011, 135 bicycle sharing programs are in operation in 160 cities and 16 countries, offering approximately 236,000 bicycles (S. Shaheen, Guzman, & Zhang, 2012). In the United States, the number of bicycle sharing programs has reached 15, with 5,238 bicycles and 172,070 members (S. A. Shaheen, Martin, Cohen, & Finson, 2012). Large metropolitan areas, such as Washington, D.C., Minneapolis-St. Paul, Boston, and New York City have citywide bike share programs (T. Hamilton & Wichman, 2015). A Google map, The Bike-sharing World Map (www.bikesharingmap.com), provides location information for all bike share programs around the world.

Technologies for bicycle fleet capacity and payment methods have played an essential role in bike share programs. Based on the technologies involved in payment and security, researchers have categorized bike share programs into four generations (Parkes, Marsden, Shaheen, & Cohen, 2013). The first generation was the *Witte Fietsen* (White Bikes) launched in Amsterdam in 1965. According to the literature, dozens of bicycles were painted white and made available for public use. They were unlocked, and no payment was required. Bicycles were damaged and even stolen, which resulted in the program's shutdown (DeMaio, 2009; Goodyear, 2017).

The second-generation bike share program adopted a coin-deposit system for payment. Copenhagen launched the first program *Bycyklen* (City Bikes) in 1995, almost 30 years after the Netherlands' first attempt. However, shared bicycles suffered from vandalism and theft. The theft risk was not solved until 1996, when Bikeabout, a small campus-wide bike share program, equipped bicycles with magnetic-stripe card machines; when bikes were checked out, program operators could track the bicycles' locations (Goodyear, 2017).

As key technologies, such as Radio Frequency Identification (RFID), became widespread, third-generation bicycle fleets are used by most current bike share systems. Features include credit card payment, GPS tracking, and smartphone apps to show real time availability (Zimmerman, 2016).

The fourth generation of bike share program will be dockless. Rather than returning bicycles to docking stations, users are allowed more flexible returns. Portland's newly launched bike share program, BIKETOWN, uses this type of bicycle fleet and allows returns to either a docking station or to any public bike rack available (BIKETOWN, 2016). Compared to older versions of bike share, dockless systems have more sophisticated back-end IT software allowing the provider to track bike locations and allowing users to check-in and check-out. The cost per fleet is more expensive, but docking station construction and operation costs decrease in the long run (Zimmerman, 2016). In addition, BIKETOWN users also can make bike reservations for up to 10 minutes, using the mobile app.

The next promising technology that will dramatically transform the way we think of bike share is e-bikes or electric-assist technology. According to the National League of Cities' report, one of two barriers preventing the growth of bike commuting is the physical effort required (The National League of Cities, 2015). The issue can be solved by new e-bike technology that will add electric pedal assistance to the bicycle fleet. With e-bikes, users can travel through hilly landscapes more easily and can travel longer distances. E-bikes have the potential to attract new users from a population that is less fit or older and those interested in longer distance travel (Zimmerman, 2016). The City of Baltimore will launch its bike share program in fall 2016; it is planned to be the largest electric pedal-assist bike share program in the western hemisphere (Baltimore City Department of Transportation, 2016).

As of the first week of September 2016, according to the Bike-sharing Blog focused on bike share programs around the world, there are 1,114 cities with active bike share programs, with the total number of public use bicycles at 1.4 million (Meddin, 2016). Most shared bicycle fleets are in China (Meddin & DeMaio, 2015). In the United States, nearly 100 cities in 34 states and the District of Columbia have bike share programs that total 31,700 bicycles (Zimmerman, 2016).

The bike share industry has been growing and has caught a lot of attention. Most recently, the car share industry leader, Zipcar, plans to launch a university campus bike share program through a partnership with Zagster(Zipcar, 2016). Zipcar's bike share program, Zipbike, will follow the company's business model, and provide a networked shared bicycle service to college students, faculty, and staff. According to Zipcar, Zipbike has the potential to relieve congestion and transit strain, save money and hassle, reduce parking demand, and decrease the bicycle theft rate, which is as high as 53%. They plan to launch 15 Zipbike programs by the end of 2017 (McFarland, 2016).

Bikeshare has even attracted a more traditional motor industry giant, Ford. Earlier this month, Ford established a seven-year partnership with Motivate, the operator of D.C.'s Capital Bikeshare and New York City's CitiBike, to change and expand the bike share program in California's Bay Area, starting in San Francisco, under the new name, Ford GoBike (Ford Media Center, 2016). By the end of 2018, there will be 7,000 shared bicycles in the Bay Area. Unlike other bike share operators, Ford is interested in the data that bike share could generate (Rosevear, 2016). Ford plans to add telemetry on shared bicycles that will send data to a communication platform. Data on how people bike, especially on those hidden paths that only local people know, has the potential to assist in the route planning of Ford's newly purchased crowd-sourced Chariot shuttle service.

In the U.S., several acts and policy programs from the federal government have encouraged the popularity of bike share programs. The Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991 and the subsequent Transportation Equity Act for the 21st Century (TEA-21) of 1998 enabled bicycle-transit integration planning and studies at state and local level (R. Wang & Liu, 2013). In 2012, the Moving Ahead for Progress in the 21st Century (MAP-21) Act created a Transportation Alternatives Program (TAP) to fund bicycle and pedestrian projects. As of September 2014, TAP had funded 342 bike and pedestrian projects in all 50 states (Joe Lindsey, 2015). In December 2015, the Fixing America's Surface Transportation (FAST) Act was passed, and was considered "an improvement on MAP-21 for biking" (Whitaker, 2015). About $800 million in funding per year will be assigned to bike and pedestrian projects for five years starting in 2015. Other primary bike share funding sources include Federal Highway Administration (FHWA), Federal Transit Authority (FTA), Congestion Mitigation Air Quality (CMAQ) Improvement Funds, Department of Health and Human Services, C.D.C., Department of Transportation, and so on. Secondary funding sources include municipalities, sponsorship, membership, and usage fees (Wasatch Front Regional Council, 2013a).

2.3 Benefits

Bike share programs have economic, social, and environmental benefits. First of all, bike share can improve transit accessibility by solving the "last-/first-mile" accessibility issue by connecting transit stations and the passengers' final destination, reducing pressure on expanding transit service (Tomer, 2012).

Convenience is the second benefit, and it is the primary perceived benefit identified by bike share users, according to a review of multiple bike share program user surveys (Fishman, 2015; Fishman, Washington, & Haworth, 2013). During peak commuting hours, bike share bicycles can reach speeds up to 3.1 miles per hour (equivalent to 15 km per hour), higher than the speed of cars in congestion, and thus can save commuters travel time(Jensen, Rouquier, Ovtracht, & Robardet, 2010; X. Wang, Lindsey, Schoner, & Harrison, 2015).

Bike share programs can increase physical activity and therefore improve cardiovascular health and reduce obesity. For example, Fishman et al. (2014) found that in 2012, London's bike share program generated an additional 74 million minutes of physical activity and the program in Minneapolis/St. Paul led to an increase of 1.4 million minutes (Fishman, 2015).

Bike share thus attracts many commuters to switch from driving, and thus help reduce car use. It is estimated that bike share programs reduce about 56,000 vehicle miles per year in Melbourne and Minneapolis/St. Paul and 150,000 miles for Washington, D.C. (Fishman, Washington, & Haworth, 2014). According to DDOT's estimate, 100 Capital Bikeshare stations can reduce gasoline use by 15,600 gallon per year, which saves drivers $62,400 (District Department of Transportation, 2012). [3]

By reducing car use, bike share programs also reduce congestion and carbon emissions. The transportation sector is the second-biggest greenhouse gas (GHG) source in the U.S., responsible for 28% of all GHG emissions (DOT, 2015b). Hamilton and Wichman (2015) researched bike share's impact on traffic congestion and found that the availability of a bike share system reduces traffic congestion by 2-3% within a neighborhood (T. Hamilton & Wichman, 2015). Bicycling is fueled by physical energy, which is entirely green, sustainable, and environmentally-friendly.

Bike share programs also have the potential to reduce bicyclist-involved traffic crashes. Fishman and Schepers (2016) compared cycling safety in cities with and without bike share programs and found that the former cities have seen fewer cycling injuries and fewer severe or fatal injuries (Fishman & Schepers, 2016). Martin et al. (2016) attributed bike share users' higher safety performance to the "larger, slower, and sturdier" bicycle design, which prevents aggressive riding behaviors (E. Martin, Cohen, Botha, & Shaheen, 2016).

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[3] The estimate was based on DDOT's survey results. In 2010, Capital Bikeshare generates 1.5 million miles of use per year, and 20% Capital Bikeshare riders reported themselves transferred from car use to bike sharing.

Bike share's positive economic impact convinced municipalities to invest. Survey results found that as high as 82% of program users patronize retail near bike docks (LDA Consulting, 2015). Another survey of business owners located within 0.1 miles of a bike share station found that 20% agreed that bike share has a positive impact on their sales, and 70% thought the program benefits the neighborhood in general (Buehler & Hamre, 2014). For most cities, offering a bike share program is an active demonstration of their commitment to addressing climate change and livability (Fishman et al., 2013).

Finally, bike share programs have the potential to improve social equity by providing affordable and accessible transportation choices to low-income and minority populations. In Philadelphia, the Better Bike Share Partnership (BBSP) was created by the city government and non-profit bicyclist organizations, and funded by a philanthropic organization to "develop a replicable and socially equitable bike sharing model" (Hoe, 2015). One-third of the program's 600 bicycles are located in low-income neighborhoods, and cash payment is allowed (A. Hamilton, 2015).

2.4 Determinants

Several factors influence bike share use. Some are associated with cycling activities in general, and others are tied specifically to riding bike share bicycles.

First, the distance between the trip origin and the destination is a determinant. Shorter distances (less than 5 miles) are more likely to be cycled than reached by other transit (Krizek & Stonebraker, 2010). Interestingly, if the transfer mode is faster, bikers are willing to bike 2 to 5 km (1.2 to 3.1 miles) to connect to the mode. However, if the transfer mode is slower, the average cycling distance reduces to 2 to 3 km (1.2 to 1.9 miles) (Krizek & Stonebraker, 2010; Martens, 2004).

Second, the availability of biking infrastructure has a positive impact on bike share use. Buck and Buehler (2012) found that one additional kilometer (0.62 miles) of bike lanes within a half-mile of a bike share station is associated with 0.86 additional bike share check-outs per day per location (Buck & Buehler, 2012). Wang et al. (2015) found that if a bike share station is connected to trails, it will have 50% more trips (X. Wang et al., 2015).

Buehler and Pucher (2012) collected bike path data from 90 large American cities and performed a rigorous quantitative analysis including the Ordinary Least Squares and Binary Logit Proportions regressions. They found that a greater supply of bike paths is associated with higher bike commuting rates, after controlling for climate, built environment, socioeconomic factors, gasoline prices and other factors. These impacts of bike facilities hold for both on-street lanes and off-street paths (Buehler & Pucher, 2012).

The scales of bike share station networks is positively associated with the number of rides. A correlation coefficient of 0.7 was found between bike share supply (measured by the number of stations per square kilometers) and demand (measured by the number of trips per bike per year), suggesting that bike share demand can be increased by the program's size (Freese & Schönberg, 2014). Therefore, a regional bike share program is always desired.

However, at the micro scale, if bike share stations are placed too close to each other, check-out per station may decrease, suggesting systematic waste. The presence of another bike share station within 1 km led to 90-95% fewer trips (X. Wang et al., 2015).

Third, weather has a significant impact on bike share use. Gerhart and Noland (2014) comprehensively studied weather's impacts and found that, in general, the temperature has a positive impact on bike share use—more trips are made when the temperature gets higher.

But when the temperature gets reaches 93° F or higher, the heat has an adverse impact. Rain has a strong impact on bike share use—the average bike share trips per hour dropped from 122.2 to 58.1 during rain. Rainy weather also decreases bike share trip duration for both registered and casual users, but casual users are affected more.

They also compared the number and duration of trips that start and end within ¼ mile of Metrorail stations and those not near Metrorail stations by comparing coefficients' difference. When a Metrorail station is an alternative to bike share, bike share trips in rainy weather and dark hours decreased more. In addition, near Metrorail stations, there are more bike share trips in peak hours, and fewer trips on weekends.

Though weather condition impacts were significantly associated with bike share use, Gerhart and Noland (2014) found that merely including weather conditions led to relatively low R-squared in all models. They suggested including socioeconomic characteristics when estimating cycling activities.

Weather's impact on bicycling activities does not hold on a more aggregated level. Buehler and Pucher (2012) found that annual precipitation and the number of cold and hot days were not statistically significantly associated with bike commuting in large cities (Buehler & Pucher, 2012).

Besides distance, bicycle infrastructure, and weather, a fourth determinant is the socio-demographic variables of people near bike share stations. Specifically, in the Nice Ride Minnesota system, a 1% increase of white population is associated with a 1.4 – 1.5% increase in bike share use. The percentage of senior and young children populations were found to negatively affect bike share station activity (X. Wang et al., 2015).

Similarly, as a fifth determinant, businesses and jobs near bike share stations have a positive impact on trips. In the Nice Ride bike share system in the Minneapolis-St. Paul metropolitan area, for every 1,000 more jobs that are accessible from a bike share station, there is a 0.8 or 0.9% trip increase. In addition, food service has a positive impact on bike share. One additional food business is associated with 1.7% more station use (X. Wang et al., 2015).

Sixth, several built environment factors were found to be associated with bike share use. Distances to CBDs, parks, and water bodies were all negatively associated with Nice Ride system's station activity. In particular, 1 km closer to the CBD is related to an 11.5-11.6% increase in bike share use, indicating that bike share is used more in high-intensity urbanized areas. In addition, bike share stations located on university campuses were used more (X. Wang et al., 2015).

Finally, rail transit affects bike share use, but the impacts are mixed. Wang et al. (2015) found that the Central Corridor Light Rail Transit in Minneapolis-St. Paul has a significantly negative impact on bike share station use. Results from log-linear and negative binomial models showed that being near a rail transit station reduced bike share station activity by 38.2% and 40.7% (X. Wang et al., 2015).

Griffin and Sener (2016) performed a descriptive analysis of the interaction between bike share and rail transit trips in Austin, Texas and Chicago, Illinois at the system scale level. They mapped bike share stations by the number of embarking trips and found that stations with the highest volume are not necessarily located near rail transit entrances. In addition, they found very little substitution effect at the system level for Chicago's Divvy bike share program and attributed that to the system's being newly launched (Griffin & Sener, 2016).

Proulx (2014) performed research on the impacts of high-frequency transit on the pattern of bike share trips, focusing on Capital Bikeshare stations in Washington D.C. and using 2013 data.[4] Proulx categorized CaBi trips into groups (weekday vs. weekend, AM peak vs. PM peak, trips made by program subscribers vs. casual users, and so on), and got mixed regression results: being near high-frequency transit stations was found to be significantly associated with CaBi trips only in specific situations, for example, for general CaBi trips. Proximity to a Metrobus station is a significant negative factor, but proximity to a Metrorail station is not. Metrobus stations are also significantly negatively associated with weekend CaBi trips, but again, Metrorail stations are not statistically significant. Metrorail stations were positively associated with AM peak CaBi trips per destination and PM peak CaBi trips per origin. Though detailed pictures and data were presented in this research, it is difficult to conclude the effect of transit on bike share use (Proulx, 2014).

Research from Melbourne, Australia analyzing activity and trip patterns across their system, found a strong relationship between docking station activity and proximity to train stations, and this trend was most pronounced during peak hour periods (Lansell, 2011).

Transit's effect on bike share use is increased by bad weather. Gebhart and Noland (2013) examined the effect of temperature, rainfall, snow, wind, fog and humidity levels' impact on bike share trips, and found that cold temperatures, rain, and high humidity levels reduce both the likelihood of using bike share and the duration of trips. Furthermore, they

[4] High frequency transit is defined as transit services with 15 minute or better frequency that operate at least 64% of the hours from 6:00 to 23:00 Monday to Friday, 6:00 to 21:00 Saturday, 7:00 to 20:00 Sunday. Services that only operated in the peak hours were excluded. Eighteen routes, including three Metrorail lines, satisfied researcher's requirement.

found that bike share trips taken near Metrorail stations (within ¼ mile of a Metrorail station) are affected more by rain than trips taken not near Metrorail stations (Gebhart & Noland, 2013).

2.5 Summary

This chapter reviews literature on bike share program's background, history, benefits and determinants, to provide the context for my study. Bike share programs are a component of a larger paradigm shift into an era of shared mobility. First seen in the 1960s, bike share programs can be divided into four generations, based on the technologies applied. Most bike share programs today belong to the third generation, supported by credit card payment, GPS bike tracking, and smartphone reservation apps.

Bike share programs provide a convenient and healthy transportation alternative to driving and can save travel time and cost. They improve transit accessibility and solve the first- and last-mile issue. Also, they have several external benefits, such as reducing traffic congestion and carbon emissions, supporting the local economy, and improving social equity.

Finally, determinants of bike share use include the distance between trip origin and destination, the availability of biking infrastructure, the weather, and the people and businesses near docks. The proximity to transit stations is a factor, but its impacts are mixed. Some found that being near rail transit reduced bike share activity, others found a positive impact, while still others found them to be uncorrelated. The impacts may depend on the cities in which bike share systems are located.

Chapter 3: Study Area

I have selected the Washington metropolitan area as my case study, because it has both a rail transit system (Metrorail) and bike share program (Capital Bikeshare). Both systems are the largest in the United States. Most Metrorail stations were built decades ago, with a few new stations opening after 2000. Therefore, the system's physical infrastructure has been stable, and the impacts of construction on ridership are limited. Capital Bikeshare is one of the earliest bike share programs in the country. Launched in 2010, it has attracted millions of users. Compared to other bike share programs in the United States, CaBi is a well-established system and has sufficient trip data for analysis.

In this chapter, I introduce the Washington metropolitan area, its rail transit system, Metrorail, and its bike share program, Capital Bikeshare, followed by detailed analysis of Metrorail ridership and CaBi trips. Two types of descriptive analysis will be conducted, one on temporal trends, such as Metrorail ridership's 40-year growth and CaBi trips' seasonality, and the other on spatial distributions, such as which stations have the largest ridership. The chapter's goal is to provide a comprehensive introduction to the two systems, so readers, especially those from outside this region, can familiarize themselves with the research context. More importantly, using a descriptive analysis of trends, patterns, and some characterizations of Metrorail and CaBi trips, I identify a suitable dataset for statistical analysis that will be elaborated on in later chapters.

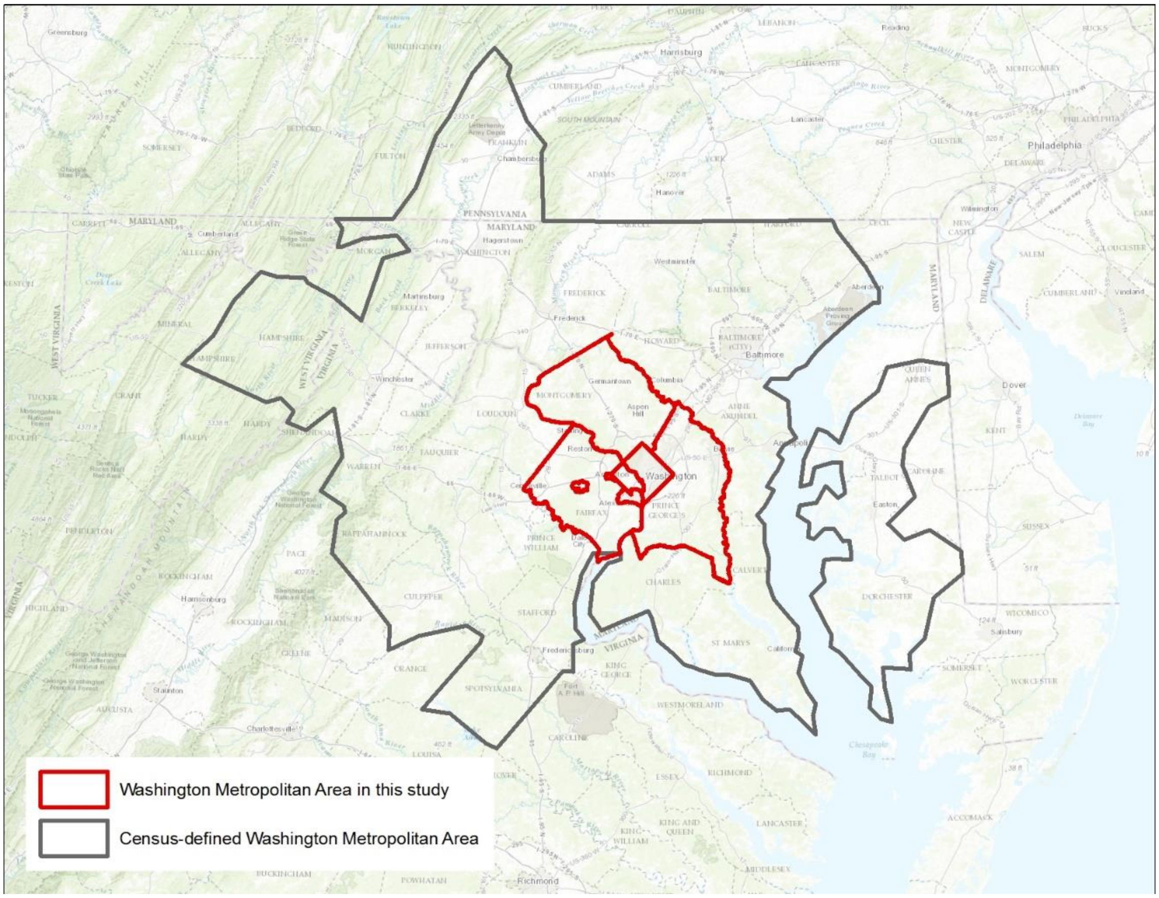
3.1 Washington Metropolitan Area

The Washington metropolitan area, whose official Census name is the Washington-Arlington-Alexandria, DC-VA-MD-WV Metropolitan Statistical Area, is anchored in the city of Washington, D.C. It is the nation's sixth-largest metropolitan area (US Census Bureau, 2016) and consists of twenty-four counties and cities in four states. Over six million people live and work in this area.

Centered in the Census-defined DC-VA-MD-WV Metropolitan Statistical Area is Washington, D.C., usually referred as "the District," and nearby municipalities. This area is surrounded by Interstate 495 and referred as "inside the Beltway." Due to their proximity, these counties and cities are closely related in their transportation and economies. The Washington metropolitan area Transit Authority (WMATA) was created to serve mainly commuters living and working in this region.

In my study, this Washington, D.C.-anchored, inside-the-beltway area defines the Washington metropolitan area. Its counties and cities include Washington, D.C., Prince George's and Montgomery Counties in Maryland, and Arlington and Fairfax Counties, Alexandria City, Fairfax City, and Falls Church City in Virginia. Figure 2 illustrates the difference between the Census-defined Washington metropolitan area and my definition (highlighted in red).

Figure 2 Definition of the Washington Metropolitan Area



Several socio-demographic characteristics distinguish the Washington metropolitan area as a public-transportation-and-walking-friendly area. As the Capital region where the federal government is located, the Washington metropolitan area is the nation's political and cultural center, and has attracted many young professionals specializing in government, statistics, law, etc. According to the Census, the median age of this area's population is about 36.

Washington provides a lot of office areas. Meanwhile, due to the city's height limit and the significant amount of federal lands not available for private development, space for residential uses is restricted. As a result, the Washington metropolitan area has grown into a monocentric spatial structure—downtown D.C. mainly functions as a job center, and commuters live in peripheral and suburban neighborhoods.

Following this spatial structure is a radiating transportation network. The Washington metropolitan area is surrounded by Interstate 495 (I-495). Several radial expressways, I-95, I-66, and I-270 connect downtown D.C. or I-495, and with peripheral communities in Maryland and Virginia. Public transportation mainly consists of a rail transit system, Metrorail, and a bus system provided by WMATA, Metrobus. Commuter rail systems provided by MTA and VRE, and local bus systems operate within municipalities and include county buses and the D.C. streetcar.

Besides public transportation, several other shared mobility modes have recently emerged. The Capital Bikeshare program was first launched in 2010 in D.C. alone, and soon expanded to other communities in this area. The public car sharing program, Car2Go, provides free-floating short-term car rentals in D.C. The ridesourcing programs Uber and Lyft allow customers to request rides using their smartphones. The pop-up ride-sharing bus Bridj meets on-demand bus commuting needs and can pick up/drop off customers at locations that may not be included in fixed bus routes.

Because of these structures and services, Washington, D.C. has become one of the most non-driver-friendly cities in the U.S. Table 1 compares the share of commuters taking subway versus those biking to work between 2009 and 2014, using data of American Community Survey 2005-2009 and 2010-2014 5-year estimates. Over those six years, both the nation and D.C. experienced a slight growth in subway users. The nation's average increased from 1.7% to 1.9%, and D.C.'s share increased from 21.3% to 22.1%. However, the share of D.C. commuters who bike to work doubled during this time period, from 2.0% to 4.1%. This growth outpaced the national average, which only slightly increased by 0.1%.

Table 1 Share of Subway and Bicycle Commuters in D.C. vs. the U.S., 2009-2014

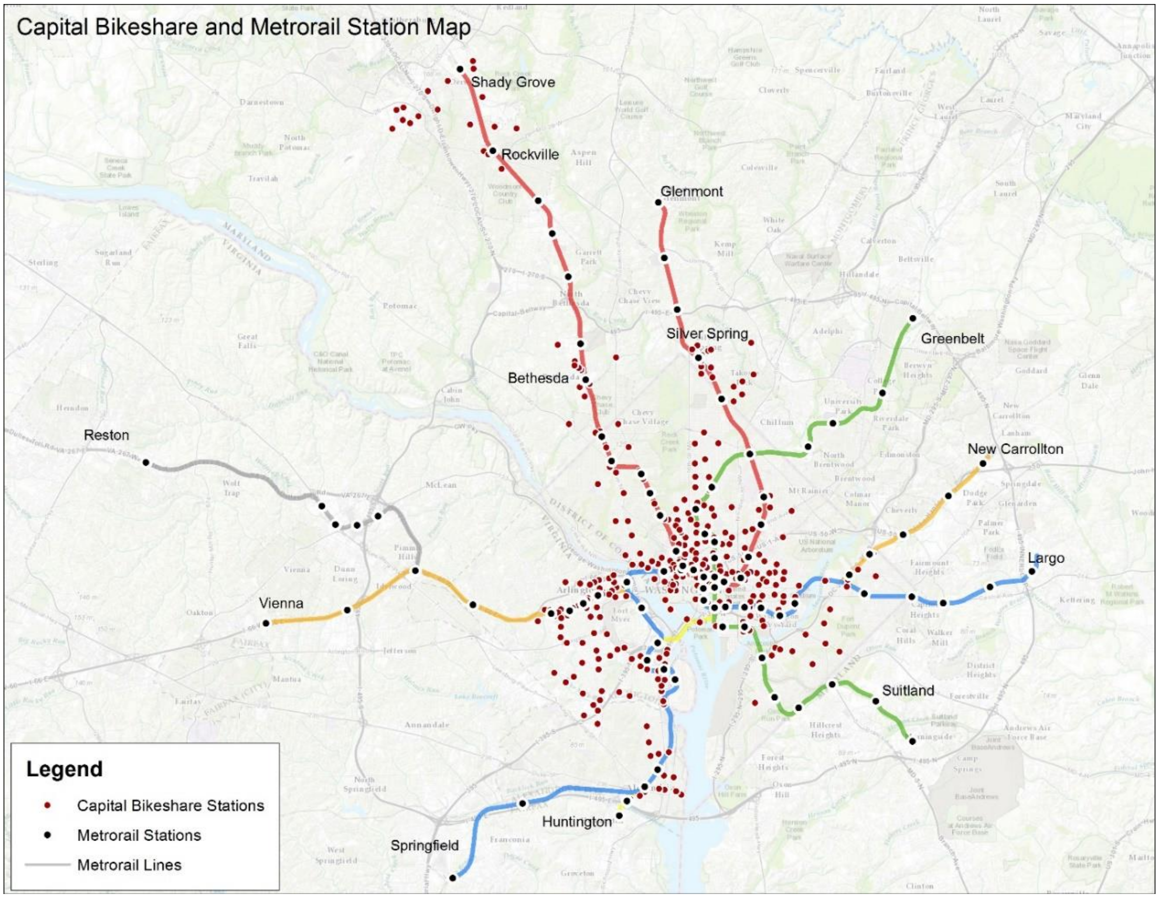
	2009		2014	
	U.S.	D.C.	U.S.	D.C.
Subway	1.7%	21.3%	1.9%	22.1%
Bicycle	0.5%	2.0%	0.6%	4.1%

According to a report prepared by the League of American Bicyclists, Washington, D.C. has been ranked in the top tier for bike use (The League of American Bicyclists, 2015). In 2014, Washington, D.C. ranked fourth in the nation and first in the East for the share of bike commuters in cities with populations between 300,000 and 1 million. The District of Columbia, as a state equivalent, has the 3rd largest share change between 2005 and 2014. If we total the number of commuters who bike, walk, or take transit, Washington, D.C. has the highest share at 53.1% among cities with populations between 300,000 and 1 million.

It was also ranked second among 30 largest U.S. Metropolitan areas as one of the top-tier walkable urban places (Leinberger & Lynch, 2014). Of the area's different land uses, 53% of office, 20% of retail, and 23% of multi-family developments are in Walkable Urban Places, defined as developments of substantially higher densities, mixed uses, new product types (such as rental apartments over a ground-floor grocery store), and supported by multiple transportation options.

Municipalities in the Washington metropolitan area have invested in bicycle infrastructure. As of 2016, there are 75 miles of bike lanes in the City of Washington alone, including six miles of protected lanes (Caro, 2016). In addition, Washington metropolitan area jurisdictions have developed several programs to promote bicycling, such as bike-to-work days.

Figure 3 Capital Bikeshare and Metrorail Station Locations



3.2 Capital Bikeshare

Established in D.C. in September 2010, Capital Bikeshare (CaBi) offered the largest bicycle sharing service in the U.S. at that time. The program was initially named SmartBike D.C. and only served the City of Washington. Later the District Department of Transportation (DDOT) created a coalition with transit authorities in surrounding communities—Arlington and Alexandria in Virginia and Montgomery County in Maryland—and renamed the expanded program CaBi. The CaBi system consists of bikes and the docking stations where users can check out and return them. As of May 15, 2016, CaBi has 380 stations with 6,483 docks. Table 2 lists the number of stations and docks by jurisdiction. CaBi began service in Fairfax County, Virginia, in October 2016 (Lazo, 2016b).

Table 2 Number of CaBi Stations and Docks by Jurisdiction

Jurisdiction	Station Number	Station Share	Dock Number	Dock Share
D.C.	219	58%	4,139	63.9%
Arlington	84	22%	1,155	17.8%
Alexandria	20	5%	314	4.8%
Montgomery	57	15%	875	13.5%
Total	380	100%	6,483	100.0%

Both CaBi's bikes and docking stations are unique. The CaBi bike, as illustrated in Figure 4, is red, DDOT's official color. The bike frame is sturdy and tires are puncture-resistant, making bike trips comfortable and safe (though sometimes slow). The bike is also equipped with a three-speed shifter, a height-adjustable seat and a front basket to meet riders' various needs.

CaBi bikes are stored in docking stations. As Figure 4 shows, a CaBi station usually consists of a payment kiosk and multiple bike docking ports. Users can purchase passes and get bike codes at the kiosk, and then check out bikes. Each dock also has a slot for the bike key allowing regular CaBi users to skip the kiosk and directly check out bikes. All CaBi docking stations are solar powered.

Figure 4 Capital Bikeshare Bicycle and Docking Station

Capital Bikeshare requires docking stations to be installed on a level and stable hard surface. The station is about 50 feet long by 8 feet wide. Since the docking stations are powered by solar panels, adequate exposure to sunlight (minimum 4 hours a day) is required. In addition, the location needs to be safe and accessible for both pedestrian and bicyclists, and not conflict with utilities such as hydrants (Capital Bikeshare, 2014). To create an efficient bike share network, the distance between docking stations cannot be too large or too small. A full 400- to 500-foot block is the minimum distance required (Capital Bikeshare, 2014).

CaBi locates new docking stations using two methods: crowdsourcing and strategic planning. An online crowdsourcing map was introduced on the CaBi website in 2011.[5] It allows the public to suggest where they would like the future stations to be located and to

[5] The link to the crowdsourcing tool is: http://www.bikearlington.com/pages/bikesharing/capital-bikeshare-crowdsourcing-map/.

comment on others' suggestions. Owen, Neita and Froehlich (2015) analyzed the correspondence between the crowdsourced location data and stations' actual usage and found that they are moderately correlated, suggesting crowdsourcing is an effective tool in bike share planning (Owen, Neita, & Froehlich, 2015).

However, besides demand, several other factors such as the existing network and feasibility need to be considered. Many jurisdictions made strategic plans to identify neighborhoods most suitable for new stations. For example, in its 2015 *CaBi Development Plan*, DDOT considered 19 market study measures to identify areas with high demand for bike share use, high revenue potential, high impacts on public welfare and health, and high regional accessibility. The Plan also considered three development scenarios and compared their estimated operating costs. After this demand analysis and financial feasibility analysis, DDOT planned an expansion of 99 stations between 2015 and 2018 (DDOT, 2015). In reality, the specific location of docking stations is usually planned through discussion and negotiation among stakeholders including the Advisory Neighborhood Commissions (ANCs) and Business Improvement Districts (BIDs).

To use CaBi bicycles, users first purchase a membership at the docking station's kiosk to receive a bike code. Using the code, they can check out a bike from the dock port and start the ride. When trips are complete, users return bikes to a docking station. Bicycles may be rented at or returned to any docking station, which gives users flexibility. Regular users who purchase an annual membership can use a bike key to check out bikes from dock ports directly.

CaBi is a publicly-owned and contractor-operated system. As introduced, CaBi is owned by the five participating jurisdictions. Regarding funding, CaBi receives support from federal government, regional and local jurisdictions, as well as private money, as shown in Table 3. In 2011, CaBi's annual operation cost was $2,300,000 (Wasatch Front Regional Council, 2013a).

Table 3 Capital Bikeshare Funding Sources

	2010	2011	2012	Total
FHWA (CMAQ) Improvement Fund	$5,120,000	$2,000,000		$7,120,000
			$1,000,000	$1,000,000
			$320,000	$320,000
Job Access and Reverse Commute (JARC)	-		$1,300,000	$1,300,000
Virginia Dept of Rail & Public Transportation	$300,000			$300,000
Arlington County Transportation Funding	$200,000	-	$250,000	$450,000
Montgomery County	-		$500,000	$500,000
Local Funding	$1,280,000	$500,000	$200,000	$1,980,000
Transportation Management Plan (TMP)	-	-	$80,000	$80,000
Private Sector Funds	$300,000		-	$300,000
Total	$7,200,000	$2,500,000	$3,650,000	$13,350,000

CaBi's operation is contracted to a private company, Motivate (formerly Alta Bicycle Share). One important part of Capital Bikeshare's routine operation is rebalancing, moving bicycles from full docking stations to empty ones, so the system remains balanced. The Washington metropolitan area's spatial structure is segregated, with most jobs clustered in downtown D.C. In the morning rush, Capital Bikeshare docking stations near workplaces may be packed with returned bicycles, but stations in residential areas are empty due to high volumes of check-outs. Motivate rebalances using van vehicles to transport about 2,600 bicycles every weekday to ensure the availability of both bicycles and dock space. Currently, there are 20 full-time van drivers and four dispatchers working on rebalancing (Capital Bikeshare, 2015; Virginia Tech, 2012).

Routine rebalancing may fail to meet the high demand for bikes at specific locations during peak hours or special events. For example, during the National Cherry Blossom Festival, stations near the Tidal Basin are quickly emptied. During Fourth of July celebrations and Presidential Inaugurations, CaBi stations near the National Mall may see many returned bikes. CaBi hire bike valets and creates temporary corrals to provide extra bikes and to receive bikes when docks are full (Capital Bikeshare, 2016b; Motivate, 2017). Also, CaBi has an innovative incentive program to encourage users to rebalance the system. In summer 2011, they established a Reverse Rider Rewards program to provide members with an incentive to ride a bike from typically full stations to typically empty stations (goDCgo, 2011). The ratio between reverse trips and forward trips was about 10:1 (Pitingolo, 2012).

CaBi's success has made bike share a favorite idea among governments in this area. The Maryland Transit Administration (MTA) is partnering with the City of Baltimore to create a bike share program with 50 stations across the city. In addition, MTA plans to spend $500,000 to fund bike share dock installation at 15 MTA MARC, Metro subway, and light rail stations. According to MTA Administrator Paul Comfort, "bike share provides customers with an effective first and last mile options for their commute" (MTA, 2016). The Northern Virginia Transportation Commission (NVTC) oversees the Transform 66 Multimodal Project and is proposing $500,000 to add 16 Capital Bikeshare stations in the City of Falls Church; some will be located adjacent to Metrorail stations. Similarly, NVTC found that Capital Bikeshare "will serve as a first-mile/last-mile solution, with the potential to increase daily trips at the two Falls Church Metrorail stations by 450" (NVTC, 2016). Fairfax County, VA approved a $1.7 million plan to bring Capital Bikeshare to Reston and Tysons Corner (Fairfax County, 2016).

3.2.2 Membership

Capital Bikeshare is based on a membership system. There are seven membership options: single-trip, 24-hour, 3-day, Day Key, 30-day, annual or annual installment. The single-trip fare was added in June 2016 to assist travel during WMATA's SafeTrack period. Table 4 summarizes CaBi membership costs.

Table 4 Capital Bikeshare Membership Fees

Single Trip	$2
24-hour	$8
3-day	$17
Day key	$10 initial fee + $7/day
30-day	$28
Annual	$85
Annual with Monthly Installments	$96 ($8/month for 12 months)

With any CaBi membership, the first 30 minutes of a trip is free and incremental charges are added per hour afterward. The total costs vary by membership type and use time. Table 5 lists CaBi usage fees for different membership types. For example, a 100-minute trip would cost an annual member $10.50 (in addition to $85 membership cost), which includes a free 30-minute ride, a $1.50 fee for the 2nd 30 minutes, a $3.00 fee for the 3rd 30 minutes, and a $6 fee for the remainder.

Table 5 Capital Bikeshare Usage Fees

Ride Time	Total Hourly Fee 24-hour and 3-day Members	Total Hourly Fee Day Key, 30-Day, Annual, and Annual with Monthly Installments Members
0 - 29:59 min	FREE	FREE
30:00 - 59:59 min	$2.00	$1.50
60:00 - 89:59 min	$6.00	$4.50
90:00 - 119:59 min	$14.00	$10.50
2:00:00 - 2:29:59 hours	$22.00	$16.50
2:30:00 - 2:59:59 hours	$30.00	$22.50
3:00:00 - 3:29:59 hours	$38.00	$28.50
3:30:00 - 3:59:59 hours	$46.00	$34.50
4:00:00 - 4:29:59 hours	$54.00	$40.50
4:30:00 - 4:59:59 hours	$62.00	$46.50
5:00:00 - 5:29:59 hours	$70.00	$52.50
5:30:59 - 5:59:59 hours	$78.00	$58.50
6:00:00 - 6:29:59 hours	$86.00	$64.50
6:30:59 - 23:59:59 hours	$94.00	$70.50

Recently, Capital Bikeshare initiated programs to provide low-cost memberships. For example, through the Capital Bikeshare Community Partners Program, organizational memberships are provided to local non-profits, government agencies and social services organizations at low annual membership cost. Those organizations' employees can get an annual membership for $5, and an extended free trip duration of 60 minutes (compared to the regular 30 minutes). Capital Bikeshare estimated that shifting from bus to bike share would save a commuter up to $638.75 per year if he or she use CaBi to replace one bus trip every day (Hilary Angus, 2016).

CaBi categorizes daily, 3-day, and single-trip fare memberships as *casual* in its trip recording system; 30-day, annual, and annual with monthly installments are labeled as a *member*. Though one may argue that commuters who use CaBi multiple times a month may still purchase a daily pass each time and labelling them as a casual user may not be precise, this dissertation uses CaBi's definition of *casual* and *member*.

As of May 15, 2016, there are 29,797 active members registered in the CaBi system. In addition, 952,371 casual users purchased daily or 3-day fares. Table 6 breaks down membership by type.

Table 6 Registered Members by Type

Membership	Count	Status
24-hour or Day key	855,057	Cumulative
3-day	67,314	Cumulative
30-day	315	Active
Annual or Annual with Monthly Installments	29,474	Active

One issue with Capital Bikeshare membership is its affordability. According to DDOT Director Leif Dormsjo, "by including need-based Capital Bikeshare annual memberships, we are ensuring that all District residents can use this healthy, affordable and efficient means of travel" (District Department of Transportation, 2016).

To incentivize bike share commuting, Capital Bikeshare, through its Community Partners Program, provides organizational discounted membership to government agencies, non-profit organizations, and social services organizations (Capital Bikeshare, 2016a). Organizational memberships include:

- A $5 annual membership for their clients
- 60 minutes of ride time included with every trip (normally 30)
- A Capital Bikeshare helmet
- An introduction to the Bikeshare system
- Instruction on how to use the stations
- How-To-Ride classes with the Washington Area Bicyclist Association

Currently, the Community Partners Program is available to employers with offices in the District of Columbia, but is planned for Arlington County and the City of Alexandria

(Capital Bikeshare, 2016a). Montgomery County has its own low-income membership program "MCLiberty" to provide free bike share memberships to qualified low-income individuals (Montgomery County Government, 2017). The County also offered discounted membership through a Job Access and Reverse Commute Program (JARC), a program which has expired (Federal Transit Administration, 2016a).

3.2.3 User Demographics

Capital Bikeshare has conducted three member surveys, in 2011, 2012, and 2014, to analyze who uses CaBi and how they use it (LDA Consulting, 2012, 2013, 2015). Survey results have revealed interesting findings about CaBi members and their bike share behaviors and preferences.

According to the 2012 Customer Survey, among all of the 3,731 survey participants, 63% are under the age of 35, 57% are male, and 80% are Caucasian. Of members, 95% possess a four-year college degree, and 56% hold advanced degrees. Nine out of ten survey participants are employed, and 78% work and live in D.C. The majority of users (91%) agreed that CaBi helps them get around more easily, faster, and over shorter distances. Of members, 80% use CaBi as a new travel option, or as a one-way travel option, and 52% find bike sharing helpful in reducing their transportation costs. Finally, 57% use CaBi to exercise. It is also important to acknowledge that the program draws many non-residents and tourists. In 2013, visitors took more than 200,000 rides.

The survey also asked users whether and how they have shifted their use of rail transit since CaBi became available. Of respondents, 54% reported Metrorail stations as their trip origins/destinations. Among them, 9% made trips starting or ending at Metrorail stations more than ten times in one month. Compared to other public transportation modes, Metrorail stations attract more CaBi trips (21% of respondents cycle to/from bus stops, and 10% to other commuter rail stations—MARC, VRE, and Amtrak). When asked how they would travel if the CaBi program were not available, 44% responded that they would take bus or Metrorail instead. As to Metrorail use, 61% reported that they used Metrorail less often, and 4% reported using it more often, after joining the CaBi program. There is some support for expanding CaBi near Metrorail station, 17% of respondents stated that they would support that expansion.

The survey also asked respondents whether and how they changed their use of non-bicycle transportation modes since they joined CaBi. Respondents could select one response from "Much less often," "Less often," "About the same," "More often" and "Much more often." Table 7 summarizes those responses for each transportation mode asked in the three survey years.

Table 7 Change in Use of Non-Bicycle Transportation

		2011	2012	2014
Metrorail	Much less often	10%	21%	20%
	Less often	37%	40%	38%
	About the same	46%	35%	38%
	More often	7%	4%	4%
Bus	Much less often	7%	19%	21%
	Less often	32%	33%	31%
	About the same	55%	45%	45%
	More often	6%	3%	3%
Walk	Much less often	2%	8%	7%
	Less often	29%	46%	44%
	About the same	52%	39%	41%
	More often	17%	7%	8%
Driving	Much less often	11%	20%	27%
	Less often	30%	30%	28%
	About the same	59%	49%	44%
	More often	0%	1%	1%
Taxi	Much less often	17%	31%	27%
	Less often	36%	29%	32%
	About the same	46%	39%	40%
	More often	1%	1%	1%

Table 7 also demonstrates Capital Bikeshare's substitute effect on Metrorail. Of respondents, 47% used Metrorail less or much less often in 2011. This share increased to 61% in 2012 and 58% in 2014. In particular, CaBi users who responded that they take Metrorail much less often doubled from 10% in 2011 to 21% in 2012 and 20% in 2014. Conversely, only 7% of respondents claimed that they use Metrorail more since joining Capital Bikeshare. That number decreased to 4% in 2012 and 2014, showing that CaBi's complementary effect on Metrorail has reduced over the years.

Not only does Capital Bikeshare reduce Metrorail rides, but it also decreases the use of other non-bicycle transportation modes. CaBi's effect on bus usage, according to the respondents, is very similar to the effect on Metrorail. In 2011, 39% claimed that they take bus rides less or much less often. The share increased to 52% in 2012 and 2014, suggesting that half of the respondents use the bus less. CaBi also appears to reduce driving frequencies with 55% of respondents driving less or much less often in 2014, which is 14% more than the share in 2011.

In addition, the surveys asked whether and how often CaBi member users took rides that started or ended at Metrorail stations in the past month. In 2012, 54% respondents reported making at least one trip from/to Metrorail stations. In 2014, the number increased to 64%. Respondents answering that they make 1-2 trips, 3-5 trips, 6-10 trips and 11 or more trips starting or ending at Metrorail stations rose by 1-3% in each group.

Table 8 Share of CaBi Trips From/To Metrorail Stations

	2012	2014
0 trips	46%	36%
1-2 trips	22%	25%
3-5 trips	15%	18%
6-10 trips	8%	9%
11 or more trips	9%	12%

Survey data only reflects answers of the respondents, and may not capture all CaBi users. To better understand users' demographics, since April 2015, CaBi has collected socio-economic information at the trip level. I contacted DDOT and Motivate and received a trip-level user demographic dataset that covers between April 2015 and August 2016. The analysis below is a complement to the surveys' findings.

Table 9 shows the number of trips made by users of different races. About two-thirds of trips are made by white or Caucasian riders, followed by Asian at 9.6%, and Hispanic at 8.9%. Black or African American riders make 6.5% of total trips.

Table 9 Capital Bikeshare Trips by Users' Race/Ethnic Groups

Race/Ethnic Group	Number of Trips	% of Total Number of Trips
White or Caucasian	82,666	60.3%
Black or African American	8,850	6.5%
Asian	13,186	9.6%
Hispanic or Latino	12,175	8.9%
American Indian or Alaska Native	643	0.5%
Other	5,467	4.0%
Prefer not to answer	14,036	10.2%

Table 10 shows the number of trips made by users in different income groups. Riders who make less the $25,000 per year made 21% of trips, a group that could be college students. The second largest income group of users is those making between $50,000 and $74,999. They make 19% of all trips.

Table 10 Capital Bikeshare Trips by Users' Income Group

Income Level	Number of Trips	% of Total Number of Trips
Less than $25,000	29,254	21.4%
$25,000 - $49,999	24,068	17.6%
$50,000 - $74,999	26,135	19.1%
$75,000 - $99,999	16,623	12.1%
$100,000 - $149,999	10,896	8.0%
$150,000 or more	5,268	3.8%
Prefer not to answer	24,779	18.1%

3.2.4 CaBi Trip Analysis

In this section, I perform a comprehensive analysis of Capital Bikeshare trips using two datasets provided by CaBi operator Motivate Co. The first trip dataset includes start date and time, start station name and station number, end date and time, end station name and station number, trip duration, and membership type of each CaBi trip made since the program's official launch through August 5, 2015. The second dataset includes socio-economic information about the CaBi users: birth year, race/ethnicity, and income level. This user dataset is new, and trips were made between April 13, 2015 and August 5, 2016.

Trip Growth

In 2010, Capital Bikeshare had 107 stations and reached 115,937 trips at the end of the year. The average number of trips made per station was 1,084. Because it was a new program, the average trip number per station was not high. But since its second year, CaBi has become an attractive transportation option. As Table 11 shows, the number of trips per station in 2011 increased to 8,475, more than eight times the 2010 number. Both the number of stations and number of trips increased over the years. As of August 5, 2016, there were 401 Capital Bikeshare stations. The highest number of annual trips was in 2015, more than 3 million trips. (At the time of writing, the 2016 annual trip number is not available.) As for the number of trips made per station, the largest number took place in 2012. For each station, about 10,580 trips were started.

Table 11 Number of Capital Bikeshare Stations and Number of Trips Over Time

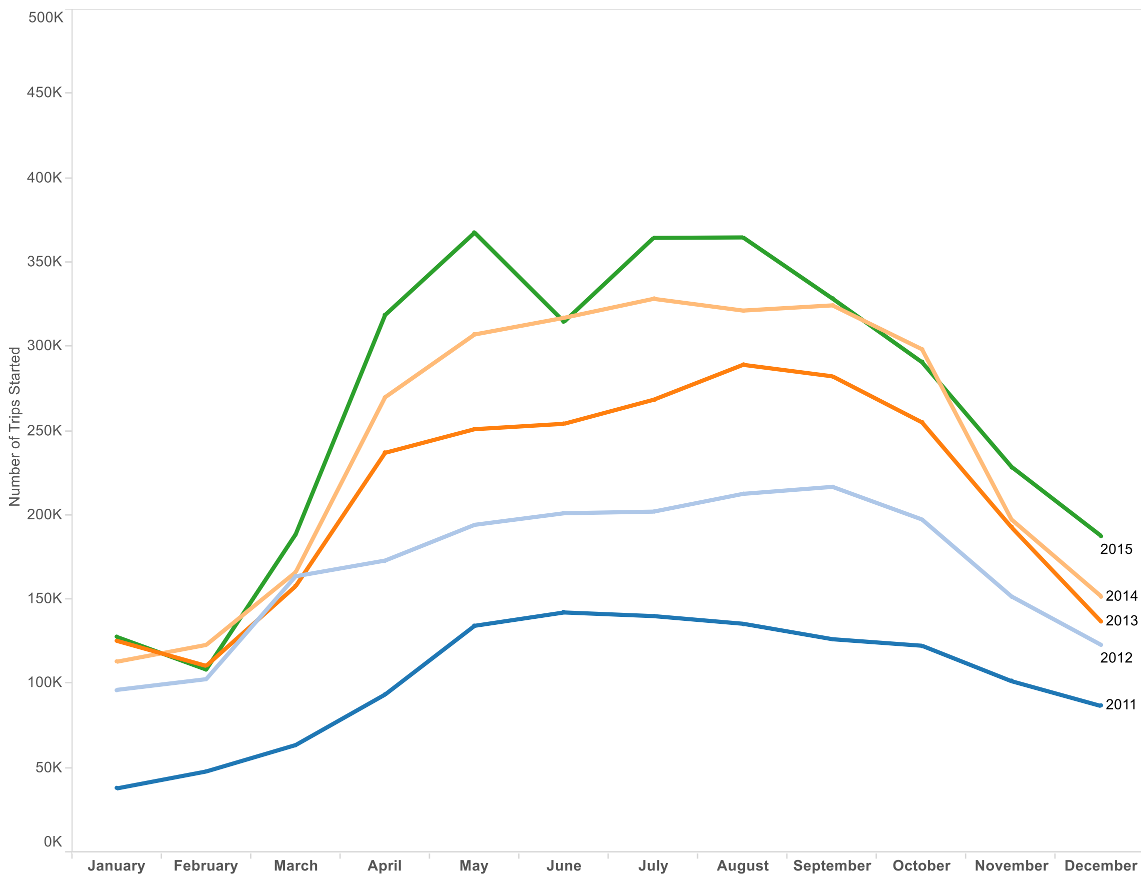
Year	Number of CaBi Stations	Number of Trips Started	Number of Trips per Station
2010*	107	115,937	1,084
2011	145	1,228,879	8,475
2012	192	2,031,415	10,580
2013	306	2,557,267	8,357
2014	347	2,914,714	8,400
2015	358	3,187,108	8,903
2016**	401	1,921,950	4,793

*2010 only has trips between October and December
**2016 only has trips between January and August

Weather's Impacts

The literature review in Section 2.4 found that weather has significant impacts on bike share use. This was confirmed by my analysis of CaBi trips. First, CaBi trips show a seasonal pattern. Figure 5 shows the number of trips by month between 2011 and 2015 (2010 and 2016 were dropped because the dataset only covers part of these two years), with each line representing one year. From the graph, we can identify a seasonal pattern that is consistent over years. More CaBi trips are made between April and October, compared to the rest of the year. I found temperature to be an appropriate explanation: people tend to cycle more in warmer weather.

Figure 5 Capital Bikeshare Trips by Month by Year

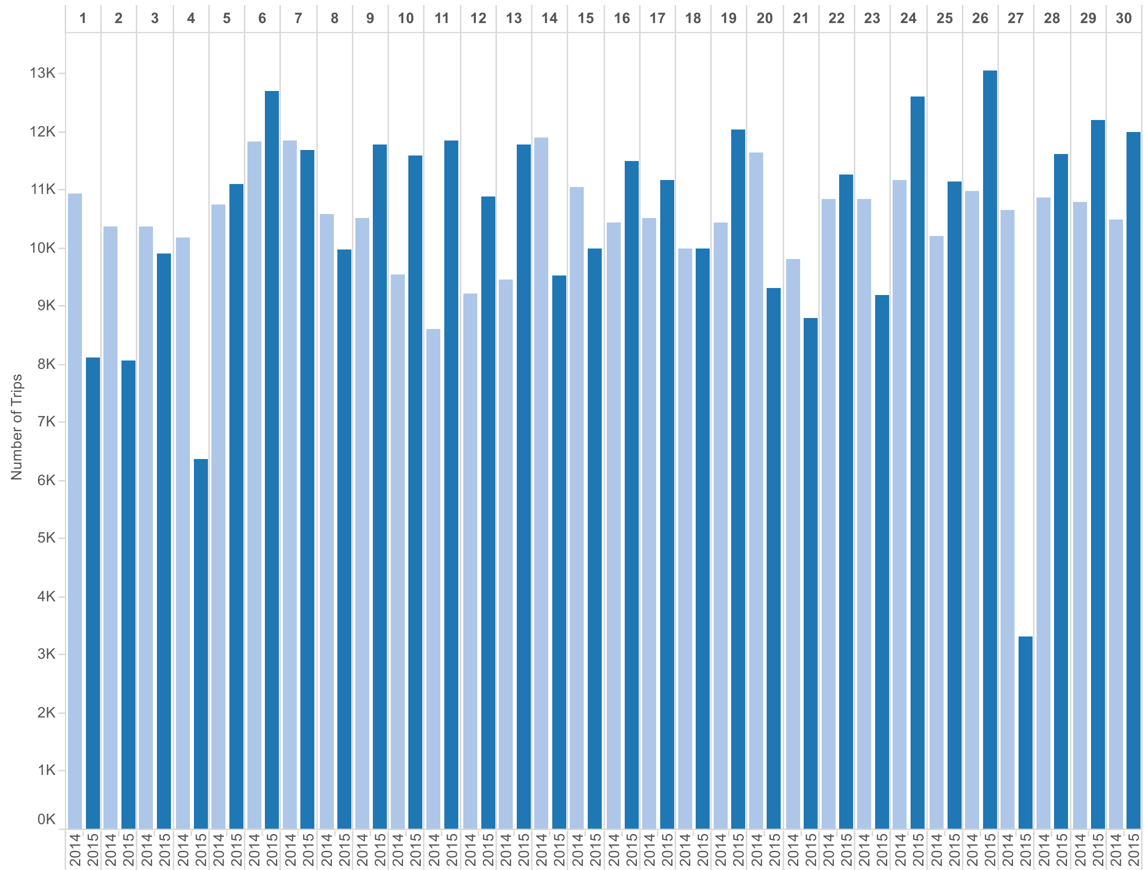


The finding that CaBi trips are affected by weather is consistent with previous studies. Fishman (2015) studied bike share trips by month in multiple cities and found that more trips were made in spring and fall than in winter. This seasonal pattern in Washington, D.C. was also observed in bike share trips in New York, London, and Boston (Fishman, 2015).

The peak month varies in different years. May was the peak month in 2011, September was the peak month in 2012 and August was the peak month in 2013. The number of rainy days may explain the inconsistency since literature review in Section 2.4 suggests that bike share trips plunge dramatically on rainy days. To test the theory, I compared daily CaBi trips for June 2014 and June 2015. In Figure 6, the light blue bar represents 2014 data and 2015 data is represented by the dark blue bar. One day, June 27, stands out; on that day, the number of CaBi trips made in 2014 was more than twice the number made in 2015. According to archived news articles, on June 27, 2015, D.C. region had a record-setting rainfall.[6] In fact, the rainfall total was 11.9 inches, making June 2015 the second highest on record since 1871. Thus, the precipitation is likely to cause CaBi trips' monthly fluctuations between April and October.

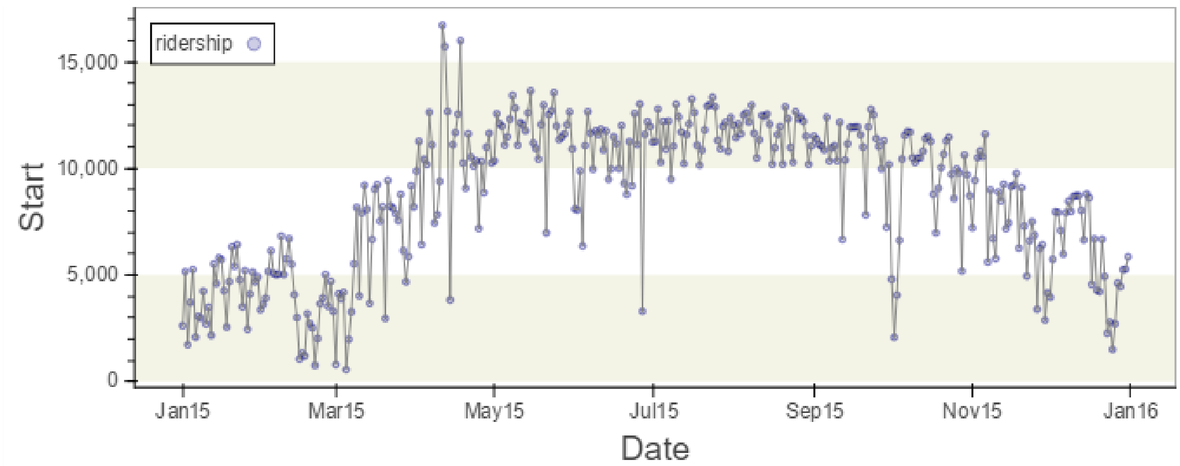
[6] Washington Post. Saturday soaker sets daily record in D.C.; second wettest June. https://www.washingtonpost.com/news/capital-weather-gang/wp/2015/06/28/saturday-soaker-sets-daily-record-in-d-c-june-2nd-wettest-on-record/

Figure 6 Capital Bikeshare Trips by Day, June 2014 and June 2015



I also created a graph to identify single days with the largest CaBi trips, using the 2015 data. As Figure 7 shows, the winter season, which is before mid-April and after mid-November, has the smallest number of CaBi trips per day. The daily trip number in winter could get down to 1,000. Conversely, during non-winter seasons, the average daily CaBi trip number is larger than 10,000. The annual peak took place during the 2015 National Cherry Blossom Festival in late April, and about 17,000 trips were made each day.

Figure 7 2015 CaBi Daily Ridership



The finding that weather impacts CaBi trips leads to an important implication for data preparation for regression analysis in the later chapters. First, the month effects should be controlled for, for example, by using dummy variables. Second, if only trips in a specific time of year are used, I should avoid using trips made in the winter when there are fewer numbers of CaBi trips due to cool weather and snowy/icy road conditions. Third, to eliminate weather's impacts and trip fluctuation by day, it is better to use the average numbers of CaBi trips, rather than using actual trip numbers. Finally, if needed, the analysis should also avoid CaBi trips during the National Cherry Blossom Festival and other events to exclude weekday tourist trips.

Weekday

Table 12 shows the number of Capital Bikeshare trips by day of the week. Trips are almost evenly distributed among weekdays, about 2 million trips every day. Friday has a slightly higher share than other days (14.8%), followed by Wednesday and Thursday (both at 14.6%). Sunday has the smallest share of trips, at 13.5%.

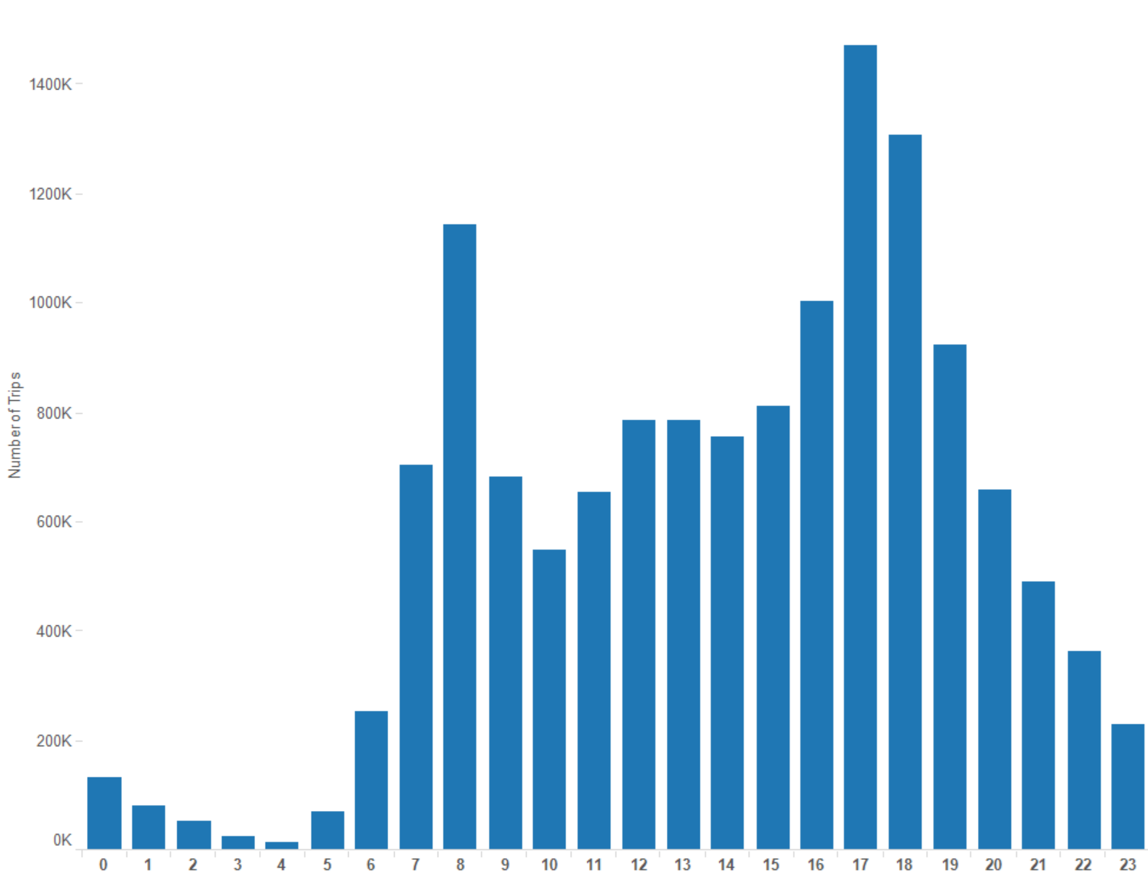
Table 12 Capital Bikeshare Trips by the Day of the Week

Weekday	Number of Trips	% of Total Number of Trips
Monday	1,932,009	13.8%
Tuesday	1,985,752	14.2%
Wednesday	2,036,185	14.6%
Thursday	2,035,985	14.6%
Friday	2,067,555	14.8%
Saturday	2,015,257	14.4%
Sunday	1,884,527	13.5%

Time of Day

Within a day, Capital Bikeshare trips have two peak periods. The AM peak happens at 8 am. The PM peak occurs between 5 pm and 6 pm, and lasts two hours. This AM-PM peak pattern is consistent with peak patterns found in other transportation modes, suggesting that many riders have been using CaBi for commuting. Comparing the two peaks, we see the PM peak has more trips per hour and lasts longer. One possible explanation is that commuters tend to rush in the morning and may choose transportation modes with a higher hourly speed, but after work, they tend to have more time and may choose CaBi for its affordability or flexibility. Another possibility is that in the evening CaBi attracts not only commuters to bike home, but also casual users to bike for other purposes, such as shopping, socializing at restaurants or bars, workouts, or sightseeing.

Figure 8 Capital Bikeshare Trips by Time of Day



Trip Duration

About 90% of Capital Bikeshare trips last 30 minutes or less. Assuming the average bicycling speed is 9.6 miles per hour, within 30 minutes, one can reach destinations within 4.8 miles. Two factors impact trip duration. First, bicycling demands physical energy. Second, Capital Bikeshare has a policy that trips within 30 minutes are free.

Table 13 Capital Bikeshare Trip Duration

Duration	Number of Trips	% of Total Number of Trips
30 minutes or less	12,562,947	90.0%
30 - 60 minutes	804,878	5.8%
60 - 90 minutes	261,944	1.9%
90 - 120 minutes	144,102	1.0%
120 - 150 minutes	75,441	0.5%
150 minutes or more	107,958	0.8%

Trip by Account Type

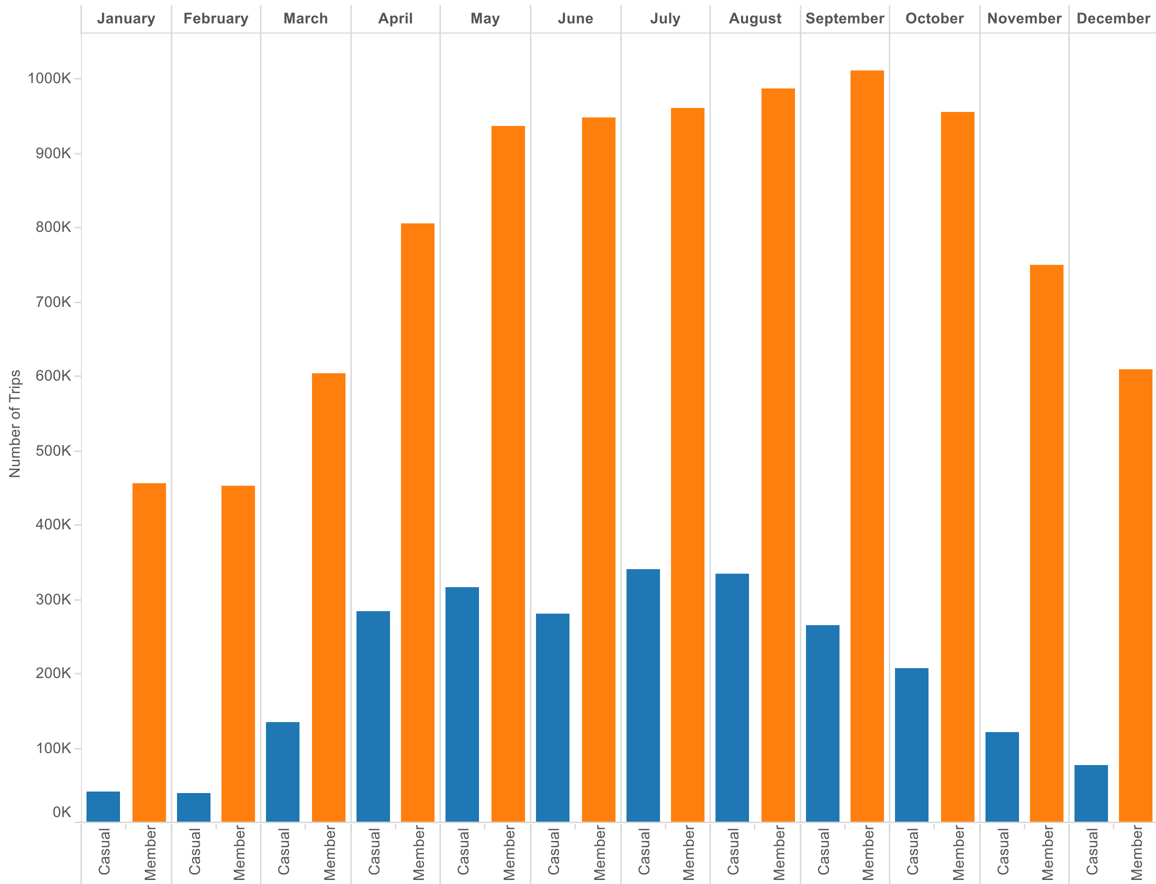
As noted earlier, Capital Bikeshare provides two account choices: casual and member. Table 14 shows the number of trips made by users in each of these two accounts. Since the launch of Capital Bikeshare program, 79.3% trips are made by members.

Table 14 Number of Trips by Account Type

Account Type	Number of Trips	% of Total Number of Trips
Casual	2,881,663	20.7%
Member	11,075,549	79.3%

Casual Capital Bikeshare riders and members differ in when and how they bike. Figure 9 shows the number of trips by account type by month. Members make more trips than casual users, confirming findings of Table 14 above. The most popular months for casual users peak between April and August. It seems that casual bike share riders are likely to be tourists, who come to town for the Cherry Blossoms in April and sightseeing in the summer. The number of member trips is high between March and November, which reflects commuters' and residents' high and lasting demand.

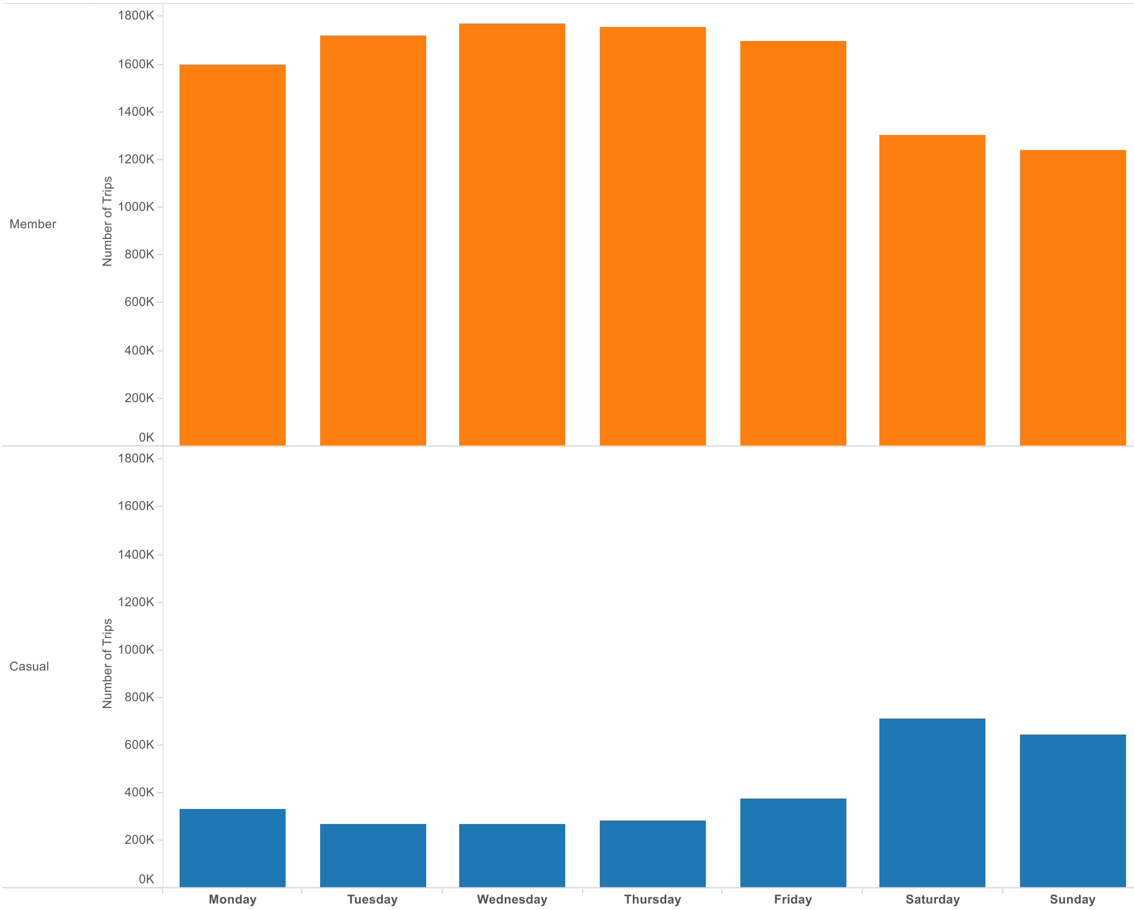
Figure 9 Capital Bikeshare Trips by Account Type by Month



Note: Only trips made between 2011 and 2015 are included.

As expected, trips made by member and casual users have different distributions among weekdays. Members tend to ride more during weekdays than on the weekends, while casual users make CaBi trips mostly on the weekends.

Figure 10 Capital Bikeshare Trips by Account Type by Weekday



In terms of time of day, trips made by members duplicate the total trip pattern that peaks twice a day, at 8 am, and between 5 pm and 6 pm. However, trips made by casual users have an entirely different pattern. Their number of trips gradually increases as the day starts, reaching a relatively high level around noon, maintaining that level to 5 pm, and decreasing into the night. There is no peak. Figure 11 again confirms the guess that members are most likely to be commuters, and casual members are tourists.

Figure 11 Capital Bikeshare Trips by Account Type by Time of Day

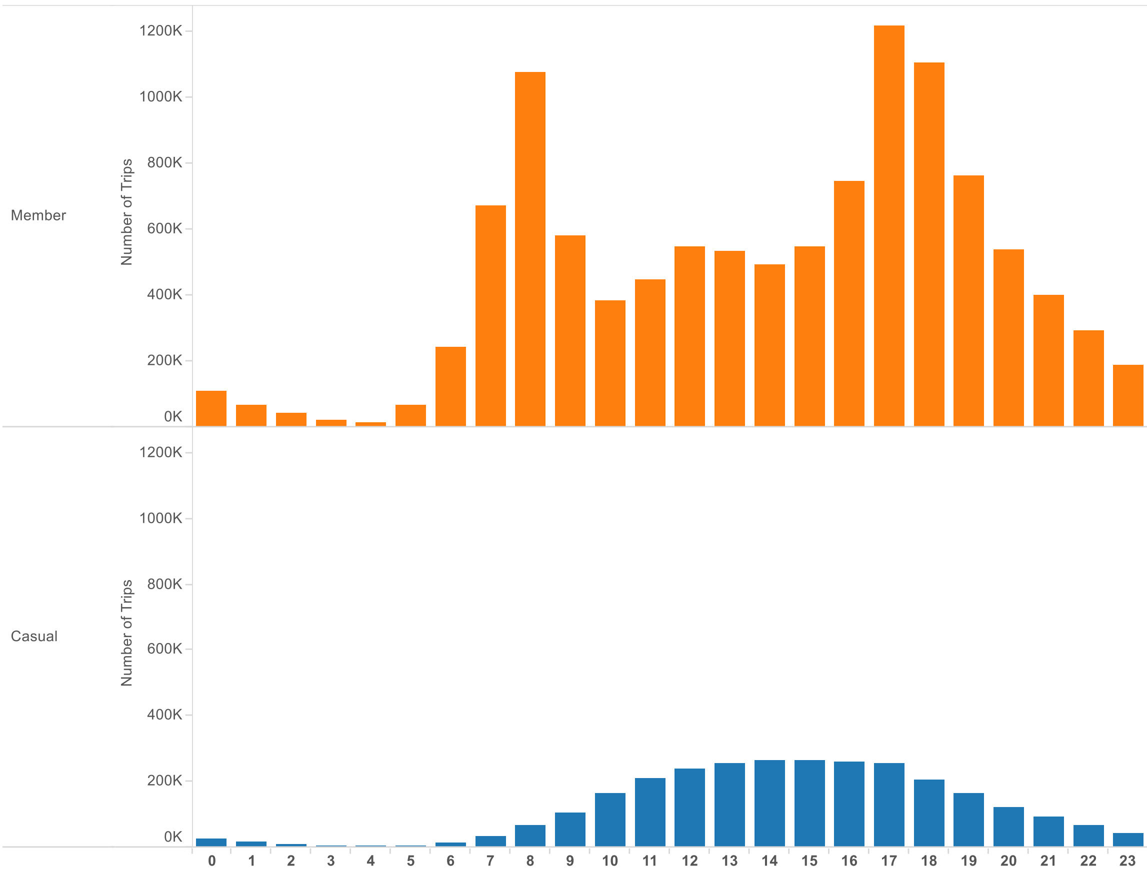


Table 15 lists the number of trips by duration made by casual CaBi users and members. Trips made by casual users tend to last longer than those made by members. For members, as much as 97.3% of trips are 30 minutes or less. Only 61.9% of trips made by casual members are in that duration range. Of trips made by casual users, 19.5% last between 30 minutes and 60 minutes, a proportion about ten times higher than member trips at 2.2%. In addition, about 15% of casual bikers make trips longer than one hour, while nearly no members (less than 0.4%) make trips that long.

Table 15 Capital Bikeshare Trips by Account Type by Duration

	Casual		Member	
Duration	Number of Trips	% of Total Number of Trips	Number of Trips	% of Total Number of Trips
30 minutes or less	1,781,919	61.8%	10,780,974	97.3%
30 - 60 minutes	562,094	19.5%	242,780	2.2%
60 - 90 minutes	236,856	8.2%	25,088	0.2%
90 - 120 minutes	135,368	4.7%	8,734	0.1%
120 - 150 minutes	71,372	2.5%	4,069	0.0%

In summary, comparing trips made by members and casual users shows that members tend to be commuters and residents while casual users tend to be tourists. Members use Capital Bikeshare mostly on weekdays in warm weather. Their trips have a shorter duration (less than 30 minutes), and have AM and PM peaks, reflecting general commuting needs. Casual users bike more on the weekends in warm weather and during events. They spent more time bicycling, and thus there is no peak.

Most Popular Stations

Which Capital Bikeshare stations are the systems most popular? Table 16 and Table 17 list the top stations ranked by the number of trips started and ended, respectively. Interestingly, the two tables have nearly the same stations in the same order. The top five stations are the same in both tables; Dupont Circle is the most popular, followed by Union Station, 15th & P St NW, Lincoln Memorial, and Jefferson Dr & 14th St NW. The next five stations are also the same, though their rankings are slightly different in the two tables: New Hampshire Avenue & T St NW, 17th & Corcoran St NW, Thomas Circle, 14th & V St NW, and Eastern Market Metro.

Table 16 Capital Bikeshare Stations with the Largest Number of Trips Started

Ranking	Start Station (Station ID)	Number of Trips
1	Massachusetts Ave & Dupont Circle NW (31200)	325,055
2	Columbus Circle / Union Station (31623)	313,940
3	15th & P St NW (31201)	230,595
4	Lincoln Memorial (31258)	214,088
5	Jefferson Dr & 14th St SW (31247)	200,533
6	New Hampshire Ave & T St NW (31229)	185,684
7	17th & Corcoran St NW (31214)	184,551
8	Thomas Circle (31241)	183,931
9	14th & V St NW (31101)	183,826
10	Eastern Market Metro / Pennsylvania Ave & 7th St SE (31613)	177,193

Table 17 Capital Bikeshare Stations with the Largest Number of Trips Ended

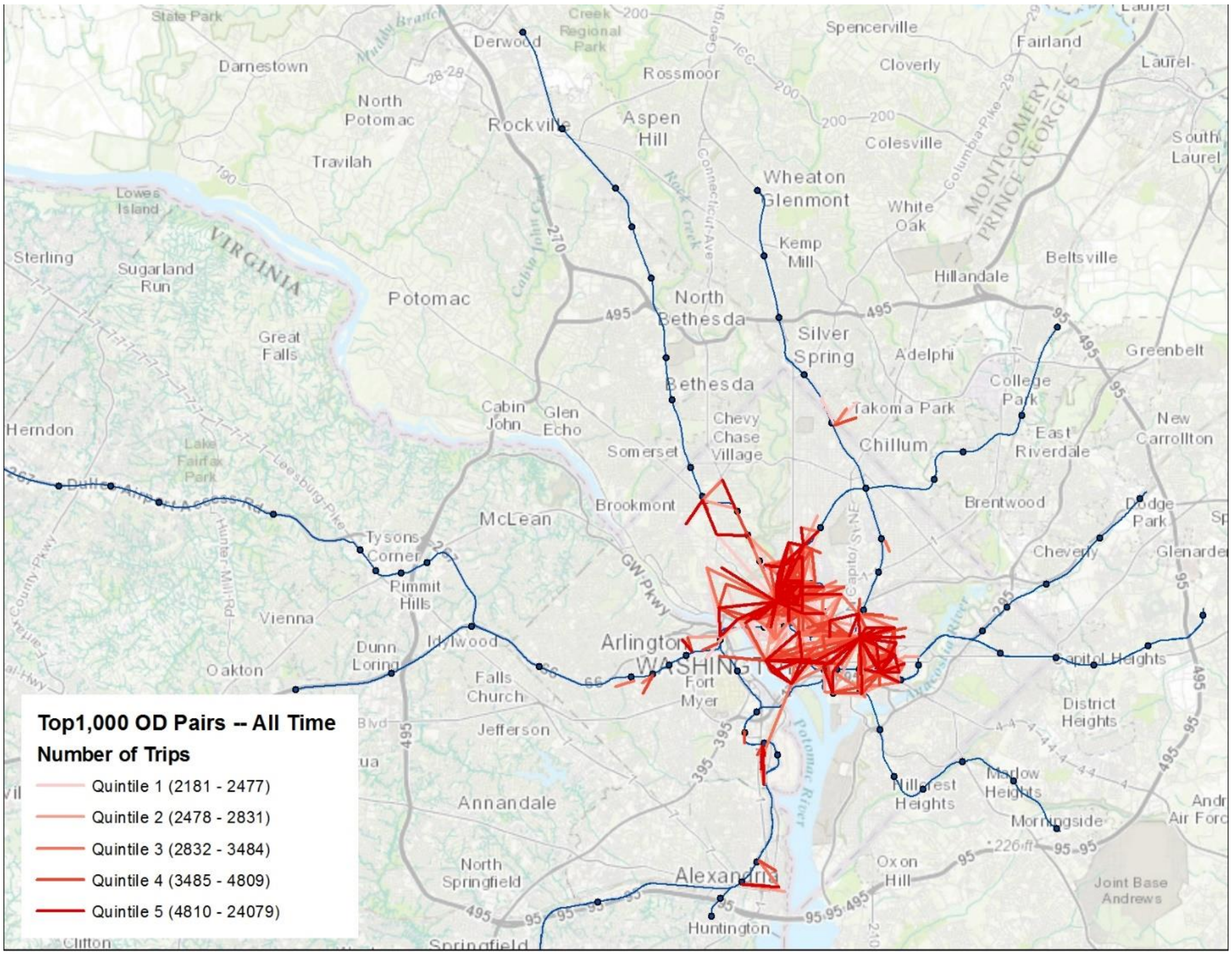
Ranking	End Station (Station ID)	Number of Trips
1	Massachusetts Ave & Dupont Circle NW (31200)	365,837
2	Columbus Circle / Union Station (31623)	321,519
3	15th & P St NW (31201)	256,137
4	Lincoln Memorial (31258)	212,008
5	Jefferson Dr & 14th St SW (31247)	206,675
6	14th & V St NW (31101)	196,522
7	17th & Corcoran St NW (31214)	191,824
8	New Hampshire Ave & T St NW (31229)	185,090
9	Thomas Circle (31241)	176,316
10	Eastern Market Metro / Pennsylvania Ave & 7th St SE (31613)	173,274

Source: CaBi

Figure 12 maps all CaBi O-D trip pairs between 2010 and 2016. From the map, almost all top 1,000 O-D pairs with the largest number of CaBi trips are in central D.C., bounded by Columbia Heights (north), the Navy Yard (south), Capitol Hill (east), and Georgetown (west). Three hot spots can be identified in D.C. from the map. They are Dupont Circle, Union Station, and Eastern Market.

On the border or outside D.C., there are several areas with large CaBi trip numbers: Alexandria, Arlington, Pentagon City and Crystal City in Virginia, and Takoma and Takoma Park in Maryland.

Figure 12 CaBi O-D Pairs, 2010-2016



3.3 Metrorail

WMATA was created by an interstate compact in 1967 to plan, build, and operate a regional transit system in the Washington metropolitan area. The regional transportation system includes two elements: Metrorail, the rail transit service, and Metrobus, the bus system. As of the end of 2015, Metrorail has made 206 million trips, and Metrobus has made 130 million trips (WMATA, 2016a).

Metrorail construction began in 1969, and the first phase between Farragut North and Rhode Island Avenue opened in 1976. In the following years, Metrorail experienced significant expansion and grew into a system with five lines and 86 stations. The Silver Line opened in the summer of 2014, adding five more stations to the network. In addition, Maryland is planning a light rail line, the Purple Line, which will connect to four Metrorail stations at Bethesda, Silver Spring, College Park, and New Carrollton. Figure 13 maps all the stations and lines, and Table 18 lists the sequence of Metrorail openings.

Figure 13 Metrorail System Map

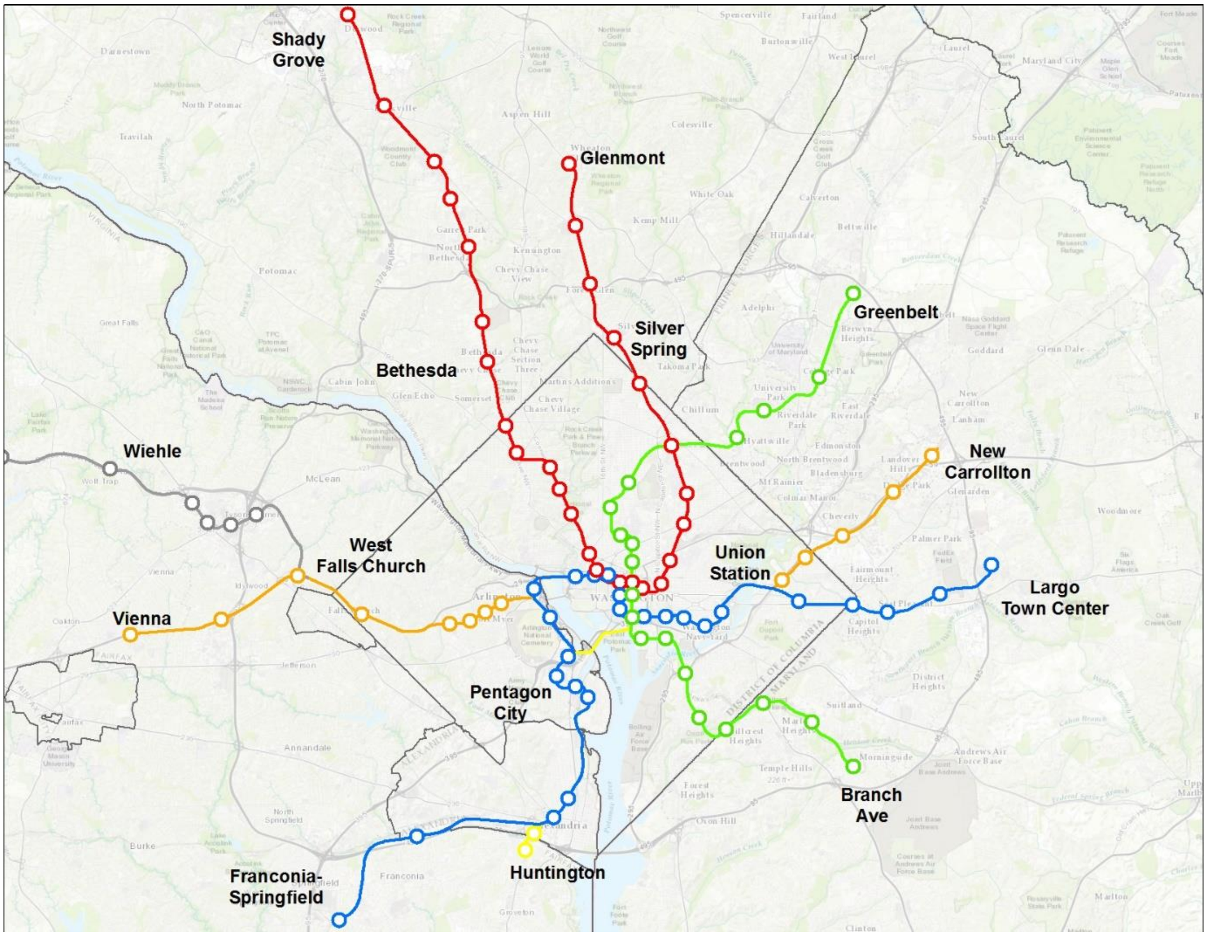


Table 18 Sequence of Metrorail Station Openings

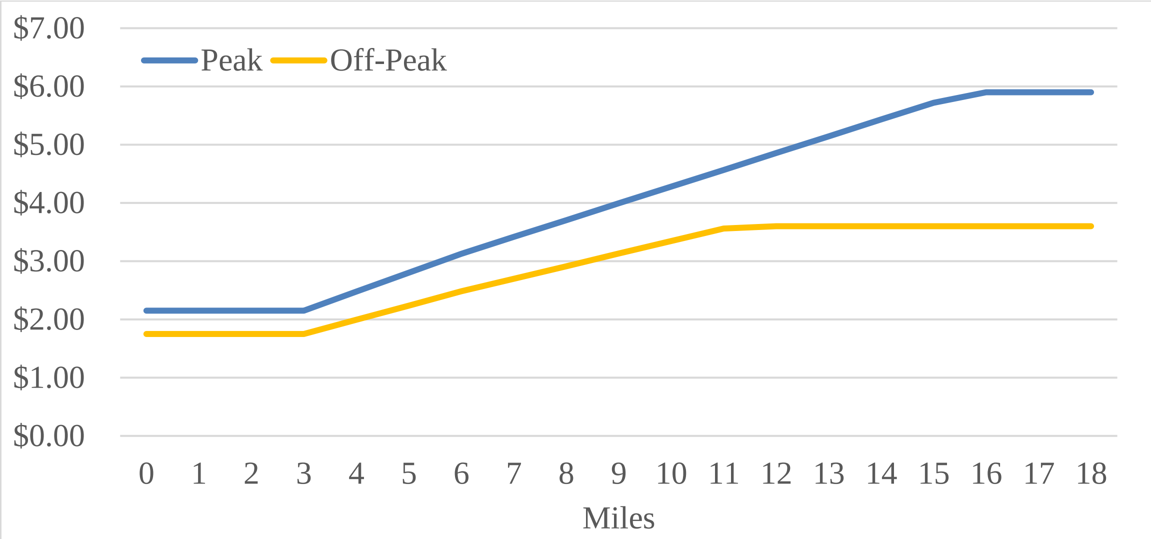
Line	Segment	Stations	Miles*	Date
Red	Farragut North to Rhode Island Ave	5	4.6	3/29/1976
Red	Gallery Place	1	none	12/15/1976
Red	To Dupont Circle	1	1.1	1/17/1977
Blue, Orange	National Airport to Stadium-Armory	17	11.8	7/1/1977
Red	To Silver Spring	4	5.7	2/6/1978
Orange	To New Carrollton	5	7.4	11/20/1978
Orange	To Ballston-MU	4	3	12/1/1979
Blue	To Addison Rd	3	3.6	11/22/1980
Red	To Van Ness-UDC	3	2.1	12/5/1981
Yellow	Gallery Place to Pentagon	1	3.3	4/30/1983
Blue	To Huntington	4	4.2	12/17/1983
Red	To Grosvenor-Strathmore	5	6.8	8/25/1984
Red	To Shady Grove	4	7	12/15/1984
Orange	To Vienna	4	9.1	6/7/1986
Red	To Wheaton	2	3.2	9/22/1990
Green	To U St	3	1.7	5/11/1991
Blue	To Van Dorn St	1	3.9	6/15/1991
Green	To Anacostia	3	2.9	12/28/1991
Green	To Greenbelt	4	7	12/11/1993
Blue	To Franconia-Springfield	1	3.3	6/29/1997
Red	To Glenmont	1	1.4	7/25/1998
Green	Columbia Heights to Fort Totten	2	2.9	9/18/1999
Green	To Branch Ave	5	6.5	1/13/2001
Blue	To Largo Town Center	2	3.2	12/18/2004
Red	NoMa-Gallaudet U	1	none	11/20/2004
Silver	To Wiehle-Reston East	5	11.7	7/26/2014
	Total system	91	118	
* The sum of miles does not equal the total because of rounding				

Metrorail's fare system is based on time and distance (WMATA, 2014b). Metrorail fares vary during peak hours and non-peak hours. According to WMATA, the AM peak, runs from system opening to 9:30 am, while the PM peak runs from 3 pm to 7 pm on weekdays and midnight to closing on weekends. Distance is the other factor in setting fares. WMATA charges $0.326 per additional mile between three and six miles and $0.288 per extra mile greater than six miles during peak hours, and $0.244 and $0.216 for off-peak hours. Senior and disabled riders are charged for half the peak fare. Table 19 and Figure 14 illustrate Metrorail's fare structure.

Table 19 Metrorail Fare Structure

	Regular Fares		Senior & Disabled Fares
	Peak	Off-Peak	
First 3 composite miles	$2.150		One-half peak fare
Each additional composite mile more than 3 and less than or equal to 6	$0.326		
Each composite mile greater than 6	$0.288		
Maximum peak fare	$5.900		
First 3 composite miles		$1.750	One-half peak fare
Each additional composite mile more than 3 and less than or equal to 6		$0.244	
Each composite mile greater than 6		$0.216	
Maximum off-peak fare		$3.600	
A $1.00 surcharge applies to all non-SmarTrip® single-ride fares ($0.50 for senior & disabled)			

Figure 14 Metrorail Fares by Mile



SmarTrip is the farecard to access Metrorail and other local transit facilities such as the D.C. Circulator bus, Montgomery County's RideOn bus, and TheBus in Prince George's County. SmarTrip is rechargeable and value can be added at SmarTrip vending machines at most Metrorail stations. Card holders can register their cards to view personal balances and usage history online. One advantage of using SmarTrip, besides convenience, is that it gives a 50-cent discount on transfers from Metrobus to Metrorail or vice versa within two hours, and free transfers between Metrobuses or Metrorail trains.

Metrorail fares are among the highest in the nation. Esteban and Muyskens (2016) collected fare ranges for major U.S. rail transit systems and found that Metrorail fares are the second highest, lower only than BART in San Francisco. After adjusting for cost-of-living, most BART fares are cheaper than Metrorail's (Esteban & Muyskens, 2016).

Besides SmarTrip, WMATA offers various pass options, including a One Day Pass, 7-Day Short Trip Pass, 7-Day Fast Pass, 28-Day Fast Pass, and special passes for students and people in need (WMATA, 2014b).

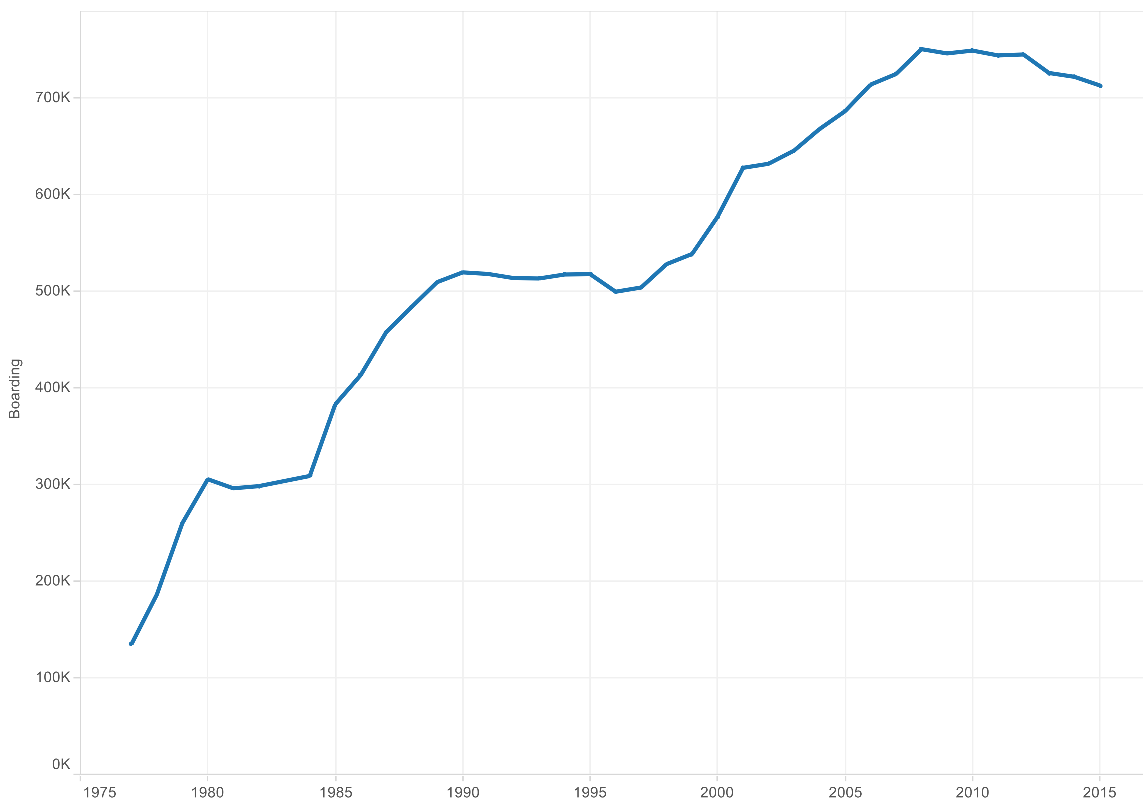
3.3.1 Metrorail Trip Analysis

Metrorail has a much longer operation history than the Capital Bikeshare program. In this section, I first review Metrorail ridership between 1977 and 2015 to get a full picture. For more in-depth Metrorail trip analysis, I then focus on trips generated between August 2010, slightly before CaBi installation, and May 2016, a scope consistent with my Capital Bikeshare trip analysis.

Metrorail Ridership 1977-2015

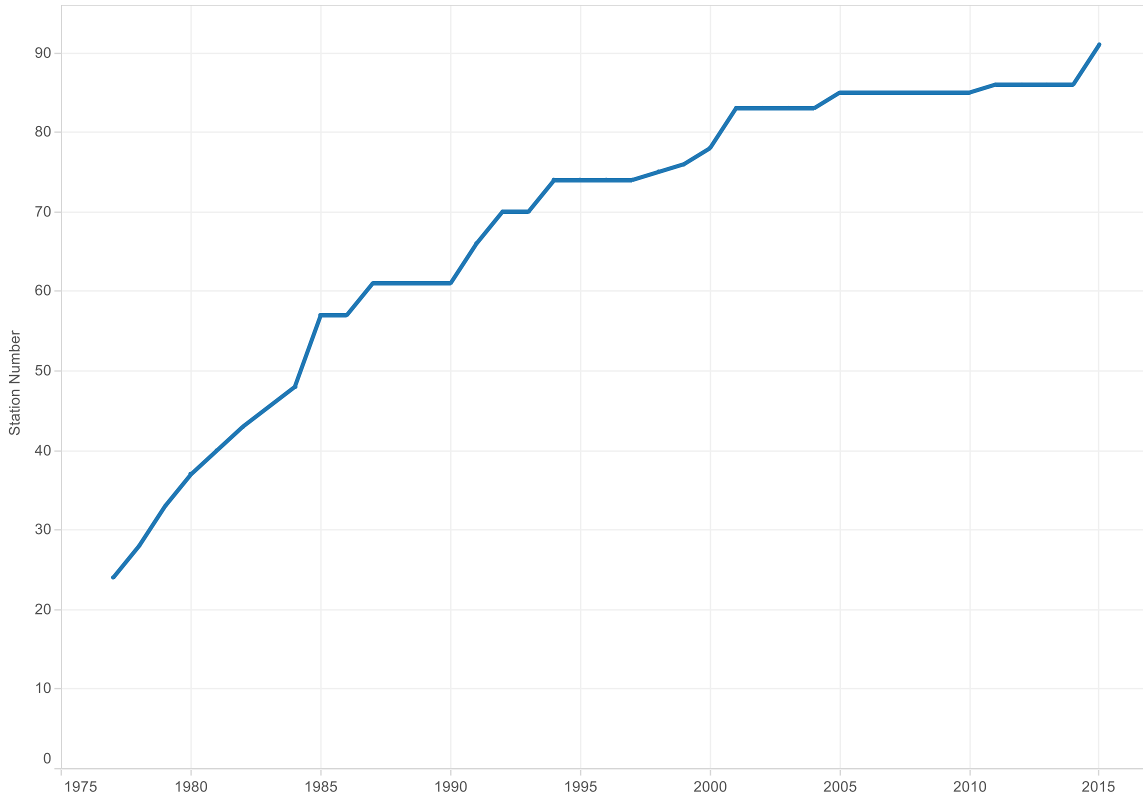
Figure 15 shows the average weekday daily boarding for the whole Metrorail system between 1977 and 2015. Over the past four decades, overall Metrorail ridership has been increasing. But ridership growth has not been consistent. There are three quick-growth periods, the system's opening in the late 1970s, between mid-1980s and 1990, and in the first decade of the 21st century. Interestingly, each fast growth period was followed by some decreases and stagnancies. The latest peak was in 2009. Since then, ridership has been declining.

Figure 15 Metrorail Average Weekday Daily Boarding, 1977-2015



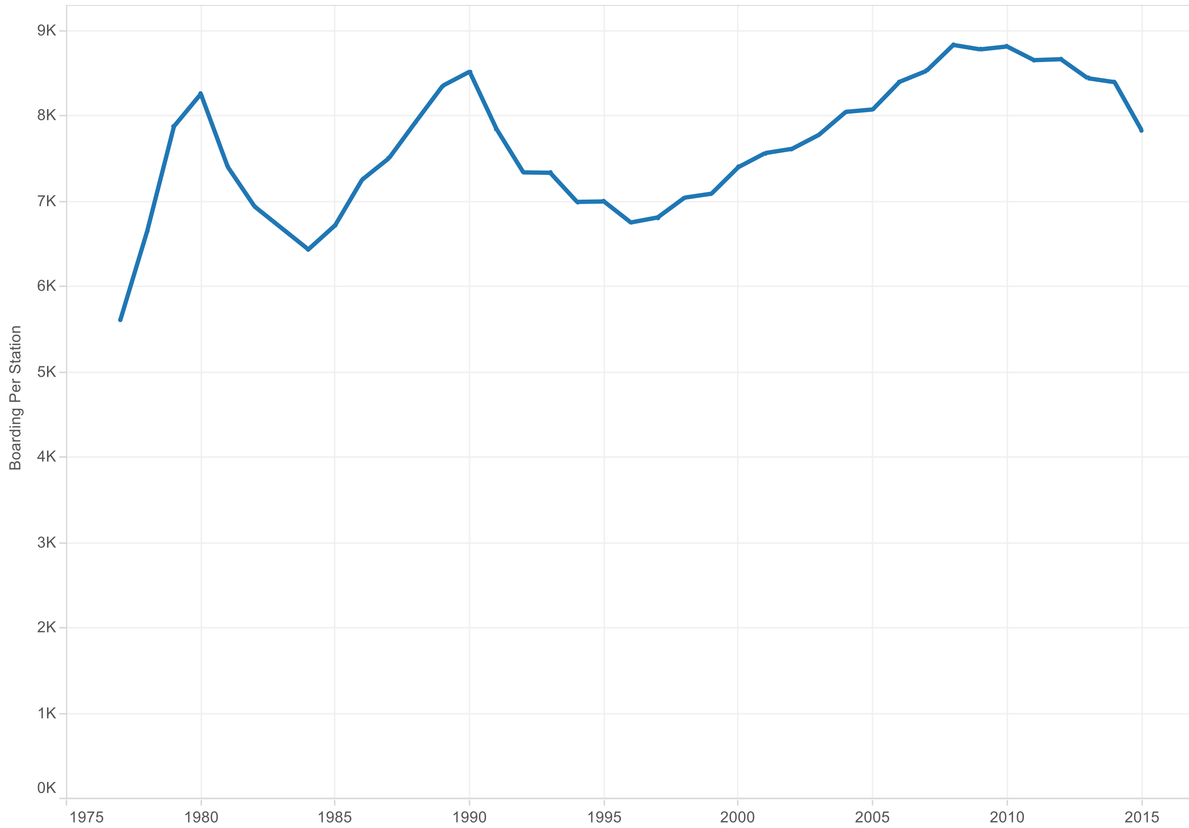
The increases in Metrorail ridership could result from system expansion. As Figure 16 illustrates, the total number of stations increased over the years. When Metrorail first opened in 1977, there were 24 stations. After two decades of expansion, the system reached 86 stations in 2001. The most recent expansion took place in 2014 when the Silver Line with four stations was added to the network, for a total of 91 stations.

Figure 16 Number of Metrorail Stations, 1977-2015



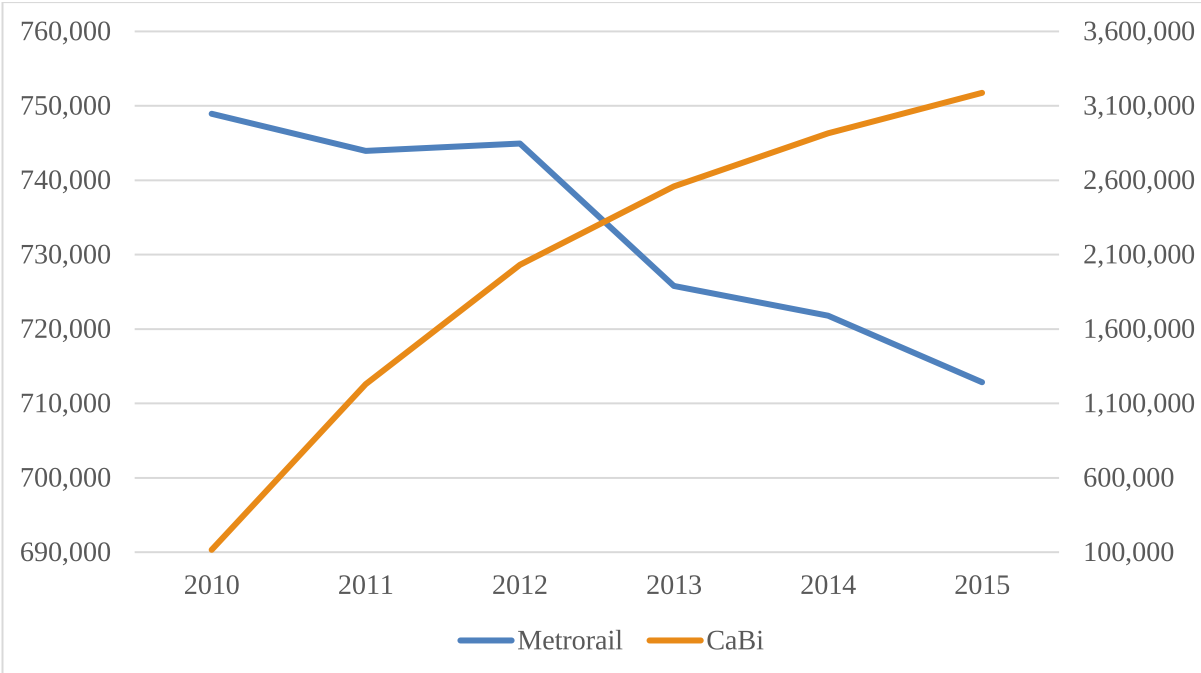
Therefore, ridership per station is a better measurement of overall ridership since it normalizes the effects of system expansion. Figure 17 shows the average weekday daily boarding per station between 1977 and 2015 and identifies three ridership peaks. The first peak took place in 1980 after a three-year increase period. However, ridership plummeted since 1980 and reached a low in 1984. The second peak happened in 1990 with per station ridership slightly higher than that of 1980. The second low arrived in 1996. Since 1996, per station ridership climbed each year and reached the third peak in 2009. Then a decrease began, with the worst one between 2014 and 2015 after the Silver Line stations' opening.

Figure 17 Metrorail Average Weekday Daily Boarding per Station, 1977-2015



What caused the decreases in Metrorail ridership? The official launch of Capital Bikeshare program in 2010 might be a reason. As illustrated in Figure 18, as CaBi trips increased between 2010 and 2015, Metrorail ridership kept decreasing, suggesting a correlation.

Figure 18 Metrorail Boardings vs. CaBi Trips, 2010-2015



Also, WMATA, in its blog, reminded people of historical fluctuations and attributed this decrease to the overall economy. To test this hypothesis, I overlaid Metrorail average weekday daily boarding per station (the blue line in Figure 19) with D.C.'s unemployment rate (the orange line in Figure 19) to see whether there is a relationship.[7] As the figure shows, there may be a negative association between them. In general, each time Metrorail ridership increased, unemployment rates decreased, especially in 1980, 1990, 2001, and 2008. However, there is an exception in recent years. Since 2012, the unemployment rate has plummeted, indicating a strong economy. However, Metrorail ridership kept decreasing. Therefore, the unemployment rate could explain historical ridership fluctuations, but we need other factors to explain the most recent decrease.

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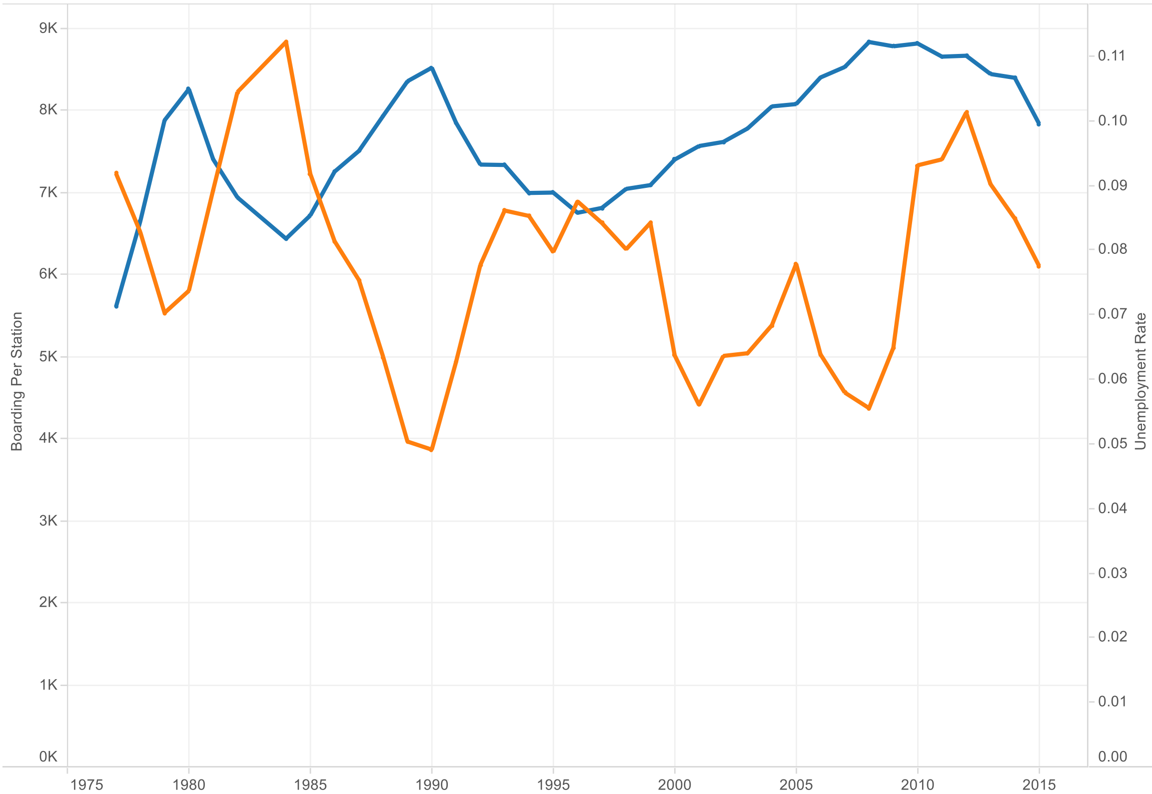
[7] Unemployment rate data was accessed from Bureau of Labor Statistics, 2016

Figure 19 Metrorail Average Weekday Daily Boarding per Station and Unemployment Rate, 1977-2015

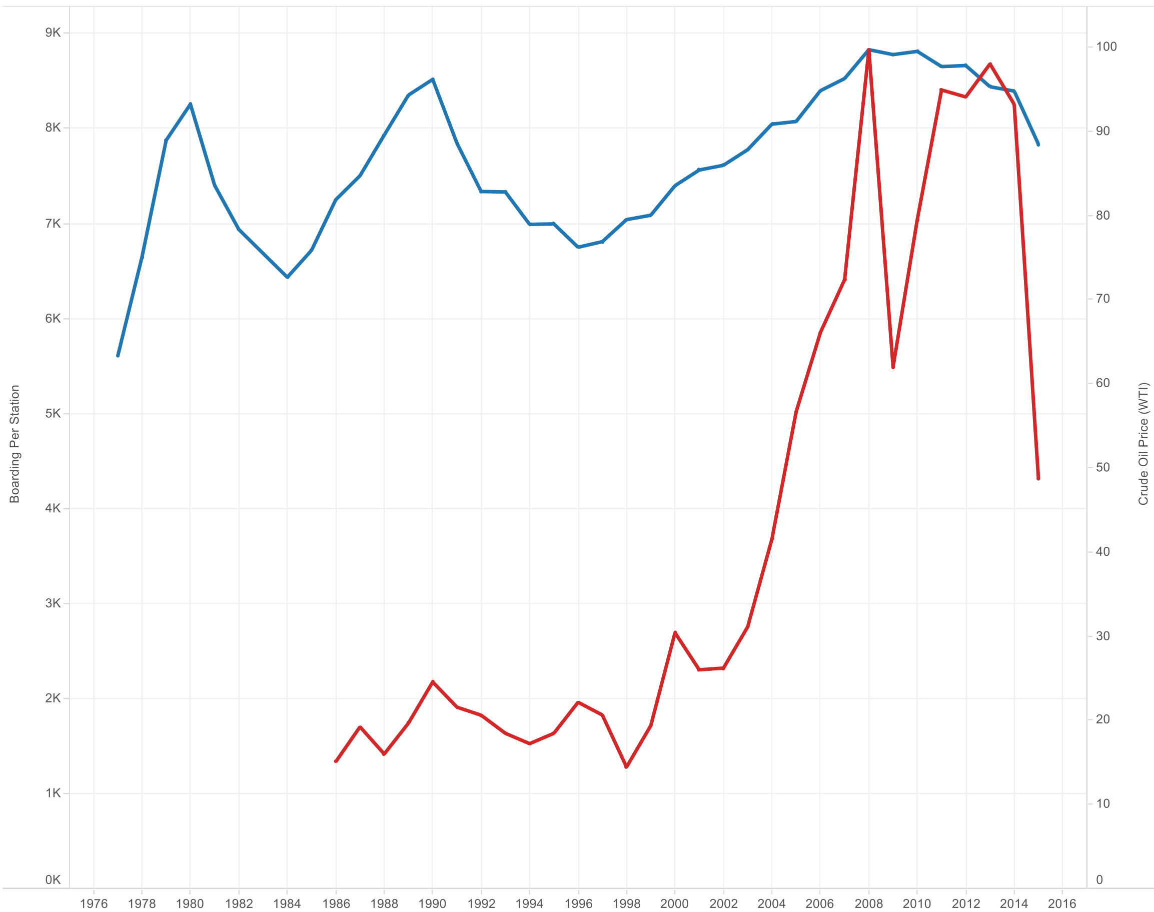


Gasoline prices, which are a significant cost of driving, also have an impact on Metrorail ridership. The annual price of crude oil per barrel (the red line in Figure 20) has a pattern that corresponds with Metrorail ridership except in 2009.[8] As crude oil prices increased, we see more commuters switching to Metrorail for its lower travel costs. When oil prices dropped, a decrease in Metrorail ridership followed. However, the price elasticity is not consistent. In the 1980s and the 1990s when oil prices were lower, a small price increase could trigger a significant Metrorail ridership growth, which peaked in 1990.

[8] Crude oil here refers the West Texas Intermediate (WTI) grade crude oil, Cushing, Oklahoma. WTI has been used as a benchmark in oil pricing, and Cushing, Oklahoma is the major trading hub for crude oil. Price data source: US. Energy Information Administration, Crude Oil Prices: West Texas Intermediate (WTI) - Cushing, Oklahoma [ACOILWTICO], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/ACOILWTICO, September 15, 2016. Note that the price is not seasonally adjusted.

However, though oil prices increased fourfold since 2000, Metrorail ridership grew at a much lower rate and amount. The ridership in 2008 was 8,829, about the same level as previous peaks (8,516 in 1990 and 8,255 in 1980). Therefore, commuters' demand for driving is less elastic to oil price than previously.

Figure 20 Metrorail Average Weekday Daily Ridership and Crude Oil Price



A third explanation for the recent ridership decline is the decrease of federal government jobs. According to WMATA, more than a third of the federal workforce commutes by Metrorail (WMATA, 2016a). However, between 2010 and 2015, federal government employment decreased by 12,900, or 6.1% (WDCEP, 2016). The job loss in this sector, by absolute value, was the largest among all industries, and by proportion, it was the third largest loss, as shown in Table 20.

Table 20 Change in Job Numbers by Sector

	Change 2006-2010		Change 2010-2015	
Sector	Change in thousands	Change in %	Change in thousands	Change in %
Mining, Logging, & Construction	1.8	15.0%	3.8	35.6%
Manufacturing	-0.8	-44.4%	-0.1	-9.1%
Wholesale Trade	0	0.9%	0	0.9%
Retail Trade	4.3	23.9%	3.9	21.2%
Transportation & Utilities	-0.8	-14.8%	0.2	5.4%
Information	-5.2	-23.2%	-1.7	-8.9%
Financial Activities	1.3	4.3%	3.8	14.0%
Professional & Business Services	10	6.6%	14.4	9.7%
Education & Health Services	33.7	35.9%	19.7	18.3%
Leisure & Hospitality	15.5	28.6%	10	16.8%
Other Services	10.6	17.5%	5.9	9.0%
Federal Government	4.9	2.5%	-12.9	-6.1%

Metrorail ridership by federal government employees has been further discouraged by Congress' transportation subsidy policy. The federal governments, as well as many other major employers in D.C., have participated in WMATA's SmartBenefits Program to provide employees with pre-tax transportation subsidies (WMATA, 2016b). Interested employees load pre-tax money onto SmarTrip cards for Metrorail and other transit commuting. In other words, the SmartBenefits program allows certain transportation costs to be tax-free. In 2013, the maximum SmartBenefits subsidy was $245 per month for public transportation. The SmartBenefits program has an enormous impact on Metrorail ridership. According to WMATA's statistics, 42% of all trips were made by SmartBenefits riders. In particular, 84% of federal employees who commute by Metrorail pay by SmartBenefits.

However, the maximum benefits were reduced to $130 per month in January 2014, almost half the previous amount (Lunney, 2013). This policy change discouraged federal government riders and decreased the number trips paid by SmartBenefits by 6,400 per average weekday (WMATA, 2014a). Meanwhile, parking subsidies were increased by $5 to $250, almost twice the value of public transportation subsidies. Therefore, it is reasonable to think that 6,400 public transportation trips were replaced by driving.

Besides these external factors, many riders criticize Metrorail's poor maintenance and its service deficiencies. Right before the most recent ridership decrease, in June 2009, two Red Line trains collided due to a faulty circuit and killed nine people aboard (eight of whom were passengers) and injured more than 50 (National Transportation Safety Board, 2010). More recent incidents include a deadly smoke incident in a Yellow Line tunnel in January 2015, the derailment of a Blue Line train in August 2015, an electrical fire at the Stadium-Armory station in October 2015, and the derailment of a Silver Line train in July 2016. The National Transportation Safety Board conducted investigations into some of these incidents. In its Yellow Line tunnel smoke investigation report, the NTSB made technical recommendations on operations, and also recommended that the U.S. Department of Transportation to transfer oversight responsibility of WMATA's transit rail operations to the Federal Railroad Administration (FRA) (National Transportation Safety Board, 2016). However, since NTSB has limited enforcement power, and despite Transportation Secretary Anthony Foxx's letter supporting the transfer (DOT, 2015a), few changes have been made since the incident.

WMATA has been aware of customer complaints about poor service quality. According to its 2015 survey, Metrorail customer satisfaction dropped from 84% in fiscal year 2013 to 67% in fiscal year 2015, while Metrobus satisfaction rate remained at the same level. The survey report suggested that “the only way to substantially improve satisfaction is through sustained and consistent service delivery” (WMATA, 2015c).

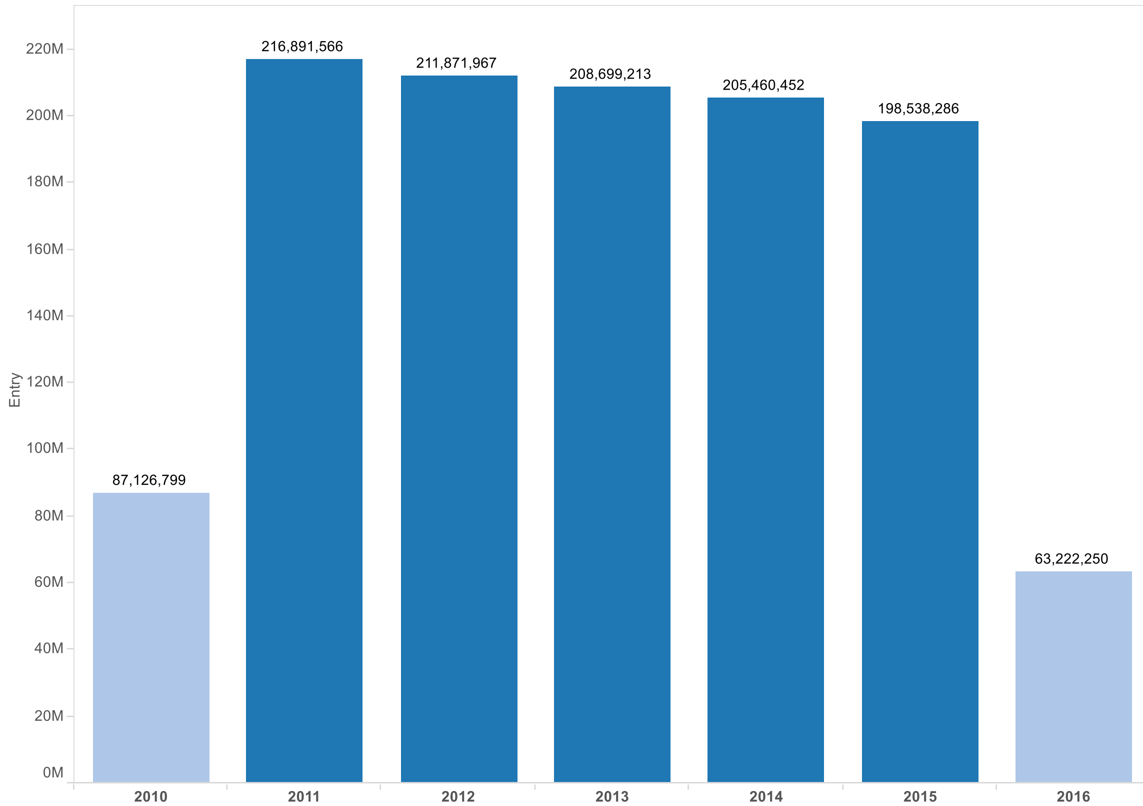
Despite critics and doubts, WMATA does not seem pessimistic about future ridership. Projected regional population and job growth, and a significant amount of ongoing/planned transit-oriented development near Metrorail stations led to WMATA’s conclusion that “while the growth trajectory for the region continues to be strong…the underlying spatial and economic data tells us that the region will continue to depend on Metro to get around” (WMATA, 2015a). However, as a recent newspaper article noted, Metrorail again experienced a ridership loss of 12% in 2016 (Smith, 2017). Its current weekday daily ridership is over 100,000 less than that was in 2009.

Metrorail Ridership 2010-2016

Analysis of 2010-2016 Metrorail ridership data provides more information on recent ridership trends and patterns.[9] As Figure 21 shows, over time, annual ridership has decreased, from 216 million trips in 2011 to 198 million trips in 2015, a reduction of 8.3%.

[9] 2010-2016 Metrorail ridership data was prepared and shared by WMATA. Data was received in May 2016.

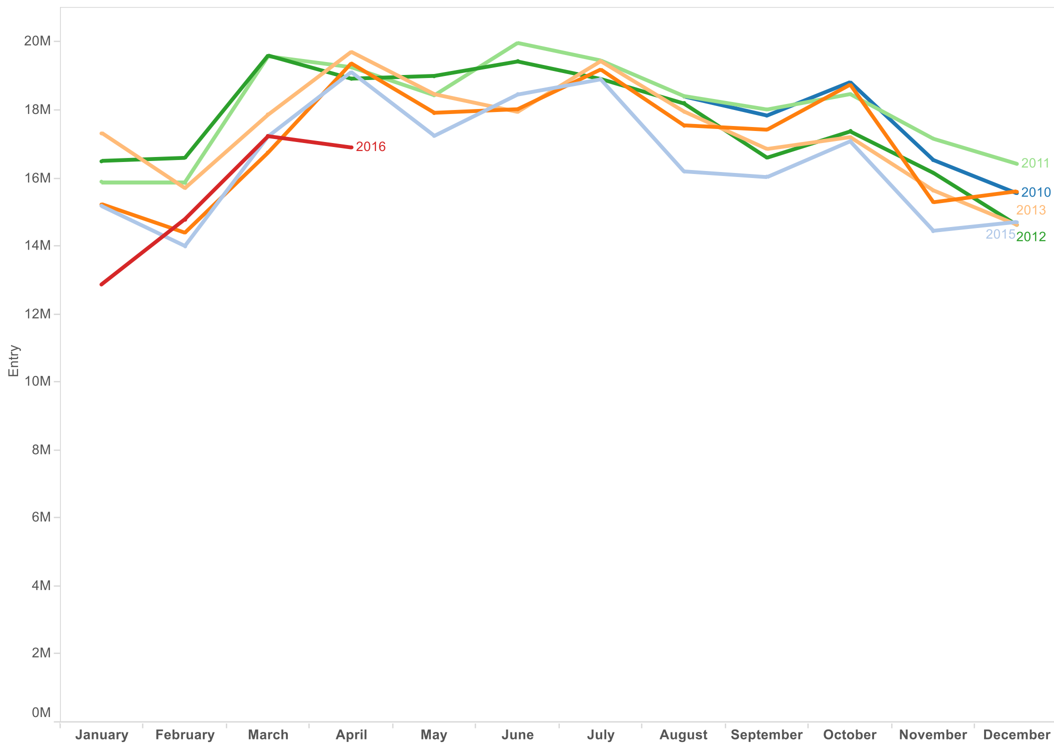
Figure 21 Metrorail Annual Ridership (Entry), 2010-2016[10]



Metrorail ridership by month, as shown in Figure 22, does not have a strong seasonal pattern, partly because the train is weatherproofed. In general, there are more trips made in warm weather seasons, between March and November, than the colder winter season. Ridership peaks in April, July, and October.

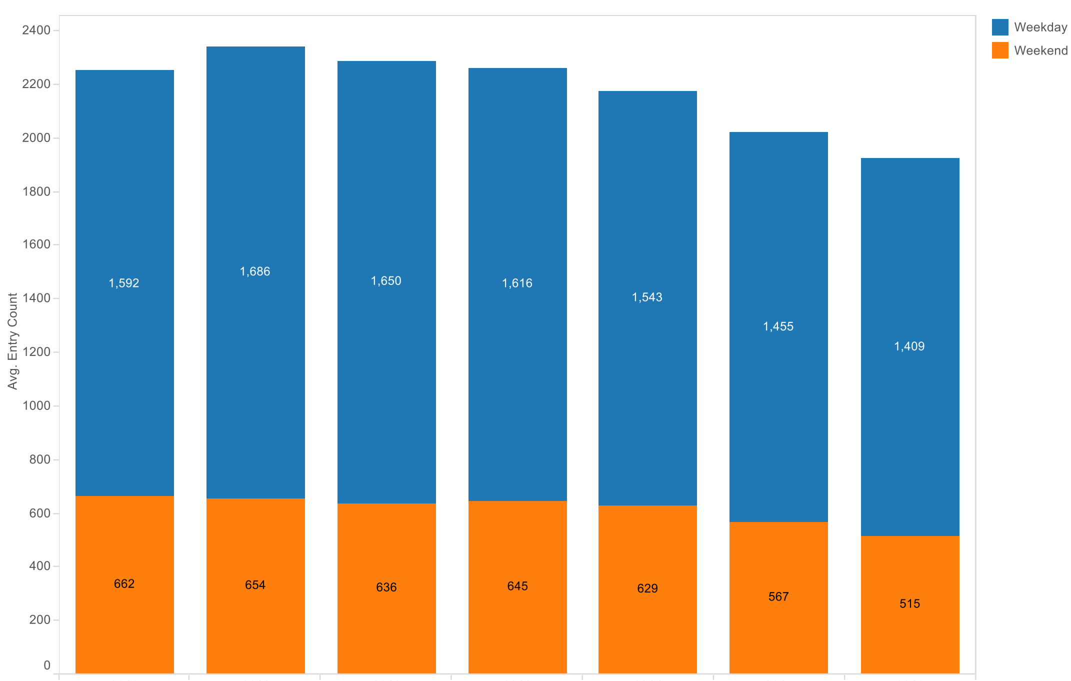
[10] Note that the dataset covers a period between September 2010 and May 2016. Therefore, the 2010 and 2016 ridership in this figure (shown in light blue) is only part of the actual annual total.

Figure 22 Metrorail Monthly Ridership (Entry), 2010-2016



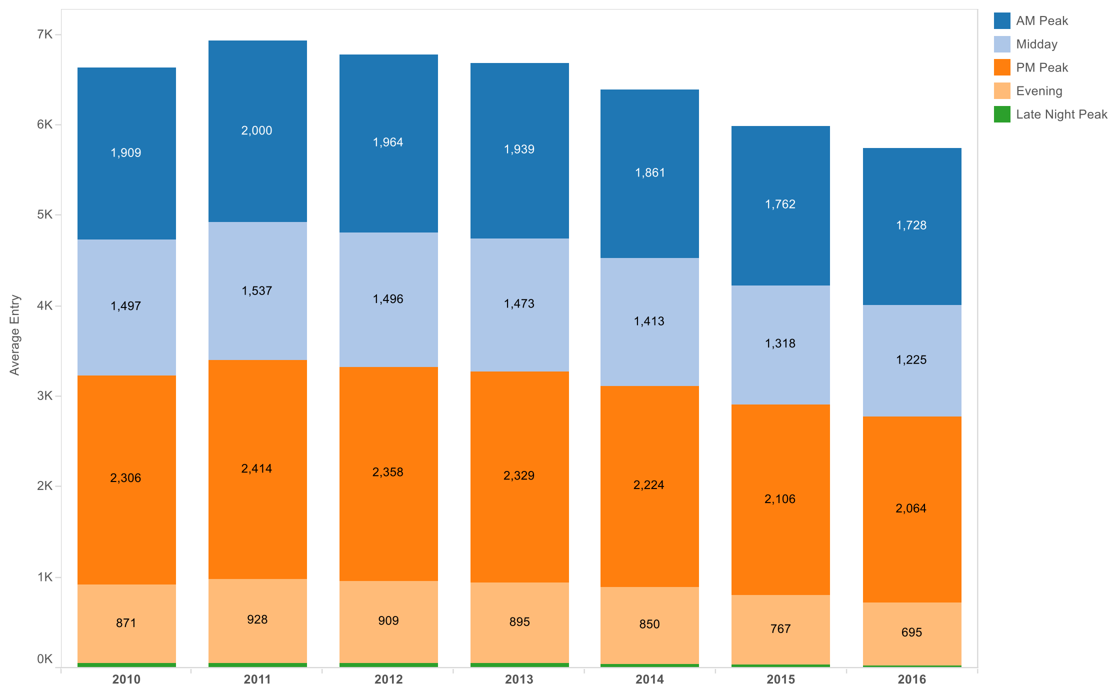
By separating Metrorail ridership into weekday and weekend trips, we can see that the average number of weekday passengers decreased more than the weekend trip number.

Figure 23 Metrorail Average Weekday vs. Weekend Daily Ridership (Entry), 2010-2016



In a day, Metrorail trips have two peaks, one in the morning and one in the evening after work. The PM peak has the largest number of trips, more than 2,000 per day. The AM peak has a slightly smaller number of trips, about 1,800. Evening and late night have the least number of trips.

Figure 24 Average Metrorail Ridership by Period (Entry), 2010-2016



3.3.2 Bike Access to Metrorail

According to WMATA's 2012 Metrorail customer survey, about 1% of passengers use a bike to access a station. Out of 243,253 total AM peak passengers, 2,384 bicycle to Metrorail stations and start a Metro trip. Compared to other modes of access as illustrated in Table 21, the share of bike access is small. However, it increased the most between 2007 and 2012, by 54% (WMATA, 2013a).

Table 21 Mode of Access, 2007-2012

Mode of access	2007		2012		2007-2012 % change
	Weekday AM Peak Trips	Share	Weekday AM Peak Trips	Share	
Walk	78,460	32.6%	89860	36.9%	15%
Park & Ride	68,969	28.7%	61559	25.3%	-11%
Metrobus	34,952	14.5%	32672	13.4%	-7%
Other bus	17,620	7.3%	19994	8.2%	13%
Shuttle	--	--	4905	2.0%	
Dropped off	21,911	9.1%	18723	7.7%	-15%
Commuter train	9,002	3.7%	328	0.1%	-96%
Ride sharing	2,463	1.0%	2085	0.9%	-15%
Bicycle	1,550	0.6%	2384	1.0%	54%
Total	240,512	100%	243253	100%	1%

WMATA accommodates bikes on Metro to assist bicycling and rail transit integration three ways: allowing bicycles on Metrorail, providing Bike & Ride facilities at stations, and providing Capital Bikeshare information. WMATA allows privately owned regular bicycles[11], on Metrorail during weekday non-peak hours (weekdays except 7 am – 10 am and 4 am – 7 am) and all day Saturday and Sunday. The number of bicycles on Metrorail is restricted to two per rail car on weekdays, and four per rail car on weekends. Bicycles are not permitted on Metrorail on July 4, Inauguration Day or other events and holidays. Regulations on foldable bicycles are less strict; they are allowed on Metrorail during all operational hours, if they remain folded and securely fastened. Bicycles are not allowed to use the center door of each rail car or escalators in Metrorail stations.

For Metrorail riders who need to park their bicycles, WMATA provides three facilities: bicycle racks, bicycle lockers, and Bike & Ride facilities. WMATA currently

[11] According to WMATA, regular bicycles are defined as maximum size 80" long, 48" high, and 22" wide. No tricycles, training wheels or tandem bicycles.

owns and operates about 2,400 bicycle racks, which are free to use. For riders who need more protection from theft, vandalism, and inclement weather, WMATA provides 2,400 bicycle lockers that hold one bicycle each and biking gear. Bicycle lockers are box-shaped storage space about four feet high by six feet five inches deep by three feet wide at the door, narrowing toward the back of the locker. Unlike the free bicycle racks, lockers are rented for $120 per year.

Currently, WMATA's Bike & Ride facilities are provided only at the College Park-University of Maryland station. Two more facilities, at the East Falls Church and Vienna stations. are under construction (expected to be completed in early 2016). Compared to bike racks, WMATA's Bike & Ride has two advantages. First, the Bike & Ride facilities are monitored via security cameras, and only riders with registered SmarTrip cards can enter for up to 10 minutes each time. Second, Bike & Ride facilities are sheltered. Without wet seats and slippery pedals, bicycles are safer to ride. Compared to the lockers, Bike & Ride facilities are free and convenient. Metrorail riders can park bicycles at Bike & Ride facilities with SmarTrip® card access. To enable this function, Metrorail riders need to start an account and register their SmarTrip cards on the WMATA website, as well as sign up for access to Bike & Ride facilities. Riders are allowed to park bicycles in station facilities for up to ten days.

To assist Metrorail riders finding biking information, WMATA lists biking amenities by type at each station.[12] In total, 81 Metrorail stations are equipped with bike racks, 55 with bike lockers, and three with Bike & Ride facilities. WMATA also provides

[12] See webpage http://www.wmata.com/rail/stations.cfm

information on Capital Bikeshare, including a map showing locations of Metrorail stations and Capital Bikeshare docks.[13]

With all these bicycling assistance programs, more riders are biking to Metrorail stations. According to WMATA's customer surveys, the number of riders bicycling to Metrorail in the morning rush hour increased from 1,550 to 2,380 between 2007 and 2012. In 2012, the share of bicycle access accounted for 1% of entries in the AM peak. WMATA predicts that by 2020, the share will increase to 2% (WMATA, 2013b).

3.4 Summary

The Washington metropolitan area provides a good case study. Not only is it the home of the Metrorail system and Capital Bikeshare, but it is also public-transportation- and biking-friendly. 4% commuters bike to work and 22% take rail transit, which is more than six to ten times the national average. In the rest of Chapter 3, I studied Metrorail and Capital Bikeshare program features and trip trends, preparing for the later regression analysis. I analyzed how CaBi users changed their use of other transportation modes, and using survey data, found very mixed attitudes. As of 2014, 58% of survey respondents reported that they made fewer Metrorail trips than previously, while 42% said they used Metrorail more often or maintained the same level. Also, 64% reported that their CaBi trips started or ended at Metrorail stations.

A closer look at CaBi trips also reveals program characteristics. CaBi trips are seasonal: there are more trips in the warmer weather between May and October. They also follow peak commuting hours as do other transportation modes. Regarding account type,

[13] The map can be accessed from http://www.wmata.com/rail/bikesharing_maps/CaBi.cfm?station_name=Metro%20Center&lat=38.898303&lon=-77.028099

weekday trips are mostly made by commuters, while on weekends there are more casual trips made by casual users. These CaBi characteristics have important implications for regression models, specifically, that CaBi trips affected by extreme weather conditions and recreational trips need to be eliminated.

Metrorail ridership has been declining since 2010, despite the opening of five Silver Line stations in 2014. I charted Metrorail ridership and CaBi trip numbers between 2010 and 2015 and found that as CaBi trip numbers increased, Metrorail ridership declined, suggesting a possible correlation between the two.

Chapter 4: CaBi on Metrorail: Complementary or Substitute?

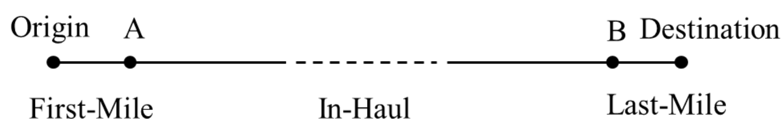
The exploration of Metrorail and CaBi historic trips in the last chapter suggests that they may be correlated. In this chapter, I discuss CaBi's impacts on Metrorail ridership from both theoretical and empirical perspectives. In general, CaBi can have two types of impacts: complementary effects and substitute effects. Complements are pairs of goods that are used together, such as coffee and sugar, and gasoline and automobiles. When the price of good A is reduced, both quantity of good A and good B will increase. Substitutes are pairs of goods that can replace each other, such as coffee and tea. When the price of good A increases, the quantity of good B will increase since demand for A decreases. If Metrorail is coffee, is CaBi's role sugar or tea?

In this chapter, I elaborate on the complementary-substitute discussion using three methods. First, from the perspective of microeconomics, I discuss how CaBi as a complementary and substitute good would drive the demand-supply. Second, I look for empirical evidence of CaBi's impacts by conducting case studies of two Metrorail stations and nearby CaBi activities. Particularly, I map changes in CaBi trips during Metrorail's SafeTrack maintenance periods Surge 2 and Surge 6. Finally, I review the current literature on bike share programs' impacts on rail transit ridership, focusing on methodologies and major findings.

4.1 Microeconomic Theoretical Analysis

As illustrated in Figure 25, a complete rail transit trip constitutes three segments: the segment between activity origin and rail transit station A, the in-haul trip between rail transit station A and station B, and the last segment between station B and activity destination. The first and last segments are usually called the first mile and the last mile. Since rail transit is fixed infrastructure, travel time of the complete trip largely hinges on speed of the first-mile and last-mile connections.

Figure 25 Illustration of Rail Transit Commute Trip Segments



How to fill the first mile and last-mile gaps depends on distance and cost. If the distance is small, most rail transit commuters may choose walking. When distances get larger, they are more likely to use driving, bus, and biking. Travel cost is another concern, which can be measured as monetary cost or time cost. Driving may have the lowest time cost, but parking may be the most expensive among all choices. Walking is free, but it also has the lowest speed.

Therefore, the cost of a complete rail transit trip can be written as:

$$Cost_{Total} = Cost_{first-mile} + Cost_{rail\ transit} + Cost_{last-mile} \quad (1)$$

Figure 26 and Figure 27 show the demand curve of bike share and rail transit trips. P denotes travel cost and Q denotes the number of trips. As the cost of bike share decreases from P1 to P2, the demand for bike share increases from D1 to D2. If bike share complements rail transit, as illustrated in Figure 26, we would see the demand curve shifts right. More commuters take rail transit even if the travel cost of rail transit remains the same. Conversely, if bike share substitutes for rail transit, as illustrated in Figure 27, rail transit demand curve shifts to the left, demonstrating that commuters switch from rail transit to bike share.

Figure 26 Complementary Effect Diagram

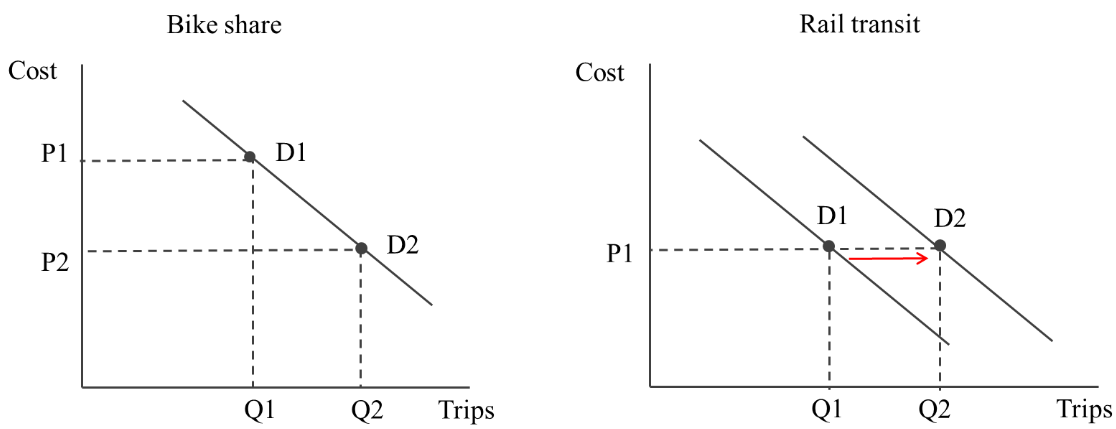
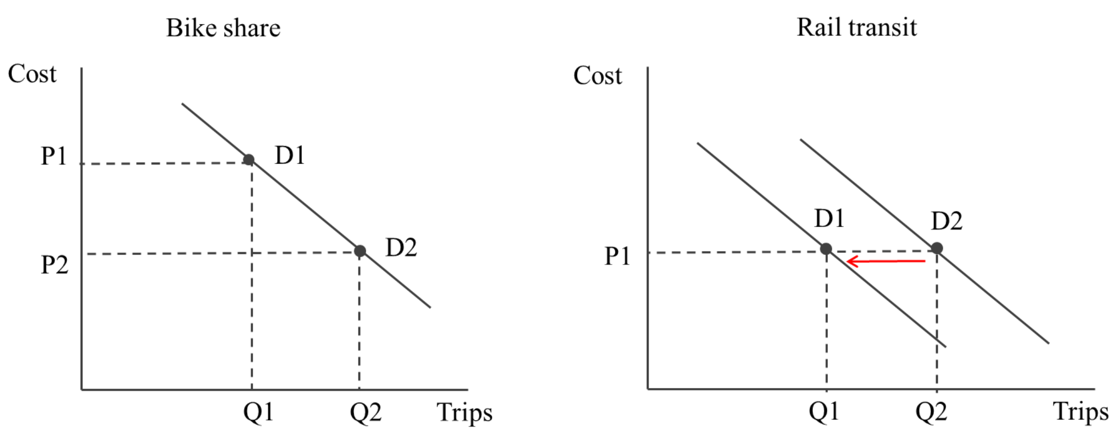


Figure 27 Substitute Effect Diagram



4.2 Empirical Analysis

One way to observe the complementary and substitute effect of CaBi is to map where trips originate and end, and their relationship to Metrorail stations. In this section, I analyze where CaBi trips cluster when Metrorail is in regular operation and where trips cluster when stations are closed. This section's purpose is to provide empirical evidence showing that CaBi can have both complementary and substitute effects on Metrorail ridership.

4.2.1 Substitute Effect

As introduced in Chapter 3, mapping the origin and destination of CaBi trips is useful in showing their spatial distribution patterns. In this subsection, I focus on two CaBi stations located near high-ridership Metrorail stations, and analyze the role of CaBi trips by mapping O-D pairs.

Union Station is the Metrorail station with the most passengers. Table 27 shows CaBi trips that originate from Union Station in the weekday AM peak period of 2015. Black lines represent O-D pairs with more than 1,000 trips, and gray lines are those with 500-1,000 trips. O-D pairs with fewer than 500 trips were excluded for better visualization results. As the map shows, all these CaBi trips end at CaBi docking stations that cannot be reached via Metrorail without at least one transfer. Therefore, it is reasonable to think that Metrorail morning commuters use CaBi as their last-mile solution to travel between Union Station and their workplaces.

Figure 28 CaBi Trips Originating from Union Station

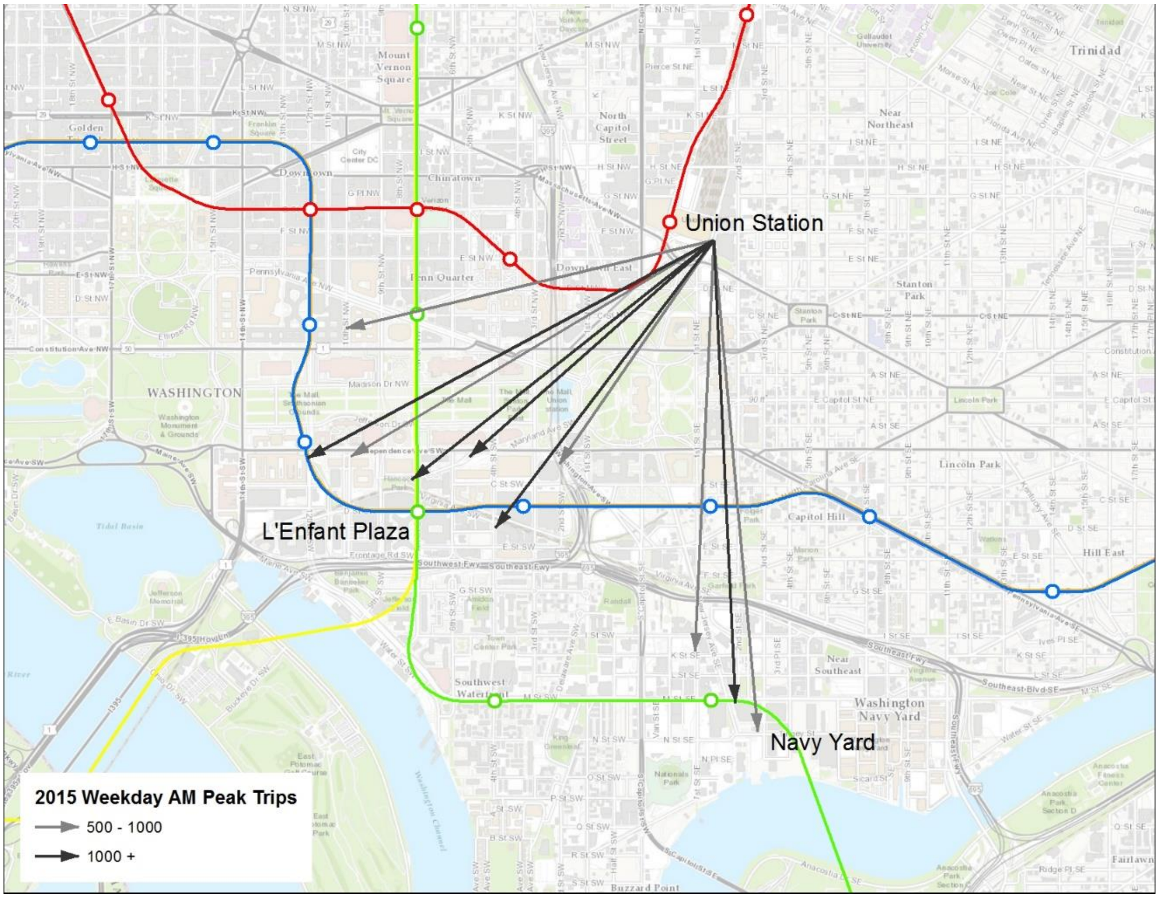


Figure 28 demonstrates that for commuters, CaBi provides a more direct link between Metrorail stations and workplaces, but does it save travel time? To answer this, I selected two CaBi O-D pairs from the map above and input both origins and destinations into Google Maps to calculate travel time by Metrorail and by CaBi, assuming trips are made at 8:00 am. The two CaBi O-D pairs are Union Station (CaBi docking station number 31623) – Smithsonian Museum (31217), and Union Station (31623) – Navy Yard (31208).

Figure 29 shows the travel time between Union Station and Smithsonian Museum by Metrorail and travel time by CaBi bicycle starting at 8:00 am on a typical weekday morning. It takes 20 minutes and one transfer for Metrorail riders to make the trip, but only takes 12 minutes for CaBi biking. If we consider the crowding of trains during the AM peak as well as the views along bicycle routes, CaBi is a better choice.

Figure 29 Travel Time Comparison 1

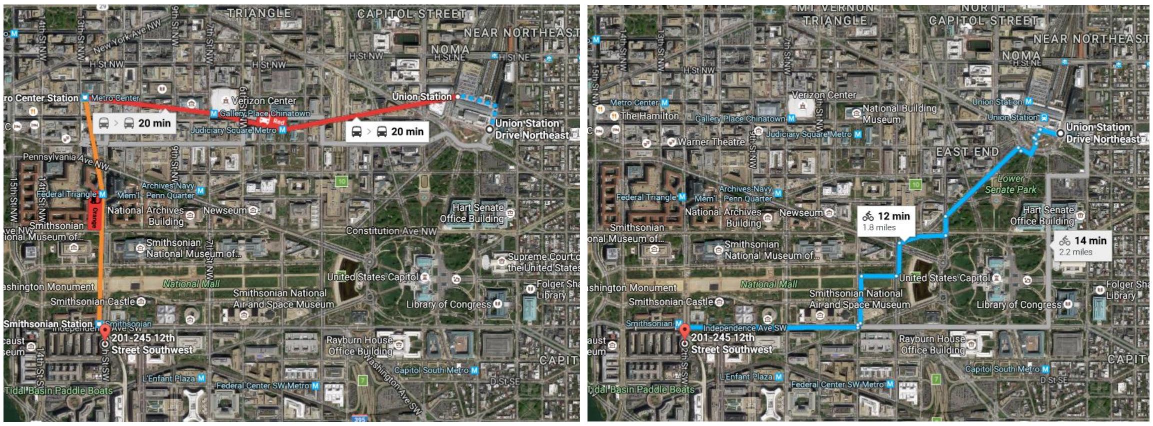
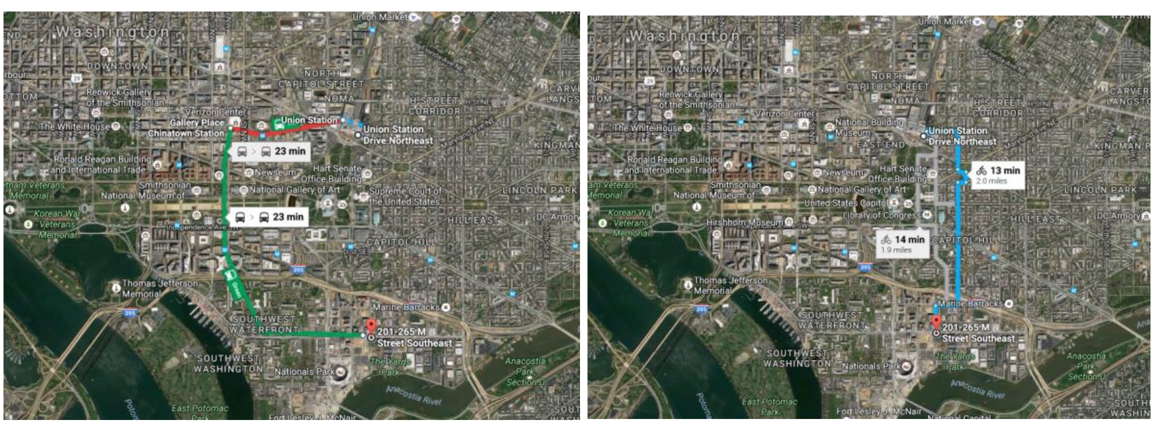


Figure 30 shows travel time by Metrorail and by CaBi between Union Station and Navy Yard. CaBi saves almost half the travel time compared to Metrorail. Both Figure 29 and .

Figure 30 suggest that CaBi could substitute for Metrorail trips starting from Union Station and ending in downtown D.C., particularly for Metrorail trips that require a transfer.

Figure 30 Travel Time Comparison 2



4.2.2 Complementary Effect

As discussed, CaBi can complement Metrorail ridership by solving the last-mile problem, especially for commuters who live in lower-density suburban communities served by limited public transportation resources. The Takoma and Silver Spring Metrorail stations provide good examples. Figure 31 and Figure 32 show CaBi trips near two stations in the weekday AM peak and PM peak separately. Black and gray lines represent CaBi O-D pairs with arrows illustrating the direction toward destinations. In Figure 31 we see that in the morning, CaBi trips start from neighborhoods located far from the two Metrorail stations and end at docking stations near Metrorail stations. We see same O-D trips in the PM peak but in the opposite directions, showing that after work, commuters take Metrorail to Silver Spring and Takoma, get off the train, and ride CaBi bicycles to complete their journey home. We could imagine that, without CaBi, there would be fewer commuters taking Metrorail because of the last-mile/first-mile gap. Therefore, CaBi induced Metrorail riders by increasing accessibility to Metrorail stations using a low-cost and convenient mode.

Figure 31 CaBi O-D Trips Complementing Metrorail—AM

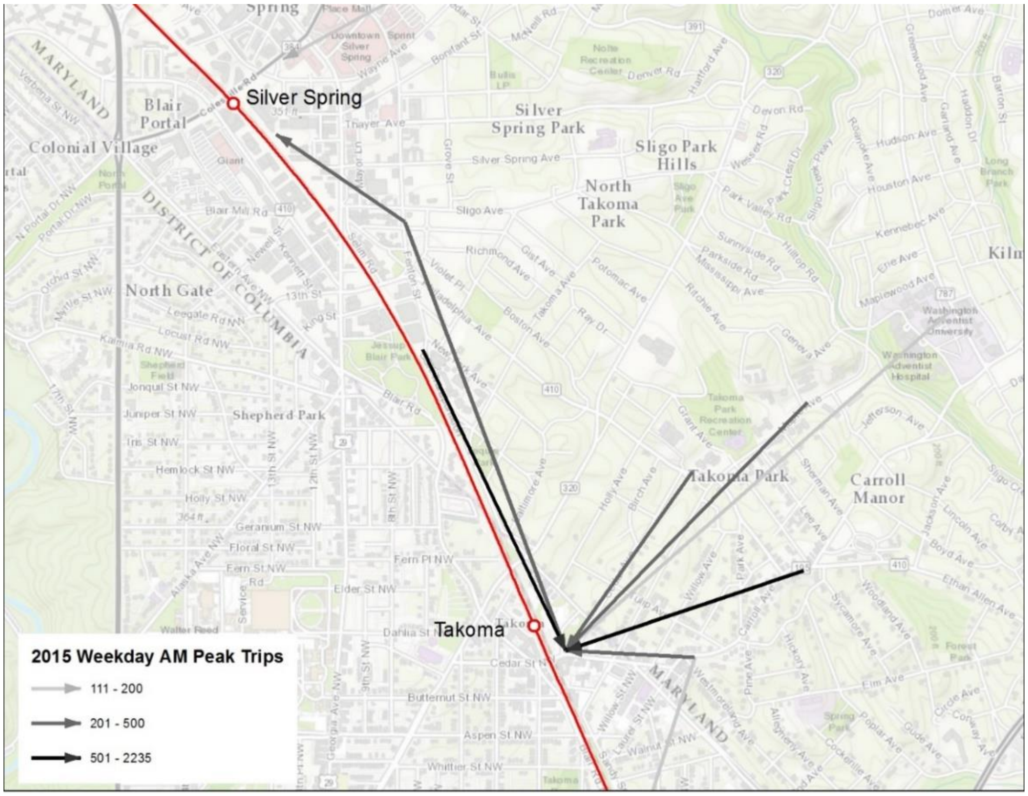


Figure 32 CaBi O-D Trips Complementing Metrorail—PM

4.2.3 CaBi Trips During Metrorail's SafeTrack

Two events in 2016 provide great opportunities to study Capital Bikeshare's substitute effects on Metrorail ridership. The first took place on March 16, 2016, when Metrorail was shut down for one-day emergency safety inspections (WTOP, 2016). The action was unprecedented and disrupted commuters, and thus provided an opportunity to observe how people travel without Metrorail.

To help with the commute during this one-day shut down, Capital Bikeshare offered free 24-hour memberships at all docking stations and corral services in downtown D.C. to ensure that bicycles were available for riders to pick-up and docking space was available for bicycle return (Lazo, 2016a). Comparing the number of Capital Bikeshare trips during that day with the trip number in the previous same weekday (Wednesday), Adam Russell (2016) found that total ridership increased by 21% (Russell, 2016). Most of the increase was from casual users who purchased a temporary Capital Bikeshare pass for one to three days. It is reasonable to assume that many new casual users were frequent Metrorail users. Therefore, Capital Bikeshare has the potential to substitute for Metrorail in a certain situation. In addition, many employers allowed telecommuting or taking leave during Metrorail's shut down but if all employees were required to commute, we would likely see a larger increase in Capital Bikeshare trips.

The second opportunity is the ongoing SafeTrack, which is an intensive and accelerated track maintenance program started June 2016 and lasting for one year. According to WMATA, Metrorail is currently open 135 out of 168 hours per week, leaving insufficient time for maintenance and other necessary track work. Therefore, during the SafeTrack period, WMATA will close the system at midnight on weekends as well as expand weekday maintenance opportunities. In addition, WMATA-planned weekday single tracking and line-segment shutdowns resulted in 15 SafeTrack Surges. In this chapter, I analyze how Capital Bikeshare changed during two SafeTrack surges, Surge 2 and Surge 6, to identify Capital Bikeshare's role in assisting Metrorail riders' commute journeys.

To compete for commuters during the SafeTrack period, many transportation providers such as Uber and Lyft offers aggressive deals and discounts (Sturdivant, 2016). Similarly, Capital Bikeshare developed new policies to attract commuters who used to take Metrorail every day.

First, a \$2 single trip fare was introduced on June 4, 2016. The new fare allows CaBi riders to take a single trip of up to 30 minutes for \$2. After 30 minutes, the normal 24-hour pass usage fees apply. The \$2 single trip fare was successful. In June and July, there were 70,568 fares sold. Table 22 lists the five CaBi stations with the largest number of purchased \$2 single-trip fares. All of them are located in the National Mall area, indicating that single-trip fares have been used primarily by tourists.

Table 22 \$2 Single-Trip Fare's Top Five Purchase Stations

Station Location	# of Trips	% of Total Trips
Jefferson Dr & 14th St SW	3,989	5.1%
Lincoln Memorial	3,460	4.4%
Smithsonian / Jefferson Dr & 12th St SW	2,424	3.1%
Henry Bacon Dr & Lincoln Memorial Circle NW	2,170	2.8%
4th St & Madison Dr NW	1,588	2.0%

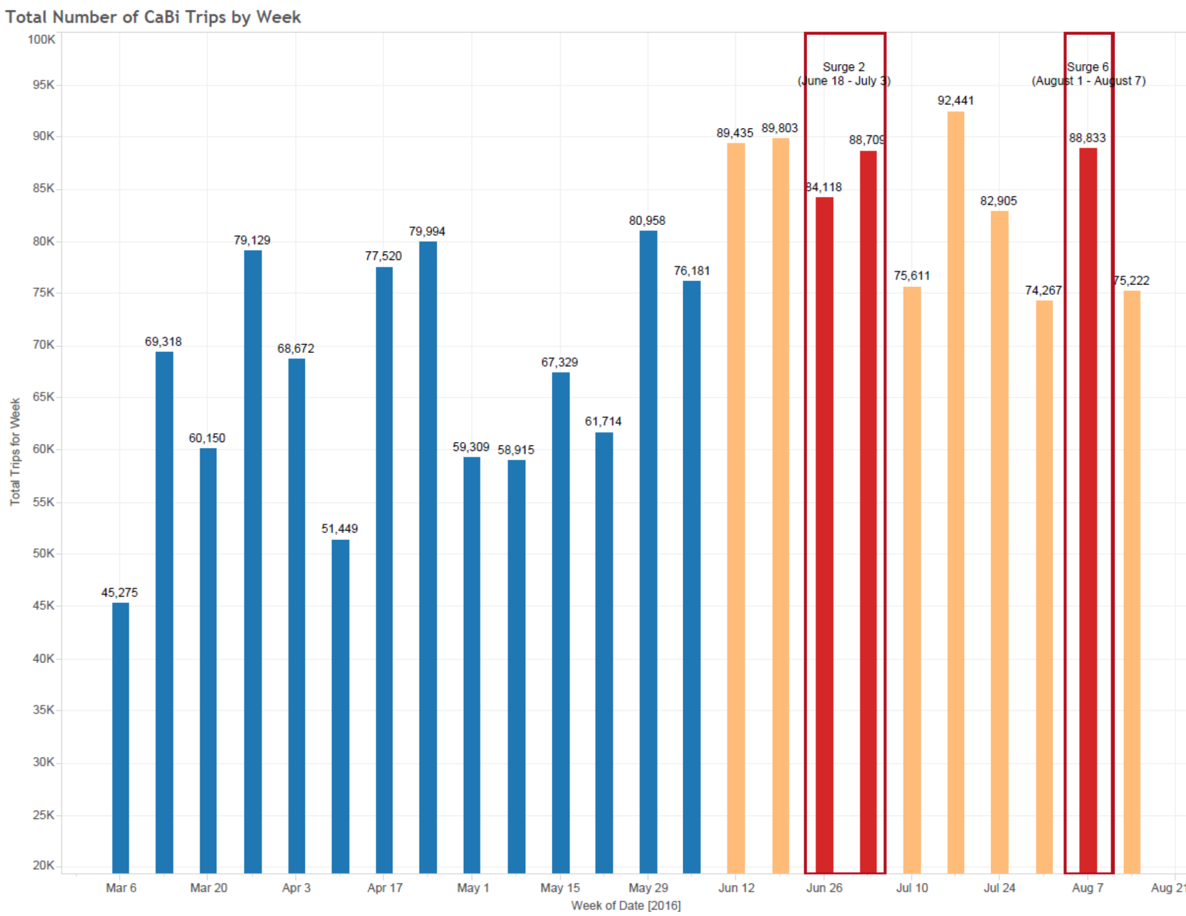
CaBi's second strategy was adding corral service, expanding the number of downtown bike share corrals from two to six, located at 21st & I Street NW (existing), 13th & New York Ave. NW (existing), 17th & K Street NW (new), 5th & F Street NW (new), Maryland Ave. & Independence Ave. SW (new), and 20th & Virginia Ave. NW (new). Corrals were introduced in March 2016 to solve the issue of CaBi docks filled in the morning with returned bikes making it difficult for users to return bikes. Before SafeTrack, there were about 160 bikes returned to AM corrals. During SafeTrack, more than 400 bikes were parked at corrals every day.

In addition, CaBi expanded capacities for docks located near affected Metrorail stations. During Surge 2, Benning Road and Minnesota Avenue docks were expanded. During Surge 6, Union Station CaBi docks were expanded. In addition, the Eastern Market dock was temporarily relocated to accommodate shuttle bus boarding.

Finally, CaBi increased marketing to attract new users during SafeTrack periods. It conducted a media campaign on traditional radio, internet radio (Pandora), social media (Instagram), as well as print advertising and ads at CaBi docks and on the website. The effort received a lot of public attention.

Comparing the number of CaBi trips before and during SafeTrack finds the shutdown of Metrorail stations boosted demand for CaBi. Figure 33 illustrates the weekly CaBi trip numbers since March, which is the CaBi busy season. Weekly trips before SafeTrack are colored in blue, trips during the SafeTrack period in orange, and trips during Surge 2 and Surge 6 are in red. In general, there were more CaBi trips during SafeTrack, particularly considering that CaBi trips usually peak in the spring during the Cherry Blossom Festival. Trips during Surge 2 and Surge 6 did not have the highest values compared to other SafeTrack weeks. A couple of weeks with relatively low volumes of CaBi trips were found during SafeTrack and could be attributed to weather variation.

Figure 33 Weekly CaBi Trips Before and During SafeTrack



Both member trips and casual user trips increased significantly during the SafeTrack period, as illustrated in Figure 34. Orange bars represent weekly trips made by member users, and blue bars represent trips by casual users.

Figure 34 Weekly CaBi Trips by Member vs. Casual Users Before and During SafeTrack

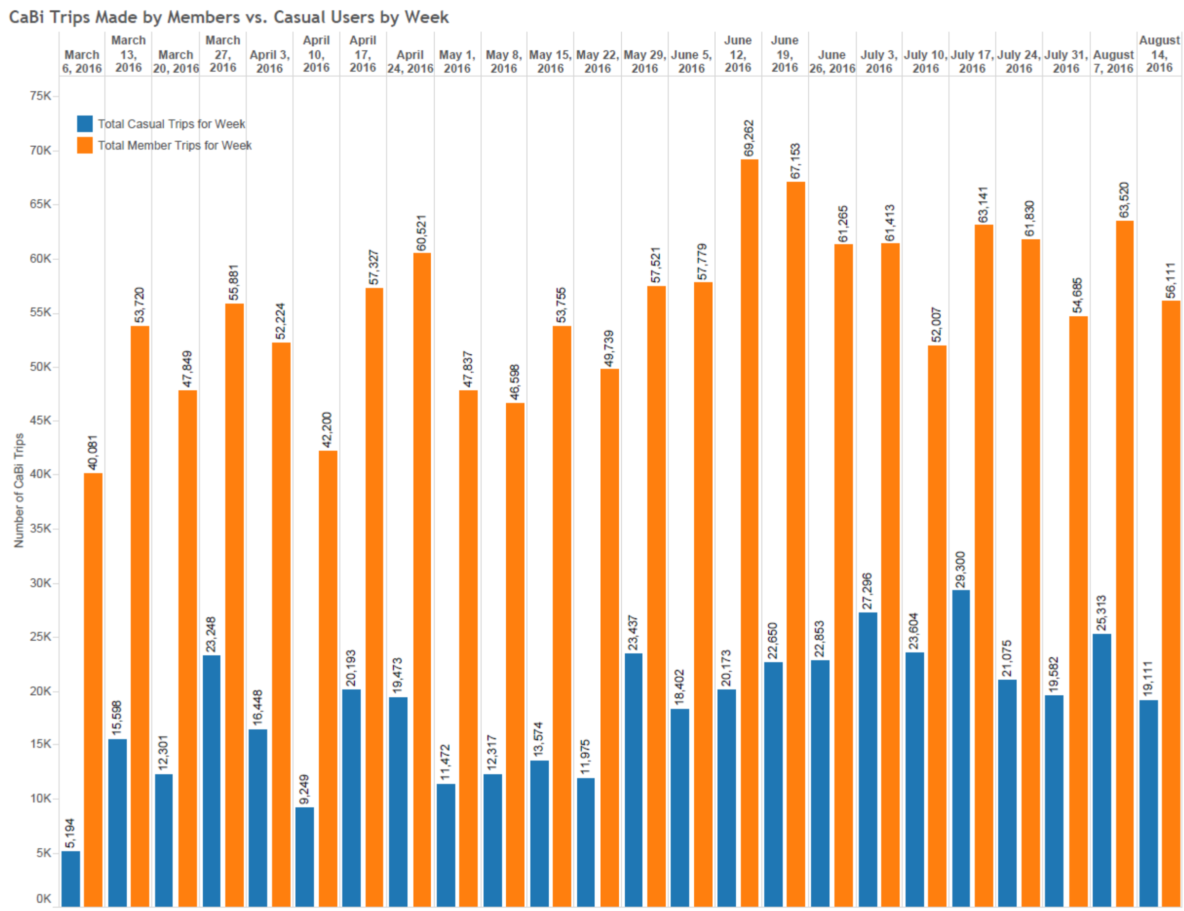


Figure 35 and Figure 36 show the difference between daily CaBi trips during Surge 2 and Surge 6 (in dark blue) compared to their baseline periods (in light blue). For each surge, I chose the same amount of days in the same weekdays right before SafeTrack. For Surge 2, which began on Saturday, June 18 and ended on Sunday, July 3, the baseline period is Saturday, May 14 to Sunday, May 29. Surge 6 began on Monday, August 1 and ended on Sunday, August 7, and its baseline period is between Monday, May 23 and Sunday, May 29. When determining the baseline, I also considered the same dates in 2015. However, CaBi experienced rapid expansion and added a lot of stations to the system. It is impossible to attribute trips change to SafeTrack alone. Therefore, I decided to use the days right before the SafeTrack as the baseline periods.

Figure 35 Daily CaBi Trips in Surge 2 (Compared with Baseline)

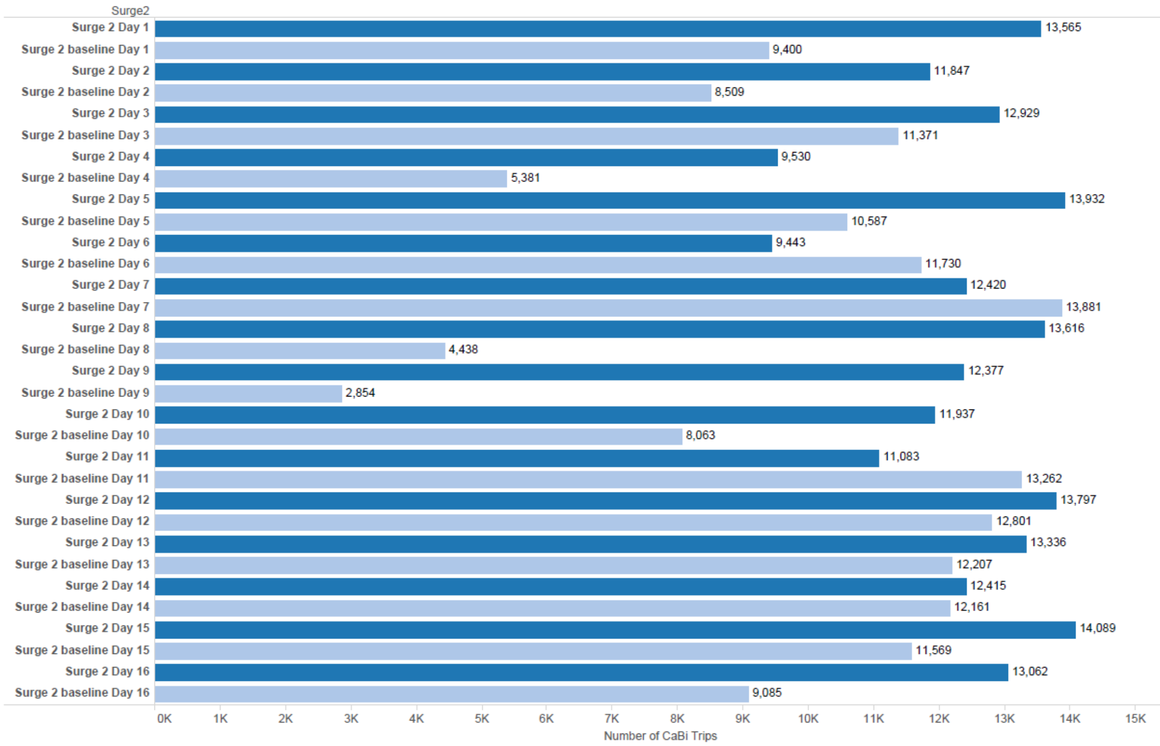
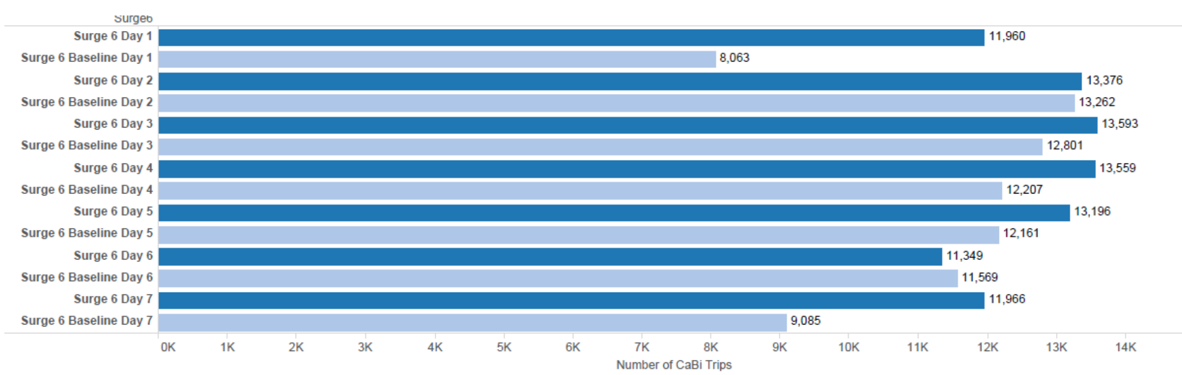
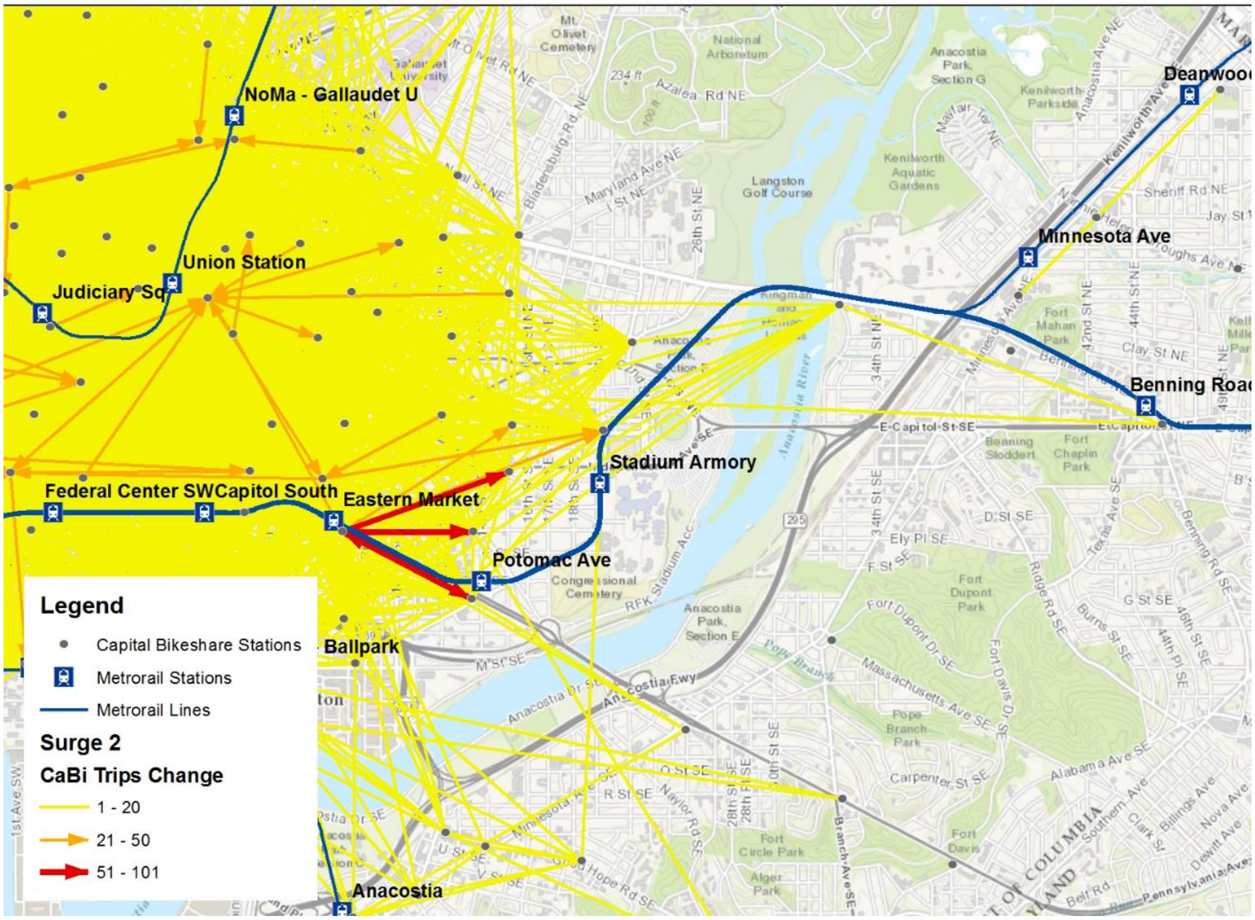


Figure 36 Daily CaBi Trips in Surge 6 (Compared with Baseline)



The O-D analysis confirmed that SafeTrack increases CaBi trips. Figure 37 maps O-D pairs by the trip change between Surge 2 and its baseline, zoomed to the impacted area between the Eastern Market Metro station and the Minnesota Ave station/Benning Road station. Red lines represent O-D pairs that have an increase of more than 50 trips, orange lines are those with 20-50 more trips, and yellow lines are those with a less than 20 trip increase. A similar analysis was performed for Surge 6, zoomed into the impacted region. However, no significant trip increase was observed.

Figure 37 CaBi O-D Pairs with Trip Changes



4.3 Literature Review

In this section, I review the literature on bike share programs' impacts on rail transit. My focus is the methods used and the impacts found. The findings of each significant study are presented and summarized at the end of this section.

Shaheen et al. (2013) completed a member survey of four bike share systems, BIXI in Montreal, BIXI in Toronto, Capital Bikeshare in Washington, D.C., and Nice Ride in Minneapolis/St. Paul (the Twin Cities). Specifically, they asked how the bike share program shifted the participants' use of rail transit. They report both increases and decreases in rail transit use. About 35% of participants in Montreal, Toronto, and Washington, D.C. reported that they use rail transit less often than before, while about 9% reported increased transit use due to the bike share program. The Twin Cities have a net increase in rail transit use; 15% either use rail transit much more often or more often than before, while only 3% use rail transit less often than before (S. A. Shaheen, Martin, & Cohen, 2013).

Martin and Shaheen (2014) mapped home locations of survey participants, and found a relationship between where people live and how their modal shift is affected. In Washington, D.C., CaBi members who reported a decreased use of rail transit mostly live in the downtown area, while those who increased their rail transit use were more likely to live in the suburbs (E. W. Martin & Shaheen, 2014).

Fishman (2015) found bike share's mode substitution to be an emerging theme in the literature. He charted the substitution rate of bike share programs on other transportation modes based on member surveys. The paper notes, "a study of a BSP in Shanghai showed that the majority of users are replacing walking and public transport (Zhu, Pang, Wang, & Timmermans, 2013)." (Fishman, 2015)

According to another study, 96% of Salt Lake City's surveyed users responded that their bike share program, GREENbike is an enhancement to existing public transportation and 30% claimed that they use mass transit more often than before (Wasatch Front Regional Council, 2013b).

Table 23 summarizes methods and major findings of these studies. Surprisingly, all the papers have used the survey method, and charts and graphs are major analysis tools.

Surveys provide good first-hand data, however, due to the low response rate, the survey may not be the most reliable research method. Also, since only bike share program members were surveyed, there is a selection bias. Ideally, a rigorous regression analysis with detailed actual trip data may be more suitable for answering the research question on CaBi's impacts.

Table 23 Literature on Bikeshare Programs' Impacts on Rail Transit Ridership

Paper	Case	Method	Findings	Impacts
Shaheen et al. (2013)	Montreal, Toronto, and Washington, D.C.	Survey	About 35 percent of participants reported that they use rail transit less often than before	substitute
Shaheen et al. (2013)	The Twin Cities	survey	15 percent use rail transit, either much more often or more often than before, while only 3 percent use rail transit less often than before	complementary and substitute
Martin and Shaheen (2014)	Washington, D.C.	survey	CaBi members who reported a decreased use of rail transit mostly live in downtown area, while those who increased rail transit use are more likely to live in the suburbs	complementary and substitute
Zhu, Pang, Wang, & Timmermans (2013), quoted in Fishman (2015)	Shanghai	survey	The majority of users are replacing walking and public transport	substitute
Wasatch Front Regional Council (2013)	Salt Lake City	survey	GREENbike is an enhancement to the existing public transportation, and 30% claimed that they use mass transit more often than before	complementary

4.4 Summary

This chapter started with a discussion of CaBi's potential complementary and substitute impacts on Metrorail ridership from a microeconomic perspective. On the one hand, the combination of CaBi and Metrorail may cost less than driving and parking, and thus increase the demand for Metrorail. On the other hand, CaBi may replace Metrorail for lower travel times and cost, and result in a decrease in Metrorail ridership.

Both theories are supported by empirical evidence. Union Station is a popular station for CaBi trips. A comparison of routes and travel times by Metrorail and CaBi between Union Station and Smithsonian concludes that because CaBi saves half the travel time by enabling travel across the National Mall and by saving transfer time, it is likely to substitute for Metrorail. CaBi's complementary effects were found at the Takoma Park station, which has many CaBi trips ending at the station area in the morning and starting in the evening, suggesting that commuters use CaBi to bridge the distance between the Takoma Park Metrorail station and their homes.

WMATA's SafeTrack maintenance shut down Metrorail stations and provides a good opportunity to observe CaBi's substitute effects. The number of CaBi trips during SafeTrack increased compared to the same days of the week just before the Metrorail stations' shutdown. Also, CaBi sold 70,568 $2 trip fares, which were designed to help commuters affected by the single tracking and shutdown of Metrorail stations, indicating an increased demand. Finally, the Origin-Destination map shows that the increased trips started or ended near closed Metrorail stations, demonstrating CaBi's substitute impacts.

A review of the extant literature shows that most studies of bike share programs' impacts on rail transit ridership rely on survey data. Surveys provide good first-hand data, however, since only bike share program members are surveyed, there can be a selection bias. Further, surveys tend to have small sample sizes and do not directly represent travel behavior. There is potential value, therefore, in regression analysis of ridership data.

Chapter 5: Introduction to Regression Analysis

Results of the descriptive analysis performed in Chapters 3 and 4 suggest that there may be a relationship between CaBi trips generated and ended at Metrorail station area and the Metrorail ridership of that station. To identify and measure CaBi's impacts, in this chapter, I apply a series of regression analyses. Regression analysis helps to understand how Metrorail ridership changes when a CaBi docking station is installed and when the number of CaBi trip changes, controlling for other factors.

After careful consideration, I applied three regression models to test CaBi's impacts on Metrorail ridership. They are the Direct Ridership Model (DRM), the Difference-in-Difference (DID) Model, and the Station-Specific Dummies (SSD) model. In this chapter, I provide an overview of these models (Section 5.1) and the input data (Section 5.2). I then discuss the possible results and their interpretation (Section 5.3). This chapter serves as an introduction to regression analysis. The chapters that follow cover a detailed analysis and results discussion (Chapter 6 for the Direct Ridership Model, Chapter 7 for the Difference-in-Difference Model, and Chapter 8 for the Station-Specific Dummies Analysis).

5.1 Overview of Methods

The Direct Ridership Model

A Direct Ridership Model is a regression model used to estimate rail transit ridership at the station level using internal and external transit data. The DRM was widely used by transit planners to replace the traditional four-step travel demand modeling process (Parsons Brinckerhoff, Cervero, Howard/Stein-Hudson Associates, & Zupan, 1996). More importantly, the DRM is responsive to development activity and it can predict ridership at the station level.

Literature has shown that rail transit ridership is likely to be affected by three groups of factors: transit service on the transit line and stations of interest, the socio-demographics of people living and working near the station, and the character of the built environment in the station areas. Transit service includes factors such as operation hours, train headway/frequency, and the reliability of schedules, fare, and safety. Station features, such as transfer/terminal stations and the number of parking spaces, also affect transit's attractiveness to commuters. The socio-demographics of people in the station area determines the travel demand and whether the station produces or attracts trips. Factors like low car ownership and low household income were found to contribute to rail transit ridership. The character of the built environment such as land use, density, and design affects the accessibility of rail transit stations. Transit-oriented development, high-density and mixed-use, is believed to have a positive impact on rail transit ridership by providing proximity and accessibility to rail transit facilities (Calthorpe, 1993).

The existing DRM studies rarely include the availability of bike share as a factor. In fact, most researchers assume that commuters walk to rail transit stations. However, as shared mobility modes emerge, commuters can now use bike share to access rail transit stations. Therefore, the existing Direct Ridership Model must expand to reflect the impacts of bike share programs.

Ideally, all variables in the Direct Ridership Model should be time-varying. However, annual data of socio-demographics and built environment are not available. The actual input data for the Direct Ridership Model includes average weekday peak period

Metrorail and CaBi ridership for each year between 2010 and 2015, as well as static transit service, socio-demographics, and built environment data.

The Difference-in-Difference Model

The Direct Ridership Model assumes that CaBi docks are randomly assigned to Metrorail stations. However, this assumption may not hold. The installation of CaBi docking stations resulted from strategic planning. Thus, those Metrorail stations with CaBi installed nearby may be different from stations without CaBi. This systematic difference is called the location effect.

Separating Metrorail stations into two groups, those with CaBi installed in the station areas, and those without CaBi, we can see the CaBi program as a policy intervention and treatment. Also, there are data for each group pre-treatment and post-treatment. From the perspective of quasi-experiment, the Difference-in-Difference model can be used to control both the time and location effects to estimate CaBi's real impacts.

The Station-Specific Dummy Analysis

The Difference-in-Difference model reveals CaBi's average program effect. Results suggest that CaBi's impacts on Metrorail ridership might be associated with station locations. To test this theory, I conduct a Station-Specific Dummies analysis to measure CaBi's impacts on core stations and non-core stations, based on WMATA's definition of system core. I also input more detailed data. The data for SSD are monthly Metrorail ridership and CaBi trips between August 2010 and August 2015. Years and months are controlled using dummy variables. Also, to compensate for not having time-varying control variables, I created dummies for 91 Metrorail stations to control for their stations' fixed effects.

The three regression analysis methods grow from the limitation of the earlier methods. Step by step, they gradually reveal how CaBi affects Metrorail ridership. Together they reflect my search for the most suitable methods. Table 24 summarizes the highlights of each model.

Table 24 Overview of Regression Models

Model	Research question	Data requirements
Direct Ridership Model	How many Metrorail ridership changes occur when CaBi trip increases by one unit, after controlling for transit service, demographics, and built environment features at the station area?	Cross-sectional
Difference-in-Difference	How many Metrorail ridership changes occur when CaBi docking stations were installed at the station area, after controlling for Metrorail station location differences and time effect?	Panel
Station-Specific Dummies	For each Metrorail station, how many ridership changes occur when a CaBi docking station was installed, after controlling for station location fixed effect and time effect?	panel

Note that for all models, I assume a linear relationship between Metrorail ridership and other variables. I also tried the negative binomial regression model. However, results are not statistically significant, suggesting that the model is not a good fit.

5.2 Overview of Data

The major data inputs for the models are Metrorail ridership and CaBi trips. Original Metrorail ridership data were shared by WMATA. The dataset includes the number of passengers entering and exiting at each Metrorail station by six time periods, which, according to WMATA's definitions, are early morning (12:00 am – 5:00 am), AM peak

(5:00 am – 9:30 am), midday (9:30 am – 3:00 pm), PM peak (3:00 – 7:00 pm), evening (7:00 pm – 9:30 pm), and midnight (9:30 pm – 12:00 am).

CaBi trip data was downloaded from CaBi's website. The dataset includes information on the origin docking station and the destination dock, and trip duration (the actual biking route is not included). The trip data was tracked back to August 2010, two months before the CaBi program's official launch that October.

The unit of my study is the Metrorail station area, defined as a ¼-mile radius. The one-quarter mile is determined by the average walking distance for ordinary people, since most riders walk from activity origin to station and from station to destination. Also, many previous studies suggest using ¼-mile as the station catchment. In their study, Cervero and Guerra (2011) compared the relationships between different sized catchment areas and rail transit ridership. Catchments tested include 0.25 miles, 0.50 miles, 0.75 miles, 1.00 miles, 1.25 miles, and 1.50 miles. Population and job densities within a ¼-mile radius of a rail station have the largest coefficients, suggesting that ridership is more influenced by density in a ¼-mile catchment area (Cervero & Guerra, 2011). Therefore, I decided to use a ¼-mile distance as the definition of Metrorail station area, and CaBi docking stations are deliberately confined to those located within the station areas.

CaBi trip analysis in Chapter 3 provides insights into data preparation. First, weekend CaBi trips are more likely to be recreational rides, and they do not replace Metrorail trips. Thus, to study CaBi's interplay with Metrorail, I exclude both Metrorail and CaBi weekend trips and focus on trips in the AM and PM peaks. Second, the weather has a considerable influence on CaBi trips. To eliminate its impacts, I calculate average CaBi trips, instead of using the actual number of daily AM/PM peak trips.

Also, to maximize the benefits of the detailed Metrorail ridership and CaBi trip data, I split them by time and by type. For Metrorail ridership, I have four measures: *mentryam*, *mexitam*, *mentrypm*, and *mexitpm* (in which *entry* and *exit* indicate the type and *am* and *pm* indicate the time). Similarly, I split the CaBi trips starting from and ending at Metrorail station areas as “start” and “end,” and thus have four CaBi measures, which are *cstartam*, *cendam*, *cstartpm*, and *cendpm*. Table 25 lists all eight variables and their definitions.

Table 25 Metrorail and CaBi Ridership Definitions

Variable	Definition
mentryam	Number of passengers that enter Metrorail station in weekday AM peak
mexitam	Number of passengers that exit Metrorail station in weekday AM peak
mentrypm	Number of passengers that enter Metrorail station in weekday PM peak
mexitpm	Number of passengers that exit Metrorail station in weekday PM peak
cstartam	Number of CaBi trips originating from Metrorail station in weekday AM peak
cendam	Number of CaBi trips ending at Metrorail station in weekday AM peak
cstartpm	Number of CaBi trips originating from Metrorail station in weekday PM peak
cendpm	Number of CaBi trips ending at Metrorail station in weekday PM peak

Variables in Table 25 help solve the research question of CaBi trips’ impacts on Metrorail ridership. Models with these inputs aim to test hypothesis 1 and to estimate how ridership change if CaBi trips increase by one unit. Slightly different, testing hypothesis 2 requires a dummy variable indicating whether a Metrorail station has any CaBi docks installed nearby. The dummy variable has a value of 1 if the station has CaBi docks within ¼ mile.

Besides Metrorail ridership and CaBi trip variables, the three models require different additional data input. Therefore, a detailed data introduction and descriptive statistics will be provided for each model in chapters 6, 7, and 8.

5.3 Possible Coefficients and Interpretations

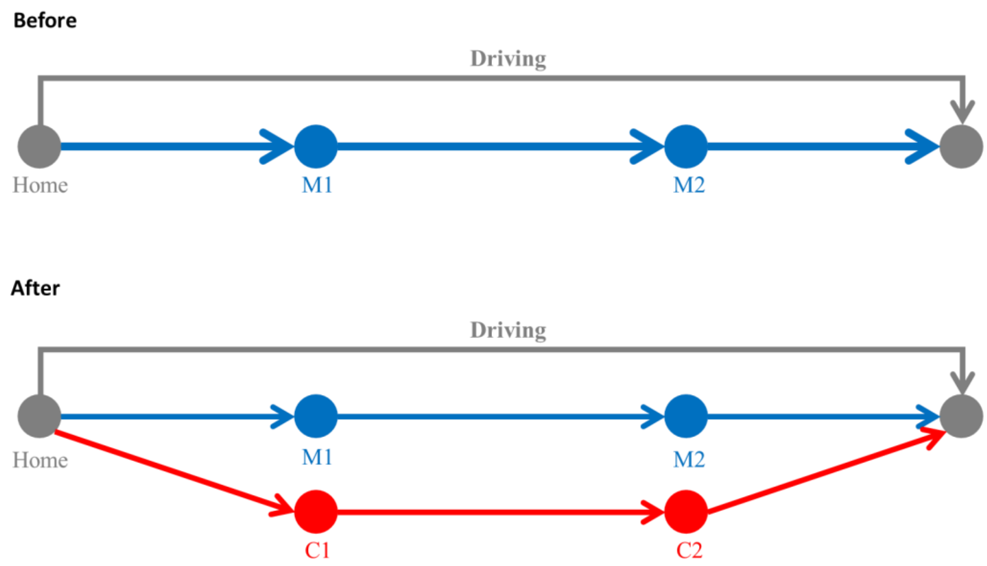
Values and signs of coefficients can illustrate relationships between Metrorail ridership and CaBi trips. Because both the dependent variable (Metrorail ridership) and the independent variable (CaBi trip numbers) have four measures, there are a total of eight coefficients. Table 26 lists all these signs and the scenarios and interpretations they may suggest. In this session, I go through each scenario in the table and visualize the relationships. I refer to these scenarios and discussions in later chapters when I discuss the actual regression results.

Table 26 Possible Signs and Scenarios

Scenario	Dependent var. Metrorail ridership	Independent var. CaBi trip number	Sign	Interpretation
1	*mentryam*	*cstartam*	-	Substitute effect
2	*mentryam*	*cendam*	+	Complementary effect (first-mile solution)
3	*mexitam*	*cstartam*	+	Complementary effect (last-mile solution)
4	*mexitam*	*cendam*	-	Substitute effect
5	*mentrypm*	*cstartpm*	-	Substitute effect
6	*mentrypm*	*cendpm*	+	Complementary effect (first-mile solution)
7	*mexitpm*	*cstartpm*	+	Complementary effect (last-mile solution)
8	*mexitpm*	*cendpm*	-	Substitute effect

Figure 38 illustrates the baseline scenario. Imagine two gray dots representing a commuter's home and workplace. Before CaBi became an option, the commuter could take Metrorail or drive to work. If the commuter takes trains, we would see one Metrorail station near their home and the other station near the workplace. Let us denote them as M1 and M2, respectively. If Metrorail stations are too far to access, the commuter is likely to drive. After the CaBi program's launch in 2010, there is a third option—bike sharing. Assume Metrorail stations M1 and M2 both have CaBi docking stations within a ¼-mile radius; we denote the CaBi station near M1 as C1 and the one near M2 as C2.

Figure 38 The Baseline Scenario



Scenario 1

In Scenario 1, as Figure 39 illustrates, the commuter takes Metrorail to work. The arrowed line Home-M1-M2-Workplace simulates the morning commute trip. However, the introduction of CaBi provides an alternative, and the commuter may take the route Home-C1-C2-Workplace. Therefore, Metrorail station M1 may experience a decrease in the number of passenger boardings in the AM peak, as some commuters switch to CaBi (and the number of trips starting at CaBi station C1 may increase). This substitute effect would be reflected by the negative sign of coefficient *cstartam*.

Scenario 2

In Scenario 2, the commuter lives far from a Metrorail station and drives to work. The factor preventing them from taking trains is the first-mile gap of no public transportation between home and Metrorail station M1. The installation of CaBi station C1 perfectly solved this issue. The commuter now can pick-up a bike near home, cycle to CaBi station

C1, and get on the train at Metrorail station M1. In this scenario, we would expect that the number of *mentryam* at M1 increases with the number of *cendam* at C2, leading to a positive sign.

Figure 39 Scenario 1

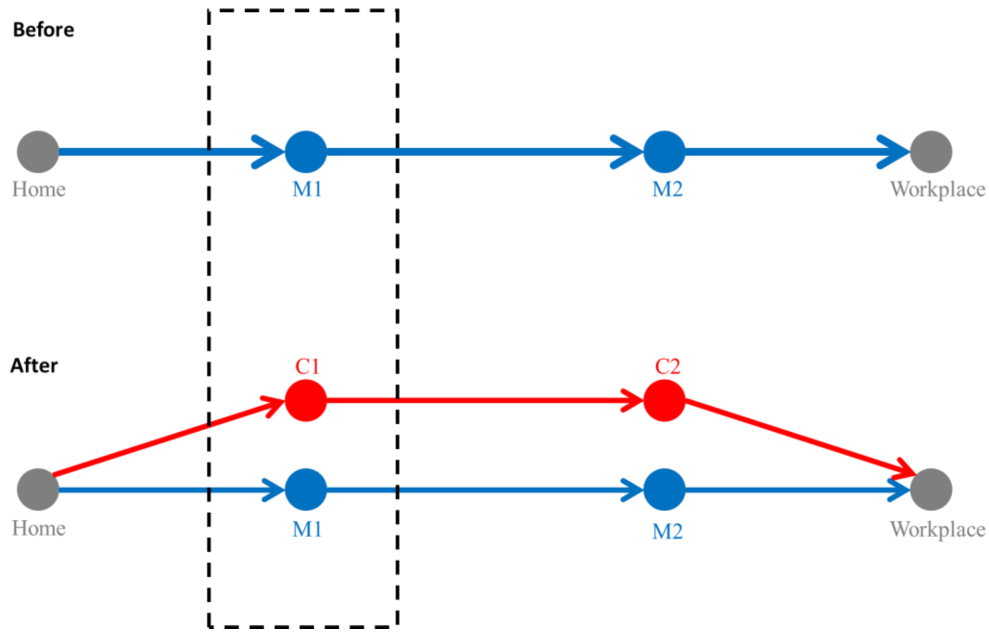
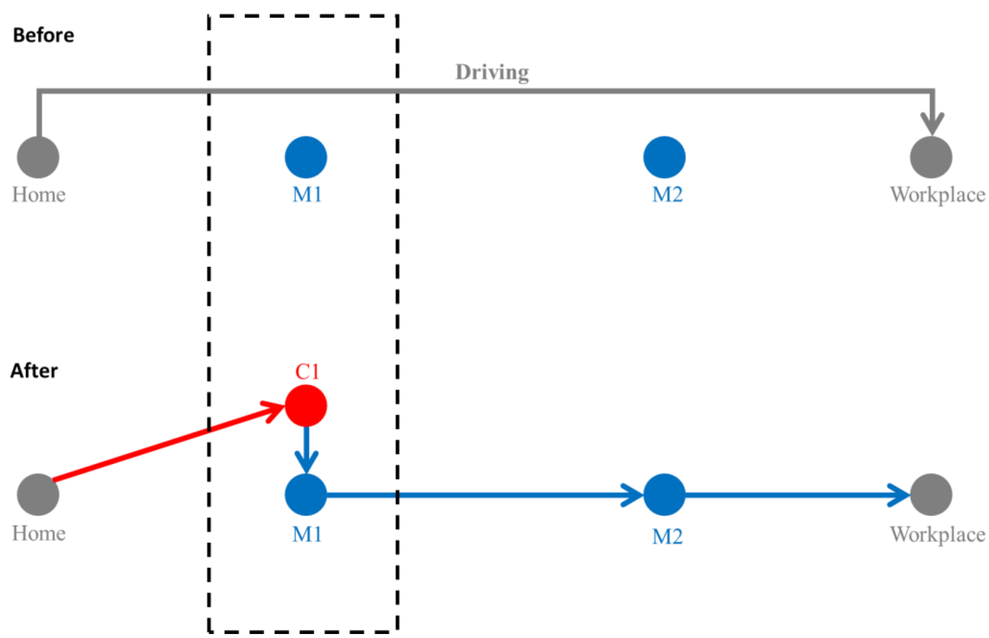


Figure 40 Scenario 2



Scenario 3

Like Scenario 2 in which CaBi solves the first-mile connection problem, in Scenario 3 CaBi solves the last-mile issue. The last-mile gap is between Metrorail station M2 and the commuter's workplace. Sometimes, due to the lack of public transportation, the distance between M2 and the workplace is too great to walk and thus becomes a barrier. However, with CaBi station C2, the commuter can grab a bike after the train trip. Since Washington, D.C. ranked as the 6th most congested place in the nation, the combination of Metrorail-CaBi is likely to be faster than driving. In this scenario, we could expect a positive sign between *mexitam* and *cstartam*, showing that CaBi provides a last-mile problem solution for Metrorail.

Scenario 4

Scenario 4, as does Scenario 1, shows how CaBi replaces part of Metrorail commuting trips. The number of passengers exiting at Metrorail station M2 in the morning peak is likely to decline after CaBi station C2's opening. If the Scenario 4 is true, we may find a negative coefficient in the regression with variables *cendam* and *mexitam*.

Figure 41 Scenario 3

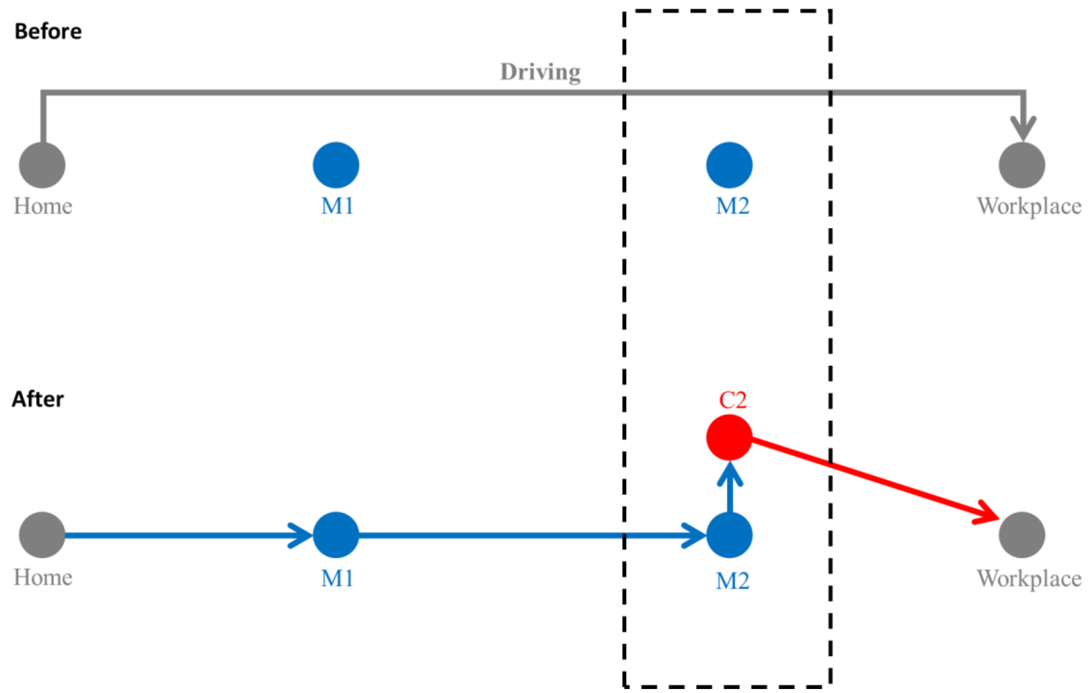
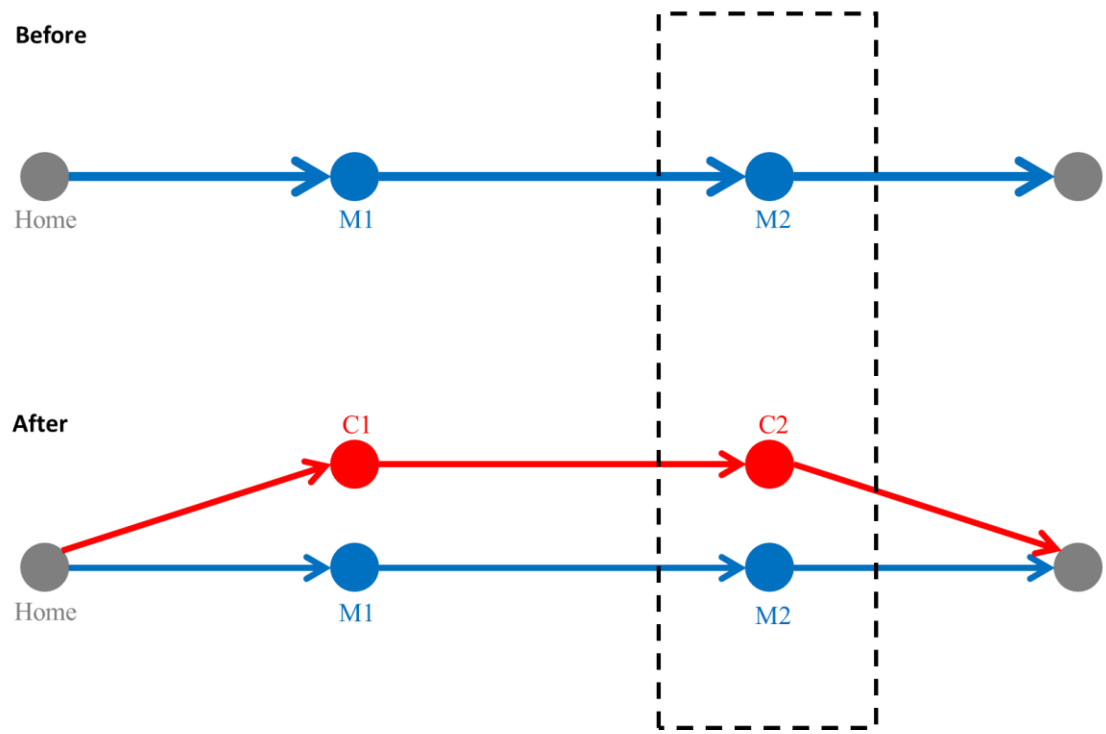


Figure 42 Scenario 4



Scenario 5

Scenarios 5 through 8 are the counterparts of Scenarios 1 through 4 in the weekday PM peak, rather than the AM peak; commuting trips originate at the workplace and end at home. In Scenario 5, the commuters used to take Metrorail to get home. However, with CaBi's opening, they switched to bike sharing. Therefore, we see a negative sign between the number of boardings at Metrorail station M2, *mentrypm*, and the number of trips starting at CaBi station C2, *cstartpm*, indicating that CaBi substitutes for Metrorail.

Scenario 6

In Scenario 6, from work to home during the PM peak, the commuter used to drive home because Metrorail station M2 was too far to walk to from the workplace. CaBi provided the first-mile solution and bridged the gap between workplace and M1. Therefore, after CaBi opened, the commuter bikes between workplace and C2, and then takes the train at M2 to return home. The CaBi trip has a positive and complementary effect on Metrorail, and in this scenario, we expect to find a positive sign between *cendpm* and *mentrypm*.

Figure 43 Scenario 5

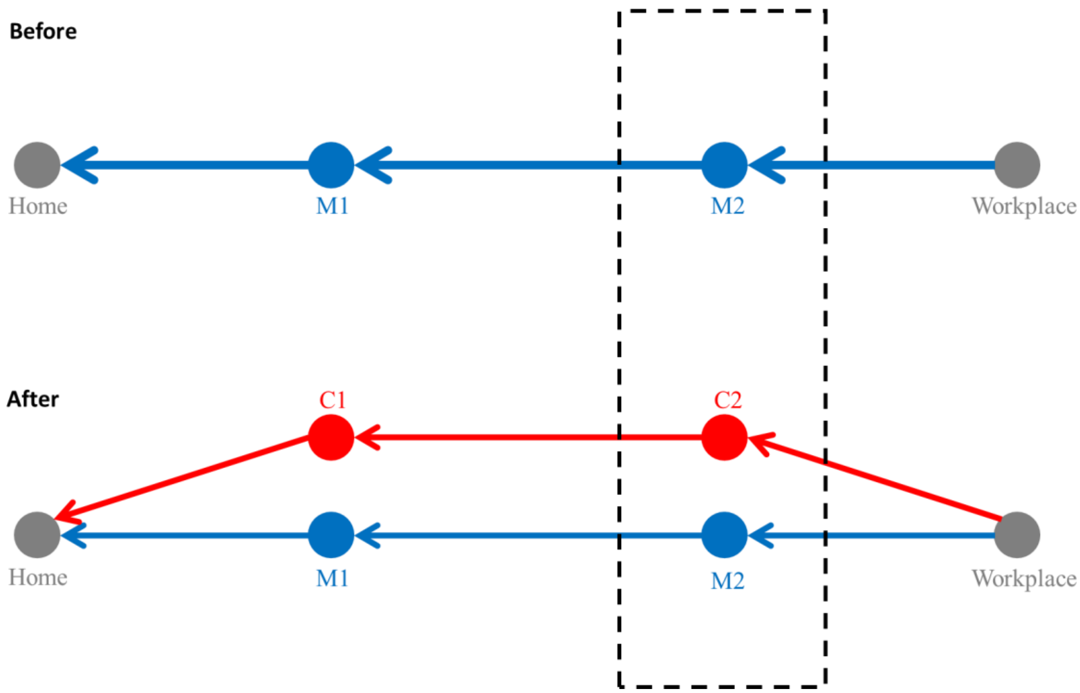
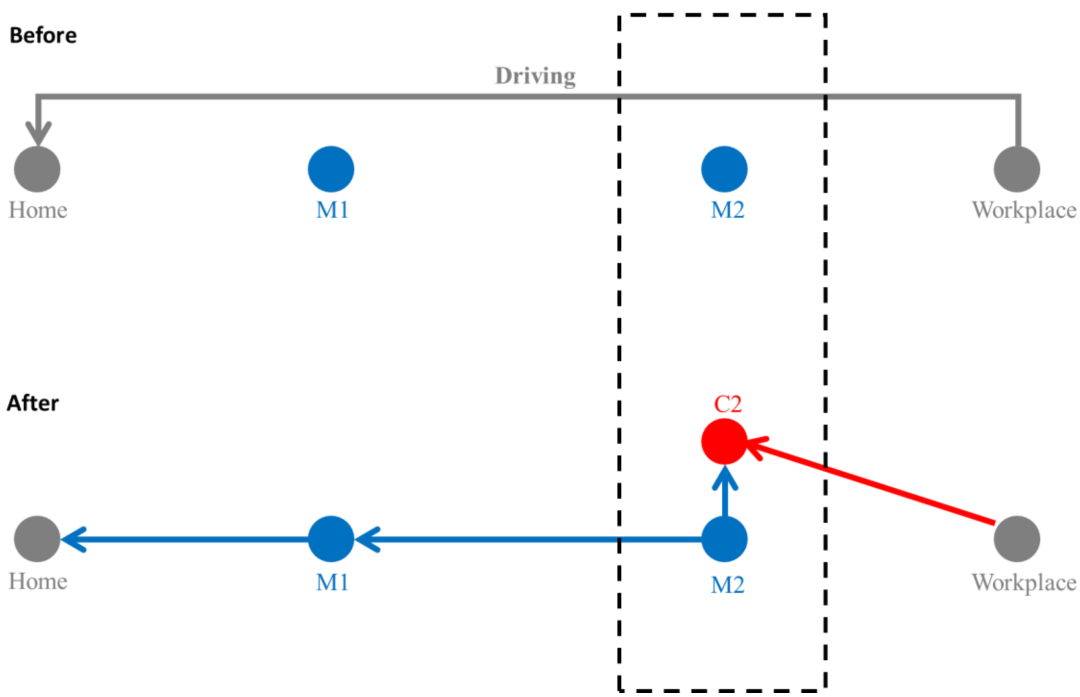


Figure 44 Scenario 6



Scenario 7

In Scenario 7, the opening of CaBi solved the last-mile issue near the commuter's home by connecting Metrorail station M1 and home. Therefore, we would expect to find a positive relationship between *mexitpm* and *cstartpm*.

Scenario 8

In Scenario 8, during evening peak hours, CaBi solves the last-mile gap between Metrorail station M1 and the commuter's home, and thus competes with Metrorail. Metrorail ridership measure *mexitpm* may decrease as CaBi trip count *cendpm* increases. Therefore, we may see a negative sign for the *cendpm* coefficient, indicating that CaBi substitutes for the Metrorail ride home.

Figure 45 Scenario 7

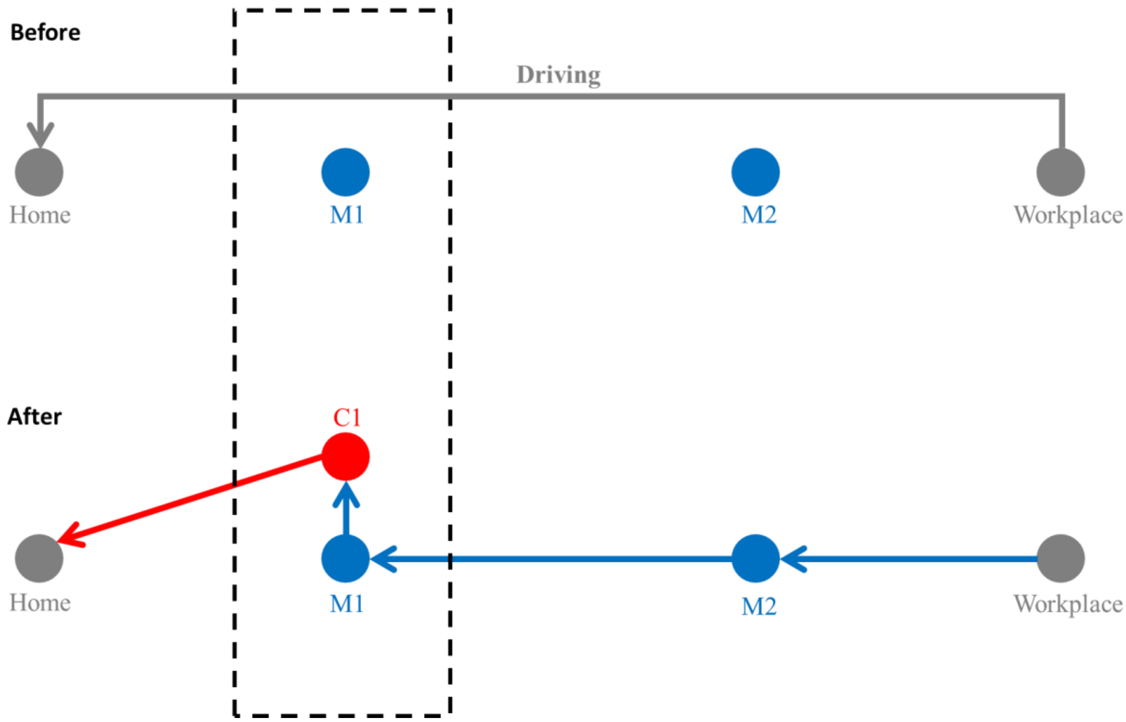
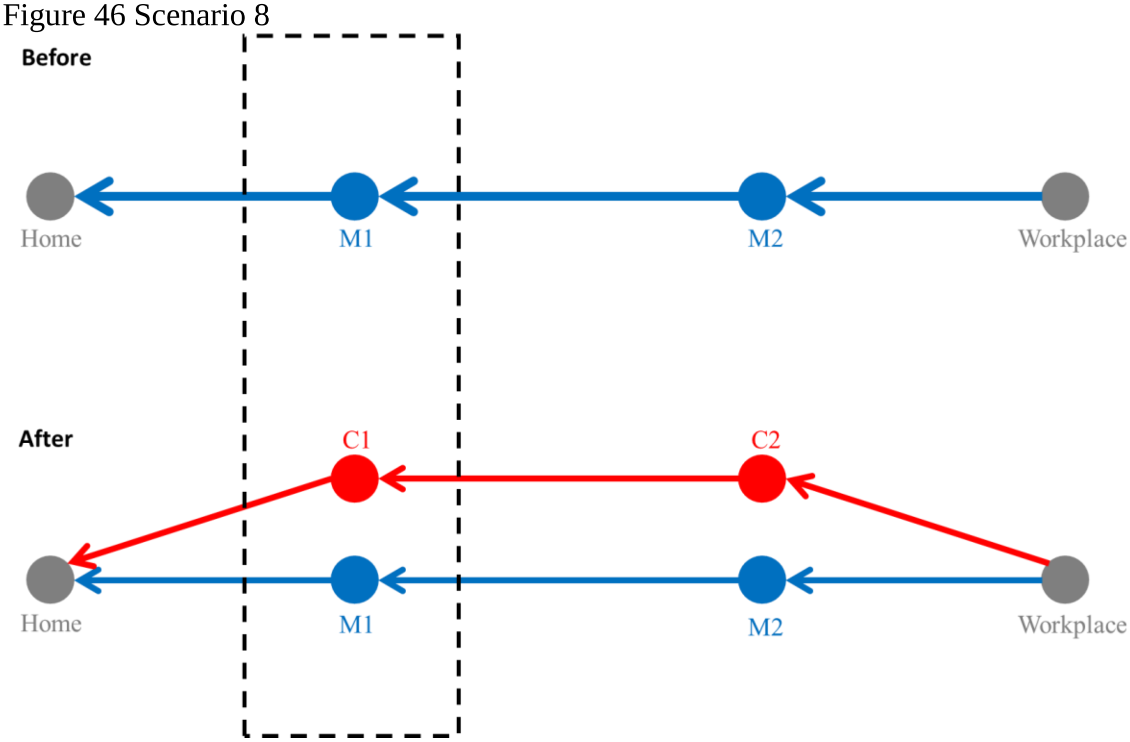


Figure 46 Scenario 8



5.4 Summary

This chapter is an introduction into the three regression models that will be used to measure CaBi program's impacts on Metrorail ridership. They are the Direct Ridership Model, the Difference-in-Difference model, and the Station-Specific Dummies model.

Model input data are Metrorail ridership and CaBi trip numbers/program dummy at the Metrorail station level. To take advantage of the high-resolution and high-frequency data, Metrorail and CaBi ridership are divided into four measures each; for Metrorail: *mentryam*, *mexitam*, *mentrypm*, and *mexitpm*, and for CaBi: *cstartam*, *cendam*, *cstartpm*, and *cendpm*. Components *entry*, *exit*, *start*, and *end* indicate trip's types, and *am* and *pm* indicate the time when the trip was made. For models that measure CaBi's program impacts, I will input a dummy variable that takes the value of 1 to indicate Metrorail stations with CaBi installed nearby.

At the end of this chapter, I discussed possible coefficients of CaBi variables and interpreted the scenarios. Contents in this chapter create a foundation of regression results analysis used in later chapters.

Chapter 6: Direct Ridership Model Analysis

The Direct Ridership Model (DRM) is a popular method of estimating rail transit ridership at the station level. It is built on intensive literature about factors of rail transit ridership. In the model, rail transit ridership is expressed as the result of internal and external factors, usually including transit service features, the socio-demographics of people living and working in the station areas, and characteristics of the built environment around the stations.

The existing DRM assumes that commuters walk to rail transit stations, and so considers the number of people working and living nearby and the pedestrian environment. However, as more bike share stations are added to the network, it is equally likely for commuters to ride shared bikes to stations. Therefore, in this chapter, I expand the DRM to include CaBi trips as a factor of Metrorail ridership, after controlling for Metrorail transit service, socio-demographics and built environment factors.

This chapter starts with an introduction to the DRM, a literature review of ridership factors, and the model's application in transit planning. A description of methodology, model specifications and data will be provided later, followed by a presentation of regression results and interpretations. This chapter is built on an article I co-authored and published in the journal of *Transportation Research Record*, but methodology and data have since been significantly updated.[14]

[14] Ting Ma, Chao Liu, and Sevgi Erdoğan. "Bicycle sharing and public transit: does Capital Bikeshare affect Metrorail ridership in Washington, DC?"*Transportation Research Record: Journal of the Transportation Research Board* 2534 (2015): 1-9.

6.1 Introduction to the Direct Ridership Model

The Direct Ridership Model (DRM), as its name shows, aims to predict rail transit ridership at the station level. It provides an alternative to the traditional four-step travel demand model that estimates ridership based on activities at the level of Transportation Analysis Zone (TAZ). The DRM is built on study findings on the factors of rail transit ridership, including transit service on the line and station, the socio-demographic characteristics of people living and working near stations, and the built environment features. In this section, I review the literature on their impacts and the application of DRM in transit planning, followed by a highlight of the model's advantages.

First, transit service, including hours of operation, train headway/frequency, speed/travel time, availability of seats/train crowdedness, the reliability of schedules, fare, and safety, is one of the determining factors of rail transit ridership. According to a recent survey of rail transit riders, "service frequency and travel time are of paramount importance" (Transit Center, 2016). This finding was confirmed by empirical studies. Evans (2004) found that, on average, a one percent service frequency change, despite the direction, is associated with 0.5% ridership change. In the Boston case study, as commuter rail frequency increased, the system attracted 1,441 new riders, 64% of whom switched from driving, 15% from carpooling, and 19% from the bus (Evans, 2004). Taylor et al. (2009) found that transit fares and service frequency have significant impacts on ridership. Transit fare has a negative impact, and service frequency has a positive impact, both at very high confidence level (p-value < 0.0001) (Taylor, Miller, Iseki, & Fink, 2009). Parking availability at activity destinations and parking cost was found to be associated with rail transit ridership. A survey of downtown Portland employees on the impact of increased parking costs on mode share found that 12% of commuters who drove alone to work switched to transit with the assistance of discounted transit benefits (Bianco, 2000).

Second, the socio-demographics of people who live and work in rail transit station areas were found to be critical to ridership. Population and jobs are two major socio-demographic measures found in empirical studies. Their strong influence on rail ridership was first studied a half century ago. Quoted from Cervero and Guerra's publication, Meyer, Kain, and Wohl (1965) addressed density's importance; "nothing is so conducive to the relative economy of rail transit as high volumes and population density" (Cervero & Guerra, 2011; Meyer, Kain, & Wohl, 1966). In their comparison study, Pushkarev and Zupan (1977) found that high density (between 7 and 30 dwellings per acre) was necessary for high transit use (Pushkarev & Zupan, 1977).[15] Cervero and Guerra (2011) compared the capital costs of 59 U.S. rail transit investment projects with population and job density and found that to achieve a high cost-effectiveness, the average population density for light-rail system needs to reach 30 people per gross acre; for a heavy rail system, 45 people per gross acre. They define high cost-effectiveness as $0.58 per passenger mile (Cervero & Guerra, 2011).

The literature also suggests that the built environment plays a role attracting commuters to taking trains. The characteristics of the built environment are sometimes referred to as the 5*D*s: density (of development), diversity (of activities), design (of public space), destination accessibility, and distance (to rail transit stations) (Ewing & Cervero, 2010). Early survey studies found that 27% to 45% of residents living near rail transit stations commute by rail transit in different cities and areas (Cervero, 1994, 2004, 2007).

[15] I did not read the original book. Findings were based on David Printchard's reading notes on Pushkarev and Zupan (1977). The reading notes were accessed from this link: http://davidpritchard.org/sustrans/PusZup77/

Boarnet and Crane (2001) found that the built environment changes travel behavior by influencing travel speed and distance (Boarnet and Crane 2001b, 224). Ozbill, Peponis, and Bafna (2009) found that accessible street lengths from a rail transit station within a ½-mile radius to be a significant factor, after controlling for transit service and other built environment measures (Ozbil, Peponis, & Bafna, 2009). The built environment's impacts on rail transit ridership have inspired urban designers to create high-density and mixed-used Transit-Oriented Development (TOD) at rail transit stations (Calthorpe, 1993).

Rather than analyzing the impact of each group of factors, more researchers conducted studies to include factors of all three categories at one time. Kuby, Barranda, and Upchurch (2004) pooled data from 268 stations in nine U.S. cities and tested the impacts of 17 factors. They found 12 independent variables significantly associated with rail transit ridership. Among them, several transit service factors, including the availability of park-and-ride service, bus connections, whether a station is a terminal and/or transfer are found to be positively associated with rail transit ridership. The only service factor that has a negative relationship with ridership is centrality, a measure of a station's relative location in the system. In terms of socio-demographic variables, the total number of jobs and population, as well as the percentage of renters, is positively associated with rail transit ridership. Built environment variables, distance to airports and whether the station is located at a jurisdiction border, are also found to be positive (Kuby, Barranda, & Upchurch, 2004).

Chu (2004) studied factors of rail transit ridership in Florida, and his results show more socio-demographic influences on ridership. The share of people under 18 who live in the catchment is negatively associated with ridership, while the share of the senior population has a positive impact. Interestingly, results also show that females tend to take more rides. The share of the Hispanic population has huge influence; a 1% share increase leads to 5.3 more weekday total boardings. The share of the white population is negatively related to transit ridership. In addition, the median household income of people living in a station catchment was found to be negatively associated with ridership. These results may suggest that in Florida minority and lower-income groups tend to use rail transit more (Chu, 2004).

In a study of Bay Area Rapid Transit (BART) ridership (a heavy rail system), among multiple predictive models with different measures of ridership and in different formats (such as log-log), the authors found that the model presented in multiplicative, log-log form was the best fit. In that model, employment and population density were positively associated with ridership, with elasticities of 0.2 and 0.5, respectively. Feeder bus service density was also a strong predictor and a 1% increase in feeder bus service per square mile of the catchment is positively associated with a 35% ridership increase. Transit fare to CBD has a negative impact with an elasticity of -0.4 (Parsons Brinckerhoff et al., 1996).

Guerra, Cervero, and Tischler (2011) pooled data from 832 heavy rail stations, 589 light rail stations, and 36 bus rapid transit stations and quantified the factors' impact. All three categories—service, socio-demographics, and the built environment—were found to be significant. Transit service measures (park-and-ride spaces, feeder bus service and frequency), built environment factors (distance to CBD), and socio-demographic variables (population and jobs) were all found to be positively significant at 99% (Guerra, Cervero, & Tischler, 2011).

Liu et al. (2014) studied rail transit in Maryland (which includes some WAMTA rail transit stations) and found that transit service factors have a strong association with ridership. Being a terminal station, feeder bus service, and level of service was found to positively influence ridership. Distance to CBD has a negative yet significant impact. The number of jobs within a ½-mile radius has a small but significant impact. However, population density was not found to be significant, partly due to the high proportion of commuters who drive to rail transit stations (Liu, Erdogan, Ma, & Ducca, 2014).

Different factors affect light rail and commuter rail differently. A Transit Cooperative Research Program (TCRP) report separated light rail and commuter rail and studied the impact of the built environment and socio-economic factors. Population density, the number of jobs in CBD, feeder bus connections to rail transit stations, and parking availability were positively associated with the ridership of both rail modes. Distance to CBD also was associated with the two modes, but the relationship was log-linear for light rail and quadratic for commuter rail. Income affected the ridership of commuter rail ridership, but not of light rail (Parsons Brinckerhoff et al., 1996).

Whether factors are found to be associated with rail transit ridership and how big or small the relationship largely depends on the study's object and scale, as demonstrated by a series of studies by Thompson and Brown as well as others conducted by collaborated researchers. Thompson and Brown (2006) performed multivariate regression analysis to explain the variation in ridership change between 1990 and 2000, and found different factors for differently-scaled metropolitan areas. In general, population change, service frequency change, and service coverage change offer the best explanation for the variation. For medium-sized MSAs, defined as those with a population between 1 million and 5 million, two factors, service coverage and frequency were found positively associated with rail ridership. For small-size MSAs with a population less than 1 million, multi-destination (or so-called decentralization) was found to have the strongest explanatory power (Thompson & Brown, 2006). In that vein, Brown and Neog (2012) studied the impact of decentralized layout on rail transit ridership in metropolitan areas larger than 500,000 persons in 2000. They found no statistical association between the strength of the CBD and ridership measured in passenger kilometers (per capita). However, they did find other factors have significant impacts on rail transit ridership, including service frequency, service coverage, percent of MSA households that don't own cars, and the unemployment rate (Brown & Neog, 2012). When looking at the Atlanta metropolitan area, Brown and Thompson (2008) found that decentralization was positively associated with the ridership on the regional rail transit system. They found that employment outside the CBD but within the rail transit service area positively influences ridership, with an elasticity of 1.331. In addition, rail service and fare also significantly affect ridership(Brown & Thompson, 2008). Therefore, studies using data for transit systems in large metropolitan areas and in small areas may end up with different results.

Findings of prior studies on transit service, socio-demographics, and built environment are summarized in Table 27, Table 28, and Table 29.

Table 27 Literature Review Findings Summary Table —Transit Service Factors

	Transit service								
Paper/Factor	Feeder bus	Parking availability	Terminal	Transfer	Fare	Operating speed	Frequency	Service coverage	Regional transit connection
(Parsons Brinckerhoff et al., 1996) (pooled study)	+	+	+						
(Parsons Brinckerhoff et al., 1996) (BART system)	+				-				
(Concas & DeSalvo, 2014)[16]									
(Pushkarev & Zupan, 1977)									
(Casello, 2007)					-	-			
(Brown & Neog, 2012)							+	+	
(Brown & Thompson, 2008)					-				
(Guerra & Cervero, 2010)		+					+		
(Ozbil et al., 2009)		+		+					
(Cervero & Guerra, 2011)	+	+	+				+		+
(Evans, 2004)	+			+	-		+		
(Chu, 2004)									

[16] Three models are built in this publication. Included in the table are results from the third model, *Endogenous Trip-Chaining, Activity Space, Transit Demand, Residential Location, and Density*. Please read the original publication for details.

Table 28 Literature Review Findings Summary Table — Socio-Demographic Factors

	Socio-demographics							
Paper/Factor	Income	Households with no car	Unemployment rate	People under 18	Senior population	Female population	Hispanic	White
(Parsons Brinckerhoff et al., 1996) (pooled study)	+							
(Parsons Brinckerhoff et al., 1996) (BART system)								
(Concas & DeSalvo, 2014)[17]								
(Pushkarev & Zupan, 1977)								
(Casello, 2007)								
(Brown & Neog, 2012)		+	-					
(Brown & Thompson, 2008)								
(Guerra & Cervero, 2010)								
(Ozbil et al., 2009)								
(Cervero & Guerra, 2011)								
(Evans, 2004)								
(Chu, 2004)	-	+		-	+	+	+	-

[17] Three models are built in this publication. Included in the table are results from the third model, *Endogenous Trip-Chaining, Activity Space, Transit Demand, Residential Location, and Density*. Please read the original publication for details.

Table 29 Literature Review Findings Summary Table — Built Environment Factors

	Built Environment						
Paper/Factor	Employment or density	Population or density	Distance to CBD	Distance to the nearest subcenter	Retail density	Pedestrian environment	Street configuration
(Parsons Brinckerhoff et al., 1996) (pooled study)	+	+	- (light rail) + (commuter rail)				
(Parsons Brinckerhoff et al., 1996) (BART system)	+	+					
(Concas & DeSalvo, 2014)[18]			-	-	+	-	
(Pushkarev & Zupan, 1977)		+					
(Casello, 2007)							
(Brown & Neog, 2012)							
(Brown & Thompson, 2008)	+						
(Guerra & Cervero, 2010)	+	+					
(Ozbil et al., 2009)		+	+				+
(Cervero & Guerra, 2011)	+	+	+				
(Evans, 2004)							
(Chu, 2004)	+						

Note: Methodologies and models/estimators varied for literature. Please read the original publications for details.

[18] Three models are built in this publication. Included in the table are results from the third model, *Endogenous Trip-Chaining, Activity Space, Transit Demand, Residential Location, and Density*. Please read the original publication for details.

Findings on transit service, socio-demographics, and built environment measures may be associated with rail transit ridership and lead to the development of a ridership prediction model at the station level. This direct demand model was used at least since the 1980s and recently was called the Direct Ridership Model (DRM). A 1996 TCRP report co-authored by Parsons Brinckerhoff, Cervero, Howard/Stein-Hudson, and Zupan, used data from 261 light rail stations across 19 lines in 11 metropolitan areas, and 550 commuter rail stations across 47 lines in six metropolitan areas to quantify the effect of each factor on ridership by mode. The models, as stated in the report, "bypass the usual four-step travel demand modeling process with a simplified approach that estimates transit demand directly, incorporating trip generation, mode choice, trip distribution, and trip assignment features" (Parsons Brinckerhoff et al., 1996). Several studies reviewed in the last subsection also covered the topic of DRM.

The DRM has several advantages. First, it provides analysis at a much more fine-grained scope, which is different from the conventional four-step transportation demand model. The transportation demand model inputs data at the Traffic Analysis Zone (TAZ) level, with zone sizes that range from block groups to census tracts. Some find that this approach "tend(s) to be too gross to pick up fine-grained design and land-use-mix features of neighborhood-scale initiatives" (Cervero, 2006; Duduta, 2013). The DRM measures at the rail transit station level, usually within a ¼- to ½-mile radius of the station entrance, which is smaller than a TAZ.

The second advantage is DRM's responsiveness to Transit-Oriented Development (TOD) at station areas. TOD, which is usually high-density, mixed-use development, attracts millennial population who commute by rail transit. DRM can capture micro-level changes in land use and population to provide precise and quick-response transit ridership predictions (Cervero, 2006; Fehr & Peers, 2005). In addition, due to its size, DRM is much less costly than transportation demand model (Cervero, 2006).

6.2 Methodology and Data

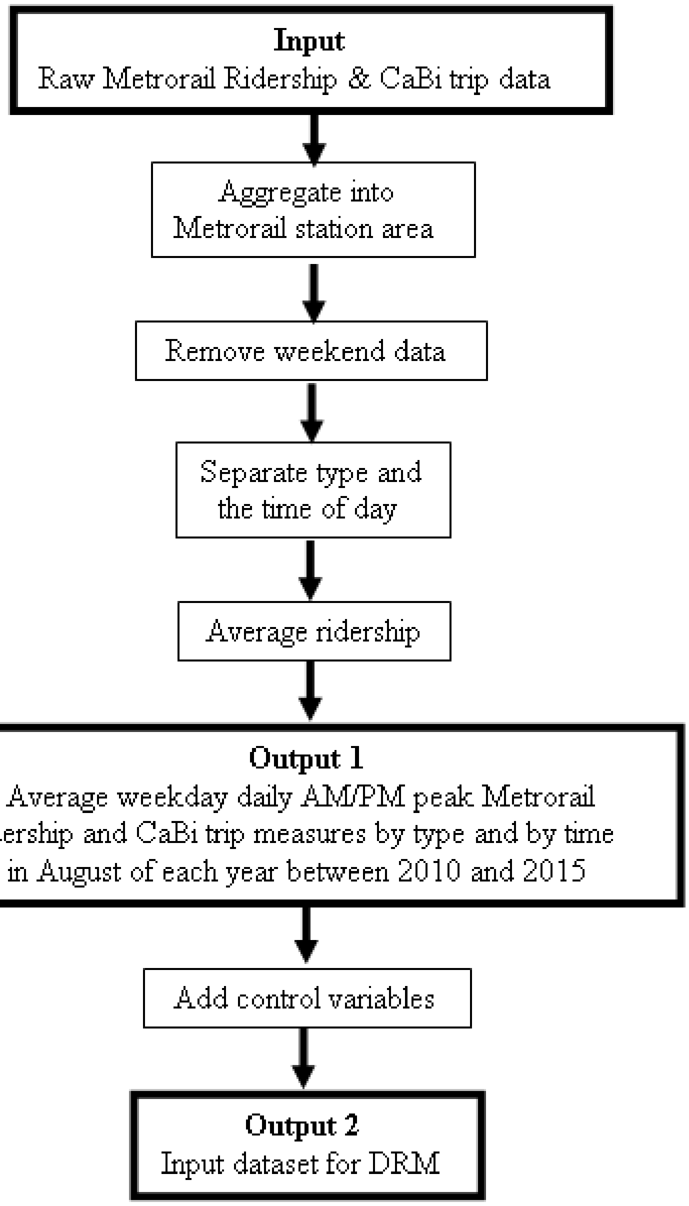
The Direct Ridership Model regression can be expressed as the results of CaBi trips, transit service, socio-demographics, and built environment variables, as shown in Equation (2). CaBi trips are further split into the number of trips starting from the station areas and the number of trips ending in the station areas.

$$\mathrm{R}_i = \alpha + \beta_1 CaBistart_i + \beta_2 CaBiend_i + \sum_{m=1}^{M} \gamma_m transit\ service_{mi} + \sum_{n=1}^{N} \delta_n socio\ demgraphics_{ni} + \sum_{k=1}^{K} \theta_k built\ environment_{ki} + e \quad (2)$$

Here, *i* indexes Metrorail stations with CaBi installed nearby, and R_i is a measure of the number of riders at station *i*. The terms *transit service*, *socio-demographic*, and *built environment* contain groups of factors of service features, of people living and working in the station areas, and of the physical environment. Their coefficients γ_m, δ_n, and θ_k are assumed to be constant across the years due to data limitations.

The data preparation process is illustrated in Figure 47. Original Metrorail and CaBi trips are first aggregated to a Metrorail station area, defined as a ¼-mile radius. Weekend trips are removed to focus on commuting trips. Both Metrorail and CaBi trips are further split into four measures, reflecting the type and the time of day (AM and PM peak). To eliminate weather impacts, I calculate the average ridership, rather than using the original daily AM/PM trips, and only keep trips made in August.

Figure 47 DRM Data Preparation Process



Therefore, Equation (2) can be specialized into Equation (3), (4), (5), and (6), each with one of four Metrorail ridership measures as the dependent variable:

$$mentryam_i = \alpha + \beta_1 cstartam_i + \beta_2 cendam_i + \sum_{m=1}^{M} transit\ service_{mi} * \gamma_m + \sum_{n=1}^{N} socio\ demgraphic_{ni} * \delta_n + \sum_{k=1}^{K} built\ environment_{ki} * \theta_k + \varepsilon_i \quad (3)$$

$$mexitam_i = \alpha + \beta_1 cstartam_i + \beta_2 cendam_i + \sum_{m=1}^{M} transit\ service_{mi} * \gamma_m + \sum_{n=1}^{N} socio\ demgraphic_{ni} * \delta_n + \sum_{k=1}^{K} built\ environment_{ki} * \theta_k + \varepsilon_i \quad (4)$$

$$mentrypm_i = \alpha + \beta_1 cstartpm_i + \beta_2 cendpm_i + \sum_{m=1}^{M} transit\ service_{mi} * \gamma_m + \sum_{n=1}^{N} socio\ demgraphic_{ni} * \delta_n + \sum_{k=1}^{K} built\ environment_{ki} * \theta_k + \varepsilon_i \quad (5)$$

$$mexitpm_i = \alpha + \beta_1 cstartpm_i + \beta_2 cendpm_i + \sum_{m=1}^{M} transit\ service_{mi} * \gamma_m + \sum_{n=1}^{N} socio\ demgraphic_{ni} * \delta_n + \sum_{k=1}^{K} built\ environment_{ki} * \theta_k + \varepsilon_i \quad (6)$$

CaBi is not the only and probably not the most significant determinant of Metrorail ridership. A literature review suggests many variables that can be included in the DRM. However, what data to include in this study largely depends on their availability. As Table 30 shows, transit service measures include the number of trains per hour, the number of parking spaces provided in WMATA's facilities, the number of bus stops within ¼-mile of Metrorail station, and whether the station is a transfer or terminal station, a total of five variables. Socio-demographic variables include job density, housing unit density, and the share of renters in the station area (renters are likely to commute by public transportation).[19] Built environment variables include employment mix and road density. For consistency, all these data are transformed into the Metrorail station or station area level. Below I introduce data and computation method for each control variable.

The number of trains per hour passing the station, *tph*, captures the transit service supply capacity. The data was converted from Metrorail AM/PM-peak headways (in minutes) using data accessed from WMATA website.[20] Equation (7) shows the method, with *l* indicating six Metrorail lines since they have different scheduled headways. It is expected that the larger *tph* a station has, the more commuters take trains at that station.

$$tph = \sum_{l=1}^{6} \frac{60}{headway_l} \quad (7)$$

Variables *terminal* and *transfer* indicate whether a station is a terminal, or whether it is a transfer station. Data was accessed from WMATA api, using Python data analysis libraries.[21] Terminal stations are expected to have more entries in the morning and exits in the evening, but fewer exits in the morning and entries in the evening, given the Washington metropolitan area's monocentric spatial structure with jobs located in downtown D.C. and commuters living in suburban communities. Conversely, transfer stations are usually in between downtown and terminal stations and assist commuters' transfer between two Metrorail lines. Thus, we would expect to see fewer people entering or exiting at transfer stations.

[19] I also considered other socio-demographic variables including the percentage of white population, the percentage of households with zero cars, and the education level. However, their preliminary results are not statistically significant and signs not as expected. Therefore, I did not include them in the final version of regression input.
[20] The link for Metrorail headway data is: https://www.wmata.com/schedules/timetables/index.cfm.
[21] The link for WMATA api is: https://developer.wmata.com/.

The number of parking space available in WMATA facilities, *parkct*, and the number of bus stops at the station area, *bus*, capture the share of Metrorail riders who drive or take the bus to access stations. Data on parking spaces comes from WMATA api. The number of bus stops at station area was computed in ArcGIS, using bus stop location information accessed from WMATA's General Transit Feed Specification(GTFS).[22]

Variables *jobden* and *huden* represent the number of jobs and housing units per acre of unprotected land at the station area. Data was prepared by the Environment Protection Agency (EPA) in its 2013 Smart Location Database (SLD), using data from the Census and other sources. Jobs and housing units at the station area show the commuting demand. The higher job density is likely to be associated with a larger number of AM exits and PM entries while the higher housing unit density is likely to be related to the larger number of AM entries and PM exits. Rental apartments tend to have a different location preference, compared to single family housing units. The share of renters, *rentp*, reflects the diversity and dynamics of development at the station area. We would expect to see a positive association between it and Metrorail ridership in all four measures. Data of *rentp* comes from the American Community Survey (ACS) 2010-2014 5-year estimate. Note that the ACS 5-year estimates should not be interpreted "for any specific day, period, or year within the multiyear time period"(U.S. Census Bureau, 2008). Therefore, the share of renters is assumed to be constant over the years.

Built environment variables *mix* and *roadden* represent the land use mix and the density of roads. Both data come from EPA's SLD database. The land use mix is calculated as the sum of entropies of five employment categories in the block group compared to the

[22] The link to WMATA's GTFS is: https://www.wmata.com/about/developers/.

area. Road density is in the unit of miles per square mile. Based on the literature, we would expect to see them having positive impacts on ridership.

It is worthwhile to point out that data for control variables are not time-variant. Transit service data collected from WMATA website represents the most recent situation. EPA's SLD was prepared one time in 2013, and thus data for the built environment variables and some socio-demographic measures are for that year only. Also, the ACS 5-year estimates represent the condition for the whole five years and can not be interpreted for a specific period of time within the five years. Since the control variables are not time varying, the Pooled OLS (POLS) regression method is used.

Table 30 Input data of the Direct Ridership Model

Dependent variables					
Category	Variable	Definition	Data Source	Geography	Year
Metrorail ridership	*mentryam*	The number of commuters that enter Metrorail station during weekday AM peak	WMATA	Metrorail station	2010-2015
	mexitam	The number of commuters that exit Metrorail station during weekday AM peak	WMATA	Metrorail station	2010-2015
	mentrypm	The number of commuters that enter Metrorail station during weekday PM peak	WMATA	Metrorail station	2010-2015
	mexitpm	The number of commuters that exit Metrorail station during weekday PM peak	WMATA	Metrorail station	2010-2015
Independent variables					
Category	Variable	Definition	Data Source	Geography	Year
CaBi trip number	*cstartam*	The number of CaBi trips starting from Metrorail station area during weekday AM peak	CaBi	Metrorail station area	2010-2015
	cendam	The number of CaBi trips ending at Metrorail station area during weekday AM peak	CaBi	Metrorail station area	2010-2015
	cstartam	The number of CaBi trips starting from Metrorail station area during weekday PM peak	CaBi	Metrorail station area	2010-2015
	cendam	The number of CaBi trips ending at Metrorail station area during weekday PM peak	CaBi	Metrorail station area	2010-2015
Transit service	*tph*	Number of trains per hour	WMATA	Metrorail station	2017
	terminal	Whether the station is a terminal	WMATA API	Metrorail station	2016
	transfer	Whether the station is a transfer	WMATA API	Metrorail station	2016
	parkct	The number of parking space available	WMATA API	Metrorail station	2016
	bus	The number of bus stops at station area	WMATA GTFS	Metrorail station area	2016
Socio-demographics	*jobden*	The number of jobs per acre of land that is not protected from development	ACS, SLD[23]	Metrorail station area	2013

[23] Job data from American Community Survey 2010-2014 5-year estimates, unprotected land data from Smart Location Database (original data from Census, Navtep parks, PAD-US)

	huden	The number of housing units that is not protected from development	ACS, SLD[24]	Metrorail station area	2013
	rentp	The share of renters among all population	ACS	Metrorail station area	2010-2014 5-year estimate
Built environment	*mix*	Employment entropy variable based on the 5-tier employment categories from LEHD	SLD	Metrorail station area	2013
	roadden	Length of roads per acre	SLD[25]	Metrorail station area	2013

[24] Housing unit data from American Community Survey 2010-2014, unprotected land data from Smart Location Database (original data from Census, Navtep parks, PAD-US)
[25] Smart Location Database (road network from NAVSTREETS)

Table 31 presents the descriptive statistics of all variables. In total, there are 526 observations, including 86 stations for years between 2010 and 2013, and 91 stations for 2014 and 2015. The increase in station numbers was due to the opening of Silver Line stations in July 2014. Among them, 184 Metrorail stations have CaBi docking stations installed within ¼-mile.

Table 31 Descriptive Statistics of Input Data of The Direct Ridership Model

Variable	Obs	Mean	Std. Dev.	Min	Max
mentryam	526	2,525.1	1,870.4	16.2	9,631.2
mexitam	526	2,297.8	3,251.5	102.1	14,201.0
mentrypm	526	2,829.2	3,505.2	141.6	15,969.0
mexitpm	526	2,745.1	1,874.4	251.0	11,258.7
cstartam	526	6.4	15.7	0.0	163.4
cendam	526	9.9	25.3	0.0	171.9
cstartpm	526	14.5	34.0	0.0	201.2
cendpm	526	11.7	26.0	0.0	193.9
tph	526	17.0	8.0	5.0	45.0
parkct	526	686.6	1262.1	0.0	5,745.0
transfer	526	1.6	0.9	1.0	5.0
terminal	526	0.1	0.3	0.0	1.0
bus	526	12.5	9.9	0.0	48.0
jobden	526	49.5	79.6	0.1	345.2
huden	526	0.8	0.6	0.0	2.3
rentp	526	0.5	0.2	0.2	1.0

6.3 Results

Table 32 reports the results of the DRM specification described in equations (2), (3), (4), and (5), estimated using OLS regression. These equations have different Metrorail ridership measures as the dependent variables, which are *mentryam*, *mexitam*, *mentrypm*, and *mexitpm* respectively. The tables include the coefficients of each variable, their p-values, and the R-squared values indicating the model's explanatory power. The signs and values of coefficients of CaBi trip variables indicate whether CaBi poses a positive or negative impact and how big the impact is. At first glance, CaBi's impacts on Metrorail ridership are mixed since coefficients' signs and values vary. Findings on control variables are consistent with previous studies that transit service, socio-demographics and built environment features impact rail transit ridership.

First, CaBi can complement Metrorail. Specifically, one unit of CaBi trip increase starting from Metrorail stations in the AM peak, or *cstartam*, is positively associated with 49.1 exits from Metrorail stations. Also, one unit of CaBi trip increase ending at Metrorail stations in the PM peak, or *cendpm*, is positively associated with 57.9 entries into Metrorail stations. Both relationships are statistically significant at the 0.000 level. One likely explanation is that in the morning, commuters who complete their Metrorail rides check out bikes at CaBi docking stations nearby and bike to their workplaces. After work, they use CaBi to access Metrorail stations and then take trains home. Therefore, CaBi solves the gap between Metrorail stations and commuters' workplaces and attracts more people taking Metrorail, which is consistent with Scenario 3 and Scenario 6 in Chapter 5.

Second, CaBi can have negative impacts on Metrorail ridership. One unit of CaBi trip increase ending at Metrorail station areas in the morning (*cendam*) is negatively associated with 16.8 Metrorail AM exits (*mexitam*). Also, one unit of CaBi trip increase starting near Metrorail stations in the PM peak (*cendpm*) is negatively associated with 37.4 entries into Metrorail stations (*mentrypm*). Both are statistically significant. Results show that CaBi rides may replace some Metrorail trips. These two relationships are consistent with Scenario 4 and Scenario 5 in Chapter 5.

Third, the positive relationships between *cstartam* and *mentryam* and between *cendpm* and *mexitpm* suggest that CaBi docking stations were installed at Metrorail stations with large riderships. If we separate Metrorail stations into two groups, the group with CaBi nearby may systematically have more passengers than the group without CaBi. In other words, $CaBistart_i$ and $CaBiend_i$ in Equation (1) are likely to be correlated with the error term ε_i and lead to a biased estimate.

Fourth, comparing the R-squared value, we see that regressions with *mexitam* and *mentrypm* as the dependent variables have an R-squared larger than 0.8, suggesting that more than 80% of observations can be explained by the DRM model. The remaining two regressions (with *mentryam* and *mexitpm*) as the dependent variables have an R-squared of about 0.5.

Table 32 Results of the DRM

mentryam			*mexitam*			*mentrypm*			*mexitpm*		
	Coef.	P		Coef.	P		Coef.	P		Coef.	P
cstartam	36.0*	0.000	*cstartam*	49.1*	0.000	*cstartpm*	-37.4*	0.000	*cstartpm*	-35.0*	0.000
cendam	-9.8*	0.030	*cendam*	-16.8*	0.000	*cendpm*	57.9*	0.000	*cendpm*	57.0*	0.000
tph	56.9*	0.000	*tph*	138.6*	0.000	*tph*	180.8*	0.000	*tph*	81.6*	0.000
parkct	1.0*	0.000	*parkct*	0.5*	0.000	*parkct*	0.6*	0.000	*parkct*	0.9*	0.000
transfer	-410.0*	0.001	*transfer*	-256.0	0.043	*transfer*	-385.9*	0.005	*transfer*	-509.6*	0.000
terminal	683.4*	0.029	*terminal*	-1151.9*	0.000	*terminal*	-1292.5*	0.000	*terminal*	448.7	0.177
bus	24.5*	0.004	*bus*	58.5*	0.000	*bus*	61.9*	0.000	*bus*	44.8*	0.000
jobden	-4.4*	0.000	*jobden*	22.8*	0.000	*jobden*	22.7*	0.000	*jobden*	-2.1	0.126
huden	366.8*	0.010	*huden*	-1438.2*	0.000	*huden*	-1222.7*	0.000	*huden*	287.7	0.051
rentp	785.0*	0.042	*rentp*	2688.0*	0.000	*rentp*	2953.4*	0.000	*rentp*	1636.7*	0.000
mix	-323.3	0.394	*mix*	495.3	0.193	*mix*	809.1	0.055	*mix*	419.2	0.302
roadden	31.2*	0.018	*roadden*	79.0*	0.000	*roadden*	86.5*	0.000	*roadden*	42.5*	0.003
_cons	-38.6	0.929	*_cons*	-4324.3*	0.000	*_cons*	-5026.7*	0.000	*_cons*	-1412.3*	0.003
		R2= 0.552			R2 = 0.851			R2 = 0.844			R2 = 0.495
* Statistically different from zero at 5% significance level											

DRM regression results also confirm that transit service, socio-demographics, and built environment factors play roles in rail transit ridership. Regarding transit service, the number of trains passing Metrorail stations per hour is positively associated with four Metrorail ridership measures. An additional one train per hour would increase ridership by up to 180.8. It demonstrates that transit service supply can significantly increase ridership.

The number of parking spaces provided by WMATA is positively associated with four Metrorail ridership measures. One parking space's impacts range between 0.5 and 1.0 ridership. Providing more parking spaces would increase the number of AM entries and the number of PM exits in larger magnitudes, suggesting that many commuters combine driving and Metrorail to complete their trips.

Being a transfer station or a terminal station has different effects on Metrorail ridership. Transfer stations have reduced entries and exits. But being a terminal station is positively associated with the number of AM entries and the number of PM exits. Terminal stations are likely to be near commuters' residences. Therefore, they serve as origins in the morning and destinations in the evening.

The availability of other public transportation in Metrorail station areas has positive impacts on the station's ridership. As results show, one bus stop in a Metrorail station area has the potential to increase up to 61.9 Metrorail rides. The small P-values in all four regressions mean that bus stops' influences are statistically significant. The finding may suggest that many commuters would combine Metrorail and other public transportation modes to complete their trips.

Socio-demographics of people who live and work in Metrorail station areas are also significantly associated with Metrorail ridership. The density of jobs within ¼ mile positively affects the number of Metrorail AM exits and PM entries. However, the density of housing units in the station area is negatively associated with Metrorail ridership measures *mexitam* and *mentrypm*. Putting them together, we could see that the Washington metropolitan area has a job-housing mismatch that results in a large number of commuting trips. Residential areas, which are likely to be suburban communities with a high density of housing units, serve as origins in the morning. The higher the housing unit density, the more Metrorail AM entries are generated. Metrorail rail stations near workplaces with a high density of jobs, such as downtown D.C., experience high passenger volumes exiting the stations in the morning. The higher the job density in workplaces, the more Metrorail AM exits.

Housing units here refer to single-family houses. However, since the Washington metropolitan area has the nation's highest cost of living, many people live in apartments. Unlike housing unit density, renter density is positively associated with all four Metrorail ridership measures. One possible explanation is that apartments are located in both suburban communities and in downtown D.C. In some cases, apartments are in Transit-Oriented Development areas. Thus, Metrorail stations near apartments can be both origins and destinations and have high volumes of entries and exits.

Built environment characteristics are mostly positively associated with Metrorail ridership. A higher level of mixed land uses increases activity in the station areas, thus making them safe and vibrant. The higher road density improves accessibility to Metrorail stations and attracts pedestrians to use Metrorail. They both boost Metrorail ridership.

However, it is puzzling why the coefficient values of CaBi trip variables are so large. Common sense says that not all CaBi activities are related to Metrorail rides so we would expect to see that one CaBi trip would lead to less than one Metrorail ride. But coefficients of CaBi trip variables range from -37.4 to -9.8 for negative impacts and from 36.0 to 57.9 for positive impacts. The coefficients suggest that one CaBi trip is associated with at least nine Metrorail rides, which sounds unrealistic. I came up with three possible explanations. The first possibility is the omitted variables, which means variables included in the DRM fail to capture all Metrorail ridership factors and lead to an overestimation of CaBi's effect. Another possibility could be the unmatched scales between CaBi trip numbers and Metrorail ridership. As Table 31 shows, on average there are ten CaBi trips starting or ending at each Metrorail station area, while per station, Metrorail ridership is 2,500. Also, the standard deviation of Metrorail ridership is about 200 times that of CaBi trips. Therefore, the estimated impacts of each CaBi trip are much larger than expected.

Besides the finding that coefficients are too large, the DRM method has two limitations. First, the DRM model is the Ordinary Least Square (OLS) estimator and thus all OLS assumptions still apply here. However, which Metrorail stations have CaBi installed is not randomly selected; as introduced in Chapter 3, the selections are based on crowdsourcing and strategic planning. Therefore, in Equation (1), $CaBistart_i$ and $CaBiend_i$ are likely to be correlated with the error term ε_i, and violates assumptions of the best linear unbiased estimator (BLUE).

Second, the estimator used in the DRM is Pooled OLS (POLS), which treats all Metrorail stations in different years as if they are cross-sectional data. It has ignored the panel structure of the original dataset, and assumed that observations are serially uncorrelated. However, the factor of time may have played a key role in this study because

CaBi is a newly launched program that has been expanding in recent years. Therefore, alternative research methods with the capacities to deal with panel data are highly desired.

6.4 Summary

The Direct Ridership Model is a common method of estimating rail transit ridership at the station level. The current DRM considers transit service features, socio-demographics of people living and working in the station areas, and characteristics of the built environment. In this Chapter, I expanded the model to include bike share trip variables to analyze how CaBi influences Metrorail ridership.

Results are mixed. CaBi can complement some Metrorail trips, but substitute for others. The number of CaBi trips starting from Metrorail stations is positively associated with the number of passengers exiting the stations in the morning, and the number of CaBi trips ending at station areas is positively associated with the number of Metrorail entries in the after-work commuting peak. They demonstrate CaBi's complementary effects and suggest that CaBi solves the connection gap between Metrorail stations and workplace. On the other hand, the negative relationship between the number of CaBi trips ending at a station area and Metrorail exits in the AM peak, and between the number of CaBi trips starting at station area and Metrorail entries in the PM peak suggest that CaBi may also replace Metrorail trips and thereby reduce ridership. Putting them together, we see that CaBi's impacts are mixed. Since the complementary effects are statistically significant, we can reject the hypothesis that CaBi only replaces Metrorail.

However, the DRM has its limitations. Coefficients are found to be too large, which might be caused by the omitted variable. Also, Metrorail stations that have CaBi installed nearby is not a random selection and violates the critical assumption for a best linear unbiased estimator (BLUE) OLS estimator. Finally, the DRM took the pooled data as input and ignored that the original dataset is panel data. Therefore, though the DRM provides useful insights, sophisticated regression models that can handle panel data and the quasi-experimental research environment are highly desired.

Chapter 7: Difference-in-Difference Analysis

As discussed in Chapter 5, the Direct Ridership Model is based on a random-assignment assumption. It assumes that Metrorail stations that have CaBi docking stations installed are randomly selected, and thus the unobservable determinants of Metrorail ridership change would not be correlated with the installation of CaBi docking stations. If we separate Metrorail stations into two groups: the treatment group, which are Metrorail stations with CaBi docks installed nearby and the control group, Metrorail stations that do not have CaBi, we would expect that no difference between the two groups before the treatment was posed. This random-assignment assumption is an ideal research environment, since it allows researchers to cleanly identify CaBi's impacts.

However, pure random selection rarely exists in the fields of urban planning and public policy. As introduced in Chapter 3, the locations of CaBi docking stations are the result of a joint process of crowdsourcing and public transportation agencies' strategic planning. It is very likely that Metrorail stations with CaBi docks installed within ¼ mile differ systematically from those stations without CaBi nearby; they may have larger ridership even in the absence of the CaBi program.

If we call the ideal random-assignment research environment *the natural experiment*, we can call this real but not random environment *the quasi-experiment*. A quasi-experiment is one that lacks the element of random assignment to treatment or control. It has a lower degree of randomization. We could assume there is an internal validity and the treatment and control groups may not be comparable at a baseline. Therefore, the regression analysis method we choose for quasi-experiment will need to reflect the baseline difference between the control and the treatment group.

The Difference-in-Difference (DID) approach is a quasi-experimental technique to overcome the randomization assumption. It admits that the treatment group and the control group have a systematic difference even in the absence of the treatment and seeks to estimate that difference. In this chapter, I apply the DID method to identify the CaBi program's real impacts on Metrorail ridership. I start with a brief introduction to the DID method, including its equations, assumptions, and a literature review of its use in urban studies and transportation research. However, the standard DID form, which has two groups and two time periods, does not apply to my research question and dataset. Therefore, I introduce a specific DID form with multiple groups and multiple periods and apply it to my study. Later, I expand the DID to include transit service, socio-demographics, and built environment characteristics. The chapter ends with a summary of regression analysis findings and a discussion of DID's limitations.

7.1 Standard Difference-in-Difference Model

7.1.1 Equations and Assumptions

The Difference-in-Difference model is built on the concept that there are systematic differences between the control and treatment groups even before policy intervention. Let's denote the control group as C, and the treatment group as T. Or we can use one dummy variable D_T to denote them. When D_T equals 1 it means a treatment group. When D_T equals 0 it is a control group. There are systematic differences between the control and treatment groups, which we can denote as β_1. This systematic difference is cross-sectional, and constant over time.

We also have two periods of time in the quasi-experiments, one pre-policy time, and the other post-policy time. Similarly, let dummy variable D_t denote each time. If D_t equals 1 it refers to post-policy time, and if 0 it refers to pre-policy time.

In addition, we will need the interactive term $D_t \cdot D_T$ to denote the treatment group in the post-policy time. In total, the DID model input is broken down into four groups of data:

- The control group before the experiment: C-before
- The treatment group before the experiment: T-before
- The control group after the experiment: C-after
- The treatment group after the experiment: T-after

These four data groups are separated using combinations of dummy variables. The equation can be expressed as:

$$\mathrm{y} = \beta_0 + \delta_0 D_t + \beta_1 D_T + \delta_1 D_t \cdot D_T + \mu \tag{8}$$

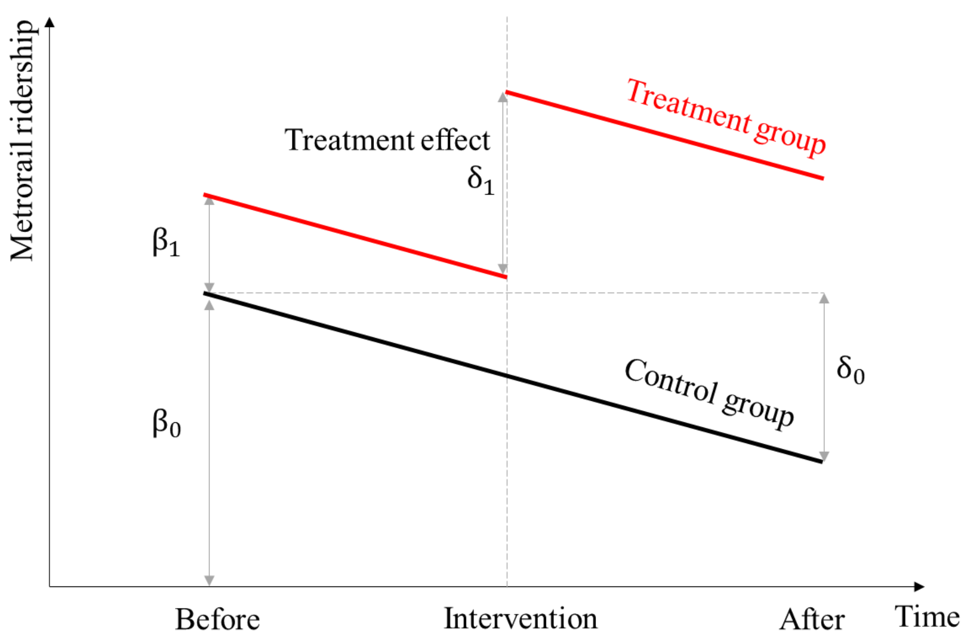
where D_t denotes a dummy variable for the post-policy period t, and D_T for those in the treatment group T. Table 33 illustrates estimators for treatment and control groups in both before and after time periods. The last column is the after-before effect for each group, with δ_1 referring to the difference between the after-before changes of the treatment and control groups, which is the coefficient of interest in the DID analysis (Wooldridge, 2015).

Table 33 Illustration of the DID estimator

	Before	After	After-Before
Control group	β_0	$\beta_0 + \delta_0$	δ_0
Treatment group	$\beta_0 + \beta_1$	$\beta_0 + \delta_0 + \beta_1 + \delta_1$	$\delta_0 + \delta_1$
Difference between treatment and control groups	β_1	$\beta_1 + \delta_1$	δ_1

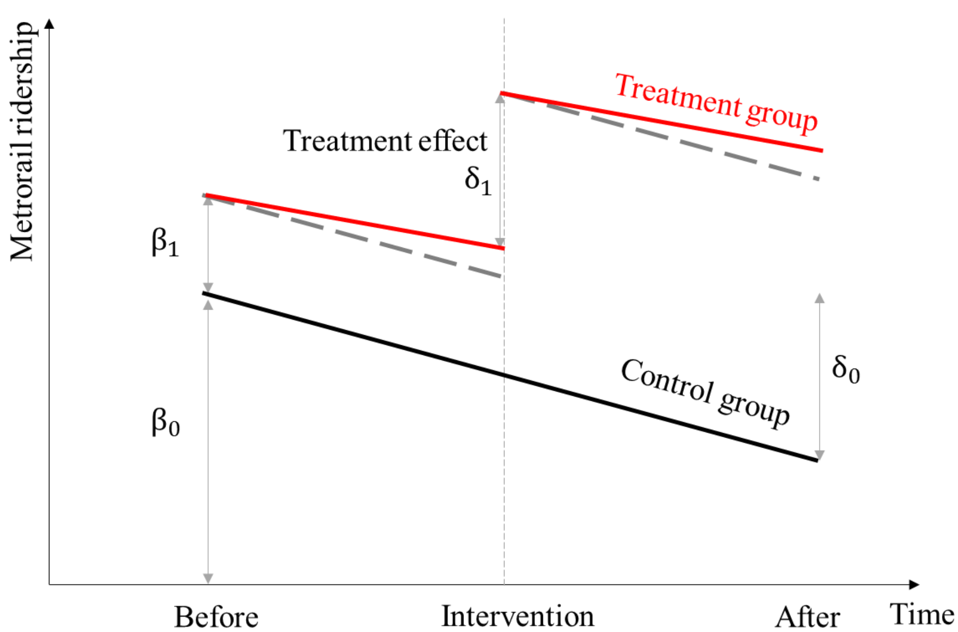
Figure 48 illustrates parameters in the DID estimator. The X-axis measures time, with before and after represented in two time stamps. The Y-axis is the measure of dependent variables. The treatment group and control group are represented by red and black lines. The difference between the two groups is captured by β_1, which is consistent along the time. Over time, control group experiences a growth, as captured by time effect δ_0. If our policy of interest has no impact on treatment group, we could expect the treatment group's growth to follow the control group's pattern, except for the mere location effect. The treatment group's growth under the null policy impact assumption is illustrated by the dotted black line. However, the treatment group is very likely to be affected by the policy of interest, and experiences additional growth. In the diagram, the policy effect is captured by δ_1 in the diagram.

Figure 48 Illustration of the Difference-in-Difference Method



The DID approach relies on the strong assumption that the change in ridership of stations in the treatment and control groups would have been the same if the treatment group remained untreated. As illustrated in Figure 49, the dotted line, which represents the treatment group's outcome growth over time without the CaBi program, should be parallel to the black line. However, if the treatment group's ridership grows at a different rate, the DID estimator will be biased. As illustrated in Figure 49, the actual over-time change of treatment group (under the without-treatment condition) follows the red line, rather than the black dotted line. As illustrated in Figure 49, the actual over-time change of treatment group (under the without-treatment condition) follows the red line, rather than the black dotted line. The estimated treatment effect δ_1 in Figure 49 (non-parallel path scenario) should be smaller than the estimated δ_1 in Figure 48 (parallel path assumption). If we ignore this assumption, we would overestimate CaBi program's treatment effect.

Figure 49 Non-parallel DID



7.1.2 DID in Urban Studies: A Literature Review

According to Imbens and Wooldridge (2007), the work by Ashenfelter and Card (1985) on estimating the effect of the 1976 Comprehensive Employment and Training Act (CETA) on workers' earning made the Difference-in-Difference model popular and widespread (Ashenfelter & Card, 1984; Imbens & Wooldridge, 2007). Since then, DID has been used in quantitative studies using time-series data to measure the impacts of policy programs.

Card and Krueger (1994) performed a DID analysis to quantify how changes in minimum wages affect employment. They looked at fast-food industry jobs in New Jersey where the minimum wage increased in 1992 as the treatment group. Employment in Pennsylvania where there was no increase in the minimum wage at that time was the control group. They used DID to compared the changes before and after the policy (Card & Krueger, 1993).

Abadie, Diamond, and Hainmueller (2010) used DID to analyze the impact of Proposition 99, a large-scale tobacco control program, on tobacco sales in California. California was the treatment group and the rest United States were the control group. Given that locations of states vary, the distance between a state and California was included as a weight to adjust its influence. In addition, the authors introduced an interesting and effective visualization method to show both tobacco sales in a synthetic California, based on model results and on actual sales over the years (Abadie, Diamond, & Hainmueller, 2012).

DID has also been used to study built environment's impact on public health (measured as obesity rate and BMI). In a literature review of methodologies, Martin, Ogilvie, and Suhrcke (2014) found that the Difference-in-Difference model "enables control of unobserved individual differences and common trends" (A. Martin, Ogilvie, & Suhrcke, 2014). Branas et al. (2011) studied the association between safety measures and greening vacant lots using decades-long data. To adjust the fixed effects of the different urban neighborhoods, Branas et al. introduced two interaction terms, one urban section by year interaction to account for geographic variability over time, and the other section by pre-treatment baseline outcome interaction to adjust for regression to the mean. They found that greening vacant properties is associated with a reduction in gun assaults in all four neighborhoods of Philadelphia, and with an additional reduction in vandalism in one neighborhood. In addition, greening vacant lots helps reduce residents' stress levels and increase their exercise. Dill et al. (2014) used DID to analyze whether adding bicycle boulevards is associated with increased physical activity (Dill, McNeil, Broach, & Ma, 2014).

Dríguez-Lesmes, Trujillo, and Valderrama (2014) used DID to analyze the impact of public libraries on students' educational performance. They divided schools into two groups, one close to newly opened public libraries, and the other far away from libraries. They compared the change in test scores of students in schools near libraries before and after the libraries' opening, with the score change of students in schools not near libraries. They found the difference was not statistically significant. Therefore, they concluded that opening public libraries has no impact on educational quality (Rodríguez-Lesmes, Trujillo, & Valderrama, 2014).

Recently, Difference-in-Difference analysis gained popularity in transportation-related studies, particularly for research on the impact of new transit investment, such as light rail. DID can tackle the endogeneity of transit infrastructure allocation (Moreno-

Monroya & Ramosb, 2015). Many scholars have also used DID to estimate the effect of rail transit infrastructure's impact on the real estate market. McDonald and Osuji (1995) used a standard DID in log-normal form to estimate the impact of a new transit line between downtown Chicago and Midway Airport. They found that a 15.4% increase in land values within near transit station can be attributed to the proximity factor (McDonald & Osuji, 1995). Billings (2011) included DID in the hedonic model to estimate new light rail transit's impact on the real estate market in Charlotte, North Carolina and found that LRT increased the price of single-family properties within one-mile by 4%, and condominium prices by 11.3% (Billings, 2011). Similarly, Cao (2016) studied the impact of two stages of light rail investment on the St. Paul real estate market, and found that the announcement of a Full Funding Grant Agreement tended to increase the number of building permits by 24% and the value by 80%; the announcement of preliminary engineering had no positive impacts (Cao & Porter-Nelson, 2016).

Holzer, Quigley, and Raphael (2002) performed DID analysis to study whether extending San Francisco's BART heavy rail system impacted minority employment at companies near new transit stations. They conducted two surveys of business owners—the first before opening and a second, one year after opening. Business owners were divided into two groups, those near a transit station and those far away. The standard DID analysis results showed that opening the BART extension significantly increased the hiring of Hispanic employees, by 20.3%. Then the authors regressed the change in minority employment on a business' distance from a transit station, controlling for factors such as unionized status and firm size, and found again that the distance to station is negatively associated with employers' propensity to hire Hispanics (Holzer, Quigley, & Raphael, 2003). Similarly, to study transit's impact on a minority group, Hess (2016) used DID to analyze light rail's impact on demographic characteristics of nearby neighborhoods. He found that light trail has a negative treatment effect on the share of black residents (Hess, 2016).

Boarnet, Wang, and Houston (2016) studied Los Angeles's newly opened Expo light rail transit line impacts on personal vehicle greenhouse gas (GHG) emissions and found that the opening significantly reduced on average daily CO2 emission from motor vehicles by 3,145g (Boarnet, Wang, & Houston, 2016). DID was also applied to study light rail's impact on other travel behavior measures (Boarnet et al., 2013). Schuetz (2014) studied rail transit's impact on retail activities using DID but found no significant association in three of four MSAs in California and one negative association in the Sacramento MSA (Schuetz, 2014). A more complicated spatial Difference-in-Difference estimator was created by Dube et al. (2014) to decompose the marginal effect to include spatial spillover (Dubé, Legros, Thériault, & Des Rosiers, 2014).

In summary, DID has become a common method to study the real social and economic impacts of new and expanded transit projects by separating both time effect and the difference between control and treatment groups. If longitudinal data is available and a control group can be identified, DID is a preferred method.

7.2 Multiple-Groups-and-Multiple-Periods DID: Methodology and Data

From the perspective of DID, the launch of the CaBi program can be taken as a quasi-experiment. The Metrorail system has been in operation for decades. In 2010, the introduction of CaBi was a policy intervention, or treatment, that has been imposed on selected Metrorail stations. These stations can be labeled as the "treatment group," while the rest are the "control group." Both the treatment and control groups existed before CaBi installation, therefore, besides the "treatment-control" dimension, we also have a "before-after" dimension. Together, four groups result from these two-by-two dimensions:

- The treatment group before the experiment, T-before: Metrorail stations WITH CaBi installed between 2010 and 2015 in the years BEFORE CaBi installation
- The control group before the experiment, C-before: Metrorail stations WITHOUT CaBi installed between 2010 and 2015 in the years BEFORE CaBi installation
- The treatment group after the experiment, T-after: Metrorail stations WITH CaBi installed between 2010 and 2015 in the years AFTER CaBi installation
- The control group after the experiment, C-after: Metrorail stations WITHOUT CaBi installed between 2010 and 2015 in the years AFTER CaBi installation

The equation can be expressed as:

$$\mathrm{R} = \beta_0 + \delta_0 D_t + \beta_1 D_T + \delta_1 D_t \cdot D_T + \mu \tag{9}$$

where D_t denotes a dummy variable for the after CaBi program launch in 2010, and D_T for Metrorail stations with CaBi installed nearby. $D_t \cdot D_T$ is an interactive term denoting Metrorail stations with CaBi installed, and in the years between 2011 and 2015 after CaBi's program launch. The hypothesis H2, that CaBi has a negative impact on Metrorail ridership, can be translated here to a negative δ_1.

However, there is a barrier to applying the standard Difference-in-Difference (DID) model to my research on the impact of CaBi. Since its launch in 2010, CaBi has been gradually expanded. Therefore, there are multiple policy events and thus multiple "before" and "after" time periods. For example, for Metrorail stations with CaBi docking stations installed in 2011, 2010 is a "before" year and 2011 is an "after" year. But for those stations with CaBi installed in 2012, both 2010 and 2011 are “before” years, while 2012 is a new “after” year. Similarly, there is more than one pair of “control-treatment” groups.

To handle this complexity, I use “multiple-groups-and-multiple-periods DID,” which is a natural extension of the two-group, two-time-period standard DID, as shown in Equation (10).

$$\mathrm{R}_{t,i} = \beta_1 + \sum_{t=2}^{6} \gamma_t * year_t + \sum_{i=2}^{6} \delta_i * group_i + \beta_2 * CaBi_{t,i} + e \tag{10}$$

where $\mathrm{R}_{t,i}$ is the ridership of Metrorail station in group i in year t. $year_t$ for t = 2, …, 6 is a vector of dummy variables taking the value 1 when the observation belongs to the t^{th} year between 2010 and 2015, and the category of reference for year is 2010. $group_i$ for i = 2, …, 6 is a vector of dummy variables taking the value 1 when the Metrorail station had CaBi installed nearby in the i^{th} year between 2010 and 2015 and zero otherwise. Since CaBi was launched in October 2010 and the input trip number was in August that year, $group_1$ is the control group, indicating stations without CaBi installed. The dummy variable $CaBi_{t,i}$ equal 1 if the station is in the treatment group and in a year after CaBi’s installation.

In Equation (1), the intercept β_1 indicates the average station ridership in 2010. Coefficients of the year dummies—γ_t—measure the year effects on all stations in the system, compared to the base year 2010. I assume that γ_t is an external factor which is influenced by elements at the macro level such as the overall regional economy and gasoline price. Coefficient of station group dummies—δ_i—indicates the difference in ridership if a station has CaBi installed nearby in years 2011, 2012, 2013, 2014, and 2015, as compared to the control group, which is stations without CaBi installed nearby. Finally, the coefficient β_2 is the focus of interest, which measures the average CaBi treatment effect at the station level.

To illustrate this method, assume three Metrorail stations, A, B, and C. Station A has no CaBi installed in any year between 2010 and 2015, B had CaBi installed in 2011, and C had CaBi installed in 2012. Table 34 illustrates input values for these three stations. It is worthwhile to highlight that $CaBi$ has a value 1 for the year CaBi was installed and each year after the installation.

Table 34 Illustration of the Multiple-Groups-and-Multiple-Periods DID

	2010	2011	2012	2013	2014	2015	g_{2010}	g_{2011}	g_{2012}	g_{2013}	g_{2014}	g_{2015}	$CaBi$
A	1						1						0
A		1					1						0
A			1				1						0
A				1			1						0
A					1		1						0
A						1	1						0
B	1							1					0
B		1						1					1
B			1					1					1
B				1				1					1
B					1			1					1
B						1		1					1
C	1								1				0
C		1							1				0
C			1						1				1
C				1					1				1
C					1				1				1
C						1			1				1

Input data are based on the same dataset for the DRM. Metrorail ridership and CaBi trips are transformed to be at the Metrorail station level. Metrorail ridership data are the average weekday daily AM/PM ridership of August between 2010 and 2015. August was chosen because CaBi was officially launched in October 2010 so August is a good month for a before-after analysis. Rather than using CaBi trips, DID intakes three dummy variables. The time scope matches that of Metrorail ridership. Ideally, station-wise control variables should be included in the model. However, time-variant data are not available. Table 35 describes the statistics of DID input data.

Table 35 Descriptive Statistics of DID Input Data

Variable	Obs	Mean	Std. Dev.	Min	Max
entryam	526	2525.1	1870.4	16.2	9631.2
exitam	526	2297.8	3251.5	102.1	14201.0
entrypm	526	2829.2	3505.2	141.6	15969.0
exitpm	526	2745.1	1874.4	251.0	11258.7
2010	526	0.2	0.4	0.0	1.0
2011	526	0.2	0.4	0.0	1.0
2012	526	0.2	0.4	0.0	1.0
2013	526	0.2	0.4	0.0	1.0
2014	526	0.2	0.4	0.0	1.0
2015	526	0.2	0.4	0.0	1.0
g_{2010}	526	0.4	0.5	0.0	1.0
g_{2011}	526	0.4	0.5	0.0	1.0
g_{2012}	526	0.1	0.3	0.0	1.0
g_{2013}	526	0.0	0.0	0.0	0.0
g_{2014}	526	0.1	0.3	0.0	1.0
g_{2015}	526	0.0	0.0	0.0	0.0
CaBi	526	0.4	0.5	0.0	1.0

7.3 Multiple-Groups-and-Multiple-Periods DID: Results

Table 36 reports the results of the multiple groups and multiple periods DID regressions. From left to right, the table shows coefficients and p-values by variable for each of four regression equations with *mentryam*, *mexitam*, *mentrypm*, and *mexitpm* as the dependent variable.

First, in 2010, on average, a Metrorail station without CaBi installed nearby, which belongs to the control group, has 3,014.3 passengers entering the station and 789.2 exiting in the morning, and 1,093.9 entering and 2,760.6 exiting in the evening. The sum of morning trips is very close to the sum of evening trips, suggesting that weekday Metrorail trips are mostly made by commuters.

Second, as coefficients of the year dummies show, Metrorail kept losing ridership in all four measures between 2010 and 2015. The only exceptions are *mexitam* and *mentrypm* which had small increases in 2011.

Third, there are systematic differences among Metrorail station groups. Note that g_{2013} and g_{2015} were omitted due to multilinearity. In fact, although CaBi has been expanding every year, the number of Metrorail stations with CaBi installed nearby did not change in 2013 and 2015. Metrorail stations with CaBi installed nearby in 2013 were the same stations as in 2012, and stations with CaBi in 2015 were the same as in 2014. For station groups g_{2011}, g_{2012}, and g_{2014}, coefficients indicate systematic ridership differences for four measures. Metrorail stations with CaBi installed nearby in 2011, or g_{2011}, tend to have more *mexitam* and *mentrypm* than the control group stations. On average, one g_{2011} group station has 3,746.5 more *mexitam* and 4,311.4 more *mentrypm*, and both are statistically significant at 0.000. The results confirm that CaBi docking stations were planned for and installed at Metrorail stations with higher ridership in 2011. Comparing coefficients of g_{2011} with those of g_{2012} and g_{2014}, we can see that through the years, the systematic differences between the treatment and control groups decrease.

So do the statistical significance levels. A possible explanation is that the CaBi docks were installed at Metrorail stations that had the largest numbers of *mexitam* and *mentrypm*. During CaBi's expansion, Metrorail ridership gradually played a less significant role and CaBi began to consider other factors, such as proximity to activity centers.

Conversely, Metrorail stations with CaBi installed in 2011 and 2012 have fewer *mentryam* than the control group. However, this trend was reversed; g_{2014} stations have more *mentryam*. Putting these pieces together we see a bigger picture on how CaBi was expanded. At the beginning of the program, only Metrorail stations with the highest *mexitam* and *mentrypm*, which are likely to be stations in downtown D.C., had CaBi installed near them. In 2014, new CaBi docks were installed at Metrorail stations near commuters' residences, leading to a positive *mentryam* difference. Therefore, regarding the location, CaBi started in downtown D.C., the area's job center, and gradually expanded into suburban communities, where commuters' homes are located.

Finally, coefficients suggest that CaBi docks at Metrorail stations, on average, lead to an increase in Metrorail ridership measures *mentryam* by 217.4 and *mexitpm* by 196.2, the numbers of AM station entries and the numbers of PM station exits. However, a closer look reveals that CaBi may also have negative ramifications for Metrorail. Installing CaBi within ¼-mile of Metrorail stations reduces the number of passengers exiting those stations in the morning, or *mexitam,* by 14.6 and reduces the number of commuters entering stations in the evening, or *mentrypm*, by 51.8. A quick comparison of coefficients reveals that the magnitude of CaBi's complementary effect exceeds the magnitude of its substitute effect.

Also, relating Metrorail ridership measures to station locations, we might interpret the results as: CaBi reduces Metrorail ridership at stations in downtown D.C. and increases ridership at stations in suburban communities. One possibility is that CaBi solved the connection gap between commuters' homes and Metrorail stations, and thus boosted the number of AM boardings and the number of PM exits. By comparison, due to its convenience and flexibility, CaBi near commuters' workplaces may substitute for Metrorail, and lead to the decrease of Metrorail ridership measures *mexitam* and *mentrypm*.

However, CaBi's treatment effects are not statistically significant. The p-values for coefficients of $D_{treatedpost}$ in four equations are 0.504, 0.976, 0.920, and 0.553 respectively, indicating low confidence levels. Since results are not statistically significant, the discussion of CaBi's complementary effects on ridership at stations near commuters' homes and substitute effects on ridership at stations near their workplaces are only hypothetical.

Table 36 Results of Multiple-Groups-and-Multiple-Periods DID

mentryam			*mexitam*			*mentrypm*			*mexitpm*		
	Coef.	P		Coef.	P		Coef.	P		Coef.	P
2011	-36.1	0.907	*2011*	48.5	0.917	*2011*	0.9	0.999	*2011*	-44.2	0.888
2012	-125.8	0.697	*2012*	-34.4	0.944	*2012*	-62.2	0.904	*2012*	-130.0	0.693
2013	-137.2	0.672	*2013*	-38.4	0.937	*2013*	-61.7	0.905	*2013*	-135.3	0.681
2014	-320.8	0.348	*2014*	-102.6	0.842	*2014*	-122.3	0.822	*2014*	-274.8	0.429
2015	-419.8	0.219	*2015*	-197.1	0.702	*2015*	-240.7	0.658	*2015*	-411.4	0.237
g_{2011}	-914.3*	0.006	g_{2011}	3746.5*	0.000	g_{2011}	4311.4*	0.000	g_{2011}	194.9	0.561
g_{2012}	-849.6*	0.018	g_{2012}	734.4*	0.173	g_{2012}	840.6	0.140	g_{2012}	-576.6	0.113
g_{2013}			g_{2013}			g_{2013}			g_{2013}		
g_{2014}	282.8*	0.318	g_{2014}	337.0	0.430	g_{2014}	655.9	0.146	g_{2014}	417.2	0.148
g_{2015}			g_{2015}			g_{2015}			g_{2015}	0.0	
$D_{treatedpost}$	217.4	0.504	$D_{treatedpost}$	-14.6	0.976	$D_{treatedpost}$	-51.8	0.920	$D_{treatedpost}$	196.2	0.553
_cons	3014.3*	0.000	_cons	789.2*	0.050	_cons	1093.9*	0.010	_cons	2760.6*	0.000
		R2 = 0.055			R2 = 0.288			R2 = 0.318			R2 = 0.026
* Statistically different from zero at 5% significance level											

7.4 Summary

In Chapter 8, I use the Difference-in-Difference approach, a quasi-experimental technique, to overcome the deficiency of DRM's random selection assumption. A standard DID separates Metrorail stations into treatment and control groups, and measures their pre-intervention and post-intervention outcomes. The difference between the treatment group's after-before ridership change and the control group's change can therefore be ascribed to the CaBi program.

However, since CaBi expanded every year between 2010 and 2015, the two-group two-period format does not apply here. In fact, there is one control group, five treatment groups (Metrorail stations with CaBi installed in different years), a pre-intervention period and five post-intervention periods. Therefore, a special multiple-group-and-multiple-period DID is introduced to capture all differences.

The analysis finds that having CaBi installed nearby reduces 14.6 Metrorail AM peak exits and 51.8 PM peak entries, but increases 217.4 AM peak entries and 196.2 PM peak exits. Given the fact that Metrorail stations in downtown D.C. tend to have a larger number of exits in the morning and entries in the evening, we may interpret results to show that CaBi reduces Metrorail ridership at stations in downtown D.C. and increases ridership at stations near commuters' homes.

However, none of CaBi's impacts are statistically significant. Therefore, the discussion of the relationship between CaBi's impacts and Metrorail station location is merely hypothetical. A new model separating CaBi's impacts by location and with more detailed trip data may help test the theory.

Chapter 8: Station-Specific Dummies Analysis

Both the DRM and DID approaches reveal interesting findings, but they have limitations. The DRM relies on a strong random assignment assumption, and DID results are not statistically significant. Also, DID results imply that CaBi's impacts may vary by the location of Metrorail stations—that the program may reduce ridership at downtown D.C. stations and increase ridership at stations in suburban residential communities. To test this theory, I apply the Observation-Specific Dummies (OSD) approach to the research question and create a Station-Specific Dummies (SSD) model to measure CaBi's impacts by station location. Also, I improve control variables and the input data in the new model. Besides the year effects, I control for the month effect since explorative analysis found a seasonal pattern. I also control for stations' fixed effects to compensate for the lack of time-varying transit service, socio-demographic, and built environment variables. Finally, I introduce a new dataset, monthly ridership between 2010 and 2015, to study the question. Some of the regression results are mapped using ArcGIS to identify spatial patterns.

8.1 Methodology and Data

The Observation-Specific Dummies (OSD) or Unique-Event Dummies approach (UED), first introduced by Salkever in 1976, is a convenient device in applied regression analysis (Kennedy, 2003; Oksanen, 1986; Salkever, 1976). In this model, one dummy variable represents one observation. For a model with *N* observations, *N-1* dummies would be created while the constant variable represents the other observation, which is usually called the *base*. Coefficients of the *N-1* dummies indicate the differences between each of the *N-1* observations and the base observation. The Observation-Specific Dummies (OSD) has been used especially when the number of observations in one time period is too small (Kennedy, 2003). If time defines different observations, then the Observation-Specific Dummies is also called the Period-Specific Dummies (Kennedy, 2003).

The Observation-Specific Dummies approach is well suited for exploring CaBi's impacts on Metrorail stations. As discussed earlier in Chapter 6, time-varying station-level control variables are not available. However, by assigning a dummy to each Metrorail station, the OSD can control for station fixed effects. Since the observations are stations in this study, the Observation-Specific Dummies can be renamed as the Station-Specific Dummies (SSD).

Besides including station fixed effect dummies, I also improve the controlling for time effects. In the DID model, year dummies are used to control time effects. However, it may also worth to control for the month effects as the explorative analysis results in Chapter 3 found seasonal patterns in CaBi and Metrorail trips. Therefore, I included 12 month dummies in the SSD model.

After time effects (by year and by month) and station fixed effect, the third group of variables are CaBi's impacts by Metrorail station location, whether a station is a downtown D.C. core station or a non-core station in peripheral and suburban communities.

Therefore, three dimensions in the interplay between CaBi and Metrorail captured in the SSD model are the time effects at the system level, the stations' fixed effects derived from their unique locations, and CaBi impacts varying by station location. The model is expressed as:

$$R_{t,m,s} = \beta_1 + \sum_{t=2}^{6} \alpha_t year_t + \sum_{m=2}^{12} \gamma_m month_m + \sum_{\substack{s=1 \\ s\neq 44}}^{91} \delta_s station_s$$
$$+\beta_2 core_s * CaBi_{t,m,s} + \beta_3 noncore_s * CaBi_{t,m,s} + e \qquad (11)$$

where $R_{t,m,s}$ is the Metrorail ridership of station *s* in month *m* of year *t*.

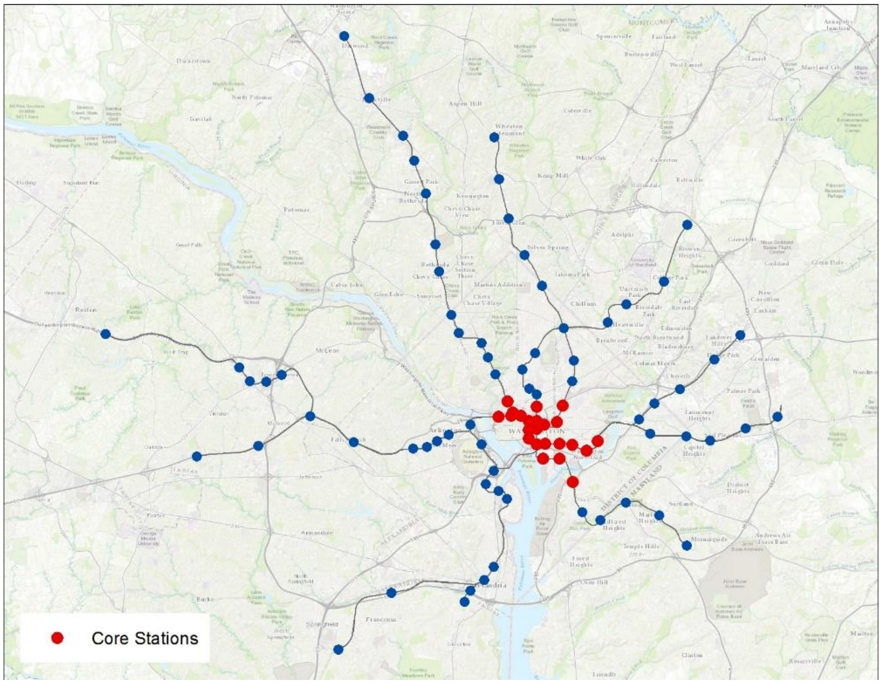
To maximize the benefits of detailed trip data, rather than using the same dataset as in the DRM and the DID, I improved the input data for the SSD. The new dataset includes monthly AM/PM peak Metrorail ridership and CaBi trip measures for each month between August 2010 and August 2015, a total of 61 months. Weekend trips are excluded to focus on commuting trips. Therefore, for time effects, I have two groups of dummy variables: $year_t$ for t = 2, …, 6 is a vector of dummy variables taking the value 1 when the observation belongs to the tth year of 2010-2015 and zero otherwise, and $month_m$ for m = 2, …, 12 is a vector of dummy variables taking the value 1 when an observation belongs to the mth month of January-December and zero otherwise.

I also assume that every Metrorail station is unique in attracting passengers and receiving CaBi's impacts. This assumption differs from earlier methods in that it takes each Metrorail station as a unit and admits the correlation between ridership and station. To represent this effect, I introduced 91 dummy variables for 91 Metrorail stations. $station_s$ for s = 1, …, 91 is a vector of dummy variables taking the value 1 when the observation belongs to the sth station and zero otherwise. The 44th station, King Street is the base for station dummy, and 2010 and January the bases for the year and month dummies.

Finally, I created two dummy variables $core_s$ and $noncore_s$ to represent Metrorail station locations, categorized as core stations and non-core stations. The concept of core stations comes from WMATA. In its report, *Station Access and Capacity Study*, WMATA identified 29 stations as the system core (WMATA, 2008). Some of them, such as the Arlington Cemetery, do not function as core stations due to land use at the station area. Therefore, I remove stations in Virginia and keep those only in D.C. as my definition of the system core. The 23 core stations are: Anacostia, Archives-Navy Memorial, Capitol South, Dupont Circle, Eastern Market, Farragut North, Farragut West, Federal Center SW, Federal Triangle, Foggy Bottom, Gallery Place-Chinatown, Judiciary Square, L'Enfant Plaza, McPherson Square, Metro Center, Mt. Vernon Square-UDC, Navy Yard, New York Ave, Potomac Avenue, Smithsonian, Stadium-Armory, Union Station, and Waterfront. Figure 50 shows core and non-core stations.

If a station is defined as a core station, $core_s$ takes the value of 1. Otherwise, it has the value of zero. $noncore_s$ is a similar dummy. It represents a station outside the Metrorail system core, which are stations in peripheral and suburban communities. $CaBi_{t,m,s}$ is a dummy variable which equals to one when station *s* has CaBi installed nearby in month *m* of year *t*. If station s is one of the core stations, dummy variable $core_s$ takes the value 1. Similarly, if s is not a core station, $noncore_s$ takes the value 1. $core_s * CaBi_{t,m,s}$ and $noncore_s * CaBi_{t,m,s}$ represent the interaction terms between the type of station (core vs. non-core) and its exposure to CaBi program.

Figure 50 Metrorail Core Stations



All variables in the model are dummies, and thus a base group is needed. I selected the King Street station as my base group because its ridership is closest to the average of all stations. Therefore, in Equation (11), the coefficient β_1, the intercept, indicates ridership of Metrorail station King Street in January 2010. Coefficients α_t and γ_m represent the year effect and the month effect on ridership. δ_s indicates the station fixed effect of station *s*, compared to King Street station. β_2 and β_3 are CaBi program's average effects on core stations and non-core stations. Therefore, the ridership of King Street station (which is a non-core station) in month *m* of year *t* can be expressed as $R_{t,m,King\ Street} = \beta_1 + \alpha_t + \gamma_m + \beta_3$, and the ridership of a core station *N* can be written as $R_{t,m,N} = \beta_1 + \alpha_t + \gamma_m + \delta_N + \beta_2$.

Since Metrorail ridership has four measures, *mentryam*, *mexitam*, *mentrypm*, and *mexitpm*, Equation (11) can be further specified into Equations (12), (13), (14), and (15):

$$mentryam_{t,m,s} = \beta_1 + \sum_{t=2}^{6} \alpha_t year_t + \sum_{m=2}^{12} \gamma_m month_m + \sum_{\substack{s=1 \\ s\neq 44}}^{91} \delta_s station_s$$

$$+\beta_2 core_s * CaBi_{t,m,s} + \beta_3 noncore_s * CaBi_{t,m,s} + e \qquad (12)$$

$$mexitam_{t,m,s} = \beta_1 + \sum_{t=2}^{6} \alpha_t year_t + \sum_{m=2}^{12} \gamma_m month_m + \sum_{\substack{s=1 \\ s\neq 44}}^{91} \delta_s station_s$$

$$+\beta_2 core_s * CaBi_{t,m,s} + \beta_3 noncore_s * CaBi_{t,m,s} + e \qquad (13)$$

$$mentrypm_{t,m,s} = \beta_1 + \sum_{t=2}^{6} \alpha_t year_t + \sum_{m=2}^{12} \gamma_m month_m + \sum_{\substack{s=1 \\ s\neq 44}}^{91} \delta_s station_s$$

$$+\beta_2 core_s * CaBi_{t,m,s} + \beta_3 noncore_s * CaBi_{t,m,s} + e \qquad (14)$$

$$mexitpm_{t,m,s} = \beta_1 + \sum_{t=2}^{6} \alpha_t year_t + \sum_{m=2}^{12} \gamma_m month_m + \sum_{\substack{s=1 \\ s\neq 44}}^{91} \delta_s station_s$$

$$+\beta_2 core_s * CaBi_{t,m,s} + \beta_3 noncore_s * CaBi_{t,m,s} + e \qquad (15)$$

Table 37 lists part of the descriptive statistics of input data. Due to the large number of dummy variables in the model, the full descriptive statistics is provided in Appendix A. In total, there are 5,316, made at 86 stations over 61 months and including the five additional Silver Line stations over 14 months (stations opened in July 2014).

Table 37 Descriptive Statistics of SSD Input Data

Variable	Obs	Mean	Std. Dev.	Min	Max
mentryam	5,316	55,735.5	40,970.6	142.0	242,376.0
mexitam	5,316	50,593.1	71,375.3	1,205.0	340,978.0
mentrypm	5,316	61,343.4	76,167.3	1,574.0	381,632.0
mexitpm	5,316	59,526.9	41,472.7	1,004.0	289,758.0
core	5,316	0.3	0.4	0.0	1.0
noncore	5,316	0.7	0.4	0.0	1.0
CaBi	5,316	0.5	0.5	0.0	1.0
*core * CaBi*	5,316	0.3	0.4	0.0	1.0
*noncore * CaBi*	5,316	0.2	0.4	0.0	1.0

8.2 Results

The results of four regressions (with *mentryam*, *mexitam*, *mentryam*, and *mexitpm* as the dependent variables) have about 109 coefficients each and are too long to show completely in the text. Therefore, only part of the results are displayed in the text; the full results are shown in Appendix B.

Table 38 illustrates the findings in four parts. The left three columns in the first row show coefficients and the p value of the constant, the King Street station, with CaBi's effects on core and non-core stations following. Below that are year and month effects. The three columns to the right are coefficients and p values of the other 90 stations. The coefficient values indicate the ridership differences between a station and the base station, the King Street station. To save space, I only show 20 stations, the top 10 and the last 10, ranked by sizes of coefficients.

8.2.1 Results of the Regression with *mentryam* as the Dependent Variable

As Table 38 shows, in 2010, the King Street station had 60,968.5 monthly entries in the AM peak. A small P value indicates that the constant is statistically significant at the 0.000 level. CaBi has positive impacts on both core and non-core stations. Specifically, the presence of CaBi in a Metrorail station area would increase the number of monthly AM entries of core stations by 2,471 and that of non-core stations by 1,111.8. P values are smaller than 0.05, showing CaBi's impacts are statistically significant.

Year effects and month effects are as expected. Over the years, *mentryam* slightly increased in 2011, but then decreased since 2012. The 2015 estimated ridership is 6,085.8 less than the 2010 level, and the difference is statistically significant. Coefficients of month dummies show that Metrorail trips have seasonality. There are more trips made between March and October, and the differences are statistically significant.

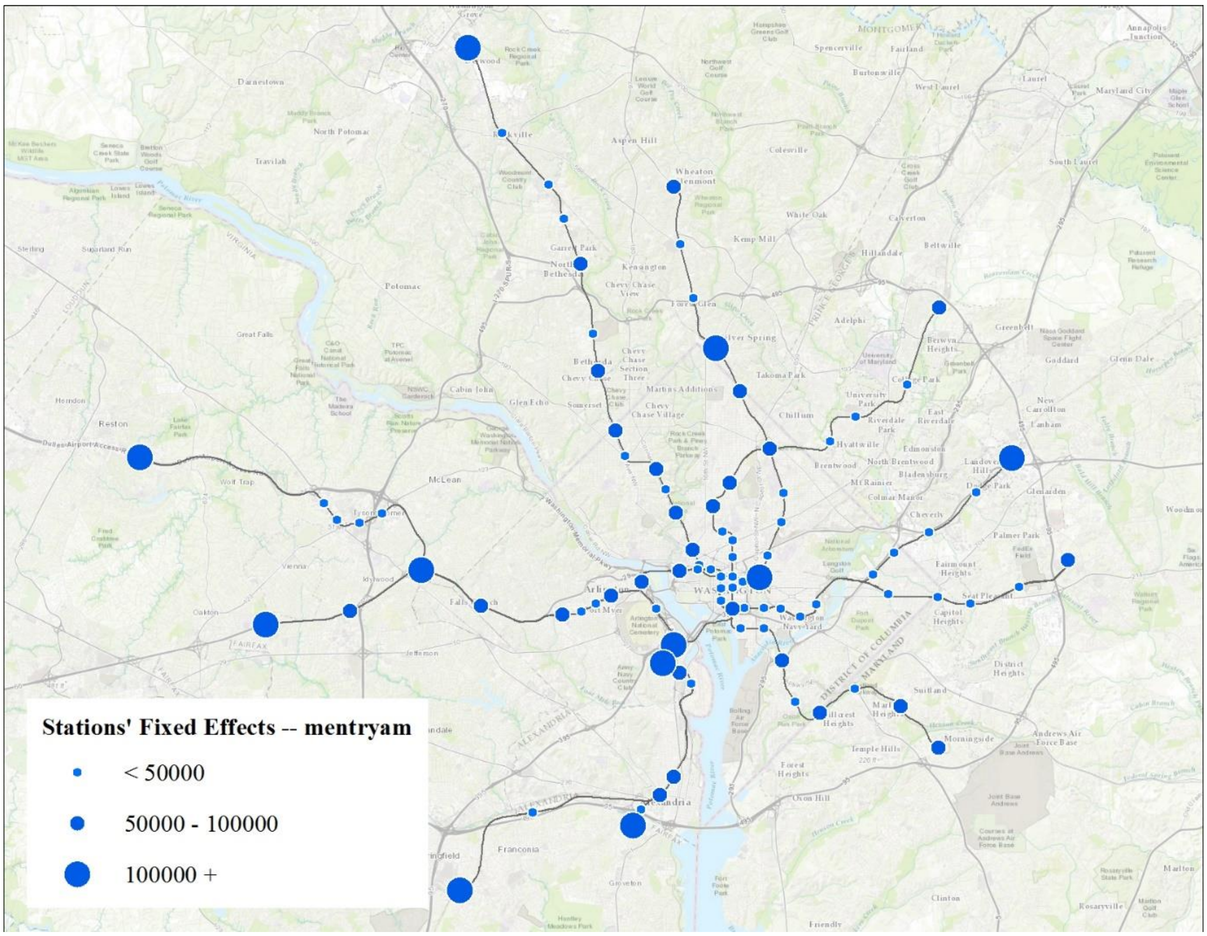
Table 38 Selected Results of SSD with *mentryam* as the Dependent Variable

mentryam					
	coef.	p		coef.	p
King Street (base)	60,968.5*	0.000	*Union Station*	136,184.9*	0.000
CaBi core	2,471.0*	0.013	*Shady Grove*	129,093.1*	0.000
CaBi non-core	1,111.8*	0.023	*Vienna*	127,068.3*	0.000
2011	127.7	0.771	*Pentagon*	68,256.8*	0.000
2012	-1,221.6*	0.006	*New Carrollton*	64,817.0*	0.000
2013	-1,998.7*	0.000	*Huntington*	63,804.9*	0.000
2014	-3,660.6*	0.000	*Silver Spring*	61,896.8*	0.000
2015	-6,085.8*	0.000	*West Falls Church*	57,760.1*	0.000
Feb	-1,634.6*	0.001	*Franconia-Springfield*	57,178.5*	0.000
Mar	4,556.3*	0.000	*Pentagon City*	54,469.9*	0.000
Apr	5,647.5*	0.000	*Capitol South*	-45,141.0*	0.000
May	4,539.5*	0.000	*Tysons Corner*	-48,221.1*	0.000
Jun	6,478.0*	0.000	*Spring Hill*	-48,803.0*	0.000
Jul	5,058.1*	0.000	*Judiciary Square*	-52,753.1*	0.000
Aug	2,159.7*	0.000	*Greensboro*	-53,103.0*	0.000
Sep	2,244.3*	0.000	*Federal Center SW*	-53,807.6*	0.000
Oct	3,259.5*	0.000	*Archives-Navy Memorial*	-55,234.4*	0.000
Nov	-2,083.9*	0.000	*Smithsonian*	-56,658.2*	0.000
Dec	-5,992.4*	0.000	*Federal Triangle*	-59,009.1*	0.000
			Arlington Cemetery	-60,504.7*	0.000
					R2 = 0.970
* Statistically different from zero at 5% significance level					

Metrorail stations are unique, as the small p values suggest. I ranked stations by coefficients, and found that those with the largest numbers of AM entries are either terminal stations such as Shady Grove and New Carrollton, or transit hubs such as Union Station. Conversely, stations with the smallest numbers of AM entries are those in downtown D.C. (Judiciary Square and Archives-Navy Memorial), stations located in other job centers

(Tysons Corner), or stations with a special land use (Arlington Cemetery). I mapped the stations' fixed effects (equal to the sum of constant and coefficients of the station) in ArcGIS. Figure 51 confirms the spatial pattern that compared to downtown stations, those in peripheral areas have more AM entries.

Figure 51 Stations' Fixed Effects in SSD with *mentryam* as the Dependent Variable



8.2.2 Results of the Regression with *mexitam* as the Dependent Variable

Table 39 shows selected results of regression with *mentryam* as the dependent variable in the same format as Table 38. It reveals that there were 47,297.9 exits at the King Street station per month in 2010. In 2011, the number slightly increased by 1,198.2, suggesting that more commuters exit Metrorail stations in the morning. However, this increase did not last long. In 2014, *mexitam* dropped to a level below 2010's, as suggested by the negative coefficient. *Mexitam* in 2015 was 4,882.7 less than in 2010, and the decline was statistically significant.

CaBi's impacts are mixed and vary by station location. It has a negative impact on Metrorail AM exits at core stations. The presence of CaBi docks at a station area decreases monthly *mexitam* of core stations by 4,814.4. However, CaBi increases *mexitam* of non-core stations by 2,143.3. Both the complementary effect and substitute effect are statistically significant.

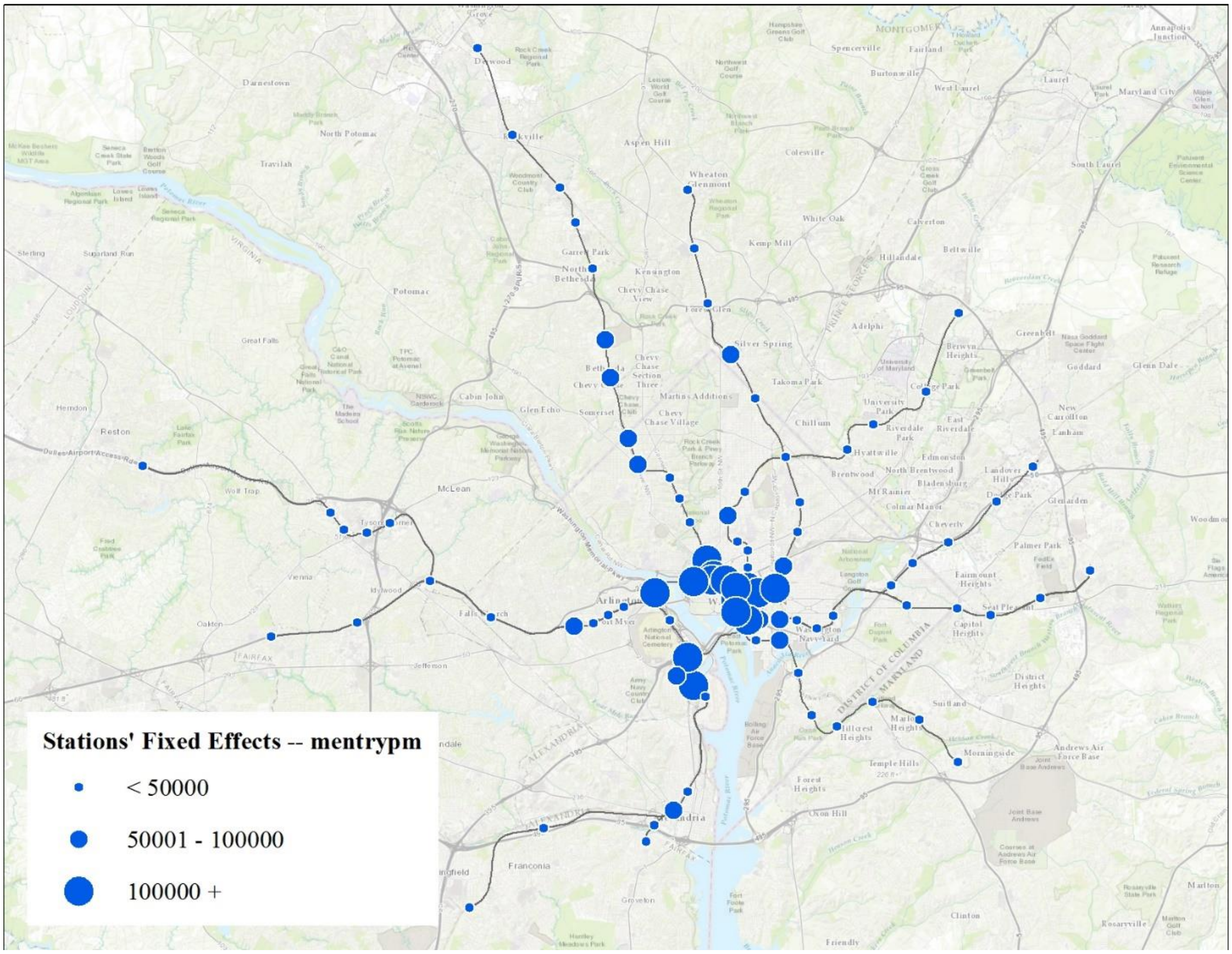
Again, month plays a role in Metrorail ridership; more commuters take trains in the warm weather. June, April, and July are the top three months in terms of *mexitam* number.

Results also show spatial patterns of AM exits by station. Core stations, even after controlling for CaBi's impacts, have the largest morning exits. The non-core station with similar numbers is Pentagon. All stations have thousands of jobs near them and are destinations of morning commute trips. Stations with the lowest levels of AM exits are located in peripheral areas, and some in residence-heavy neighborhoods. Figure 52 visualizes this spatial pattern.

Table 39 Selected Results of SSD with *mexitam* as the Dependent Variable

mexitam					
	Coef.	P		Coef.	P
King Street (base)	47,297.9*	0.000	*Farragut North*	252,908.0*	0.000
CaBi core	-4,814.4*	0.000	*Farragut West*	251,839.7*	0.000
CaBi non-core	2,143.3*	0.000	*Metro Center*	238,956.0*	0.000
2011	1,198.2*	0.014	*L'Enfant Plaza*	204,653.1*	0.000
2012	-331.2	0.504	*Union Station*	179,529.3*	0.000
2013	-1,131.7*	0.023	*McPherson Square*	159,432.8*	0.000
2014	-2,741.1*	0.000	*Foggy Bottom*	157,149.8*	0.000
2015	-4,882.7*	0.000	*Gallery Place-Chinatown*	154,546.5*	0.000
Feb	-1,158.5*	0.030	*Dupont Circle*	91,639.5*	0.000
Mar	4,196.2*	0.000	*Pentagon*	87,273.7*	0.000
Apr	5,128.2*	0.000	*Congress Heights*	-44,059.5*	0.000
May	4,355.1*	0.000	*Arlington Cemetery*	-44,095.2*	0.000
Jun	5,990.1*	0.000	*Deanwood*	-44,311.9*	0.000
Jul	4,708.8*	0.000	*Cleveland Park*	-44,573.8*	0.000
Aug	2,213.3*	0.000	*Morgan Blvd.*	-44,787.1*	0.000
Sep	2,416.3*	0.000	*Benning Road*	-44,943.5*	0.000
Oct	3,202.8*	0.000	*Forest Glen*	-45,114.6*	0.000
Nov	-1,644.1*	0.003	*Landover*	-45,206.6*	0.000
Dec	-5,217.6*	0.000	*Cheverly*	-45,407.2*	0.000
			Capitol Heights	-45,423.3*	0.000
					R2 = 0.988
* Statistically different from zero at 5% significance level					

Figure 52 Stations' Fixed Effects in SSD with *mexitam* as the Dependent Variable



8.2.3 Results of the Regression with *mentrypm* as the Dependent Variable

Results of SSD regression with *mentrypm* as the dependent variable are similar to results of SSD with *mexitam* as the dependent variable (Section 8.2.2). In 2010, the King Street station had a monthly ridership of 59,189. The presence of a CaBi dock within ¼ mile of a Metrorail station would decrease the number of entries at core stations, but increase those of non-core stations. The results are statistically significant.

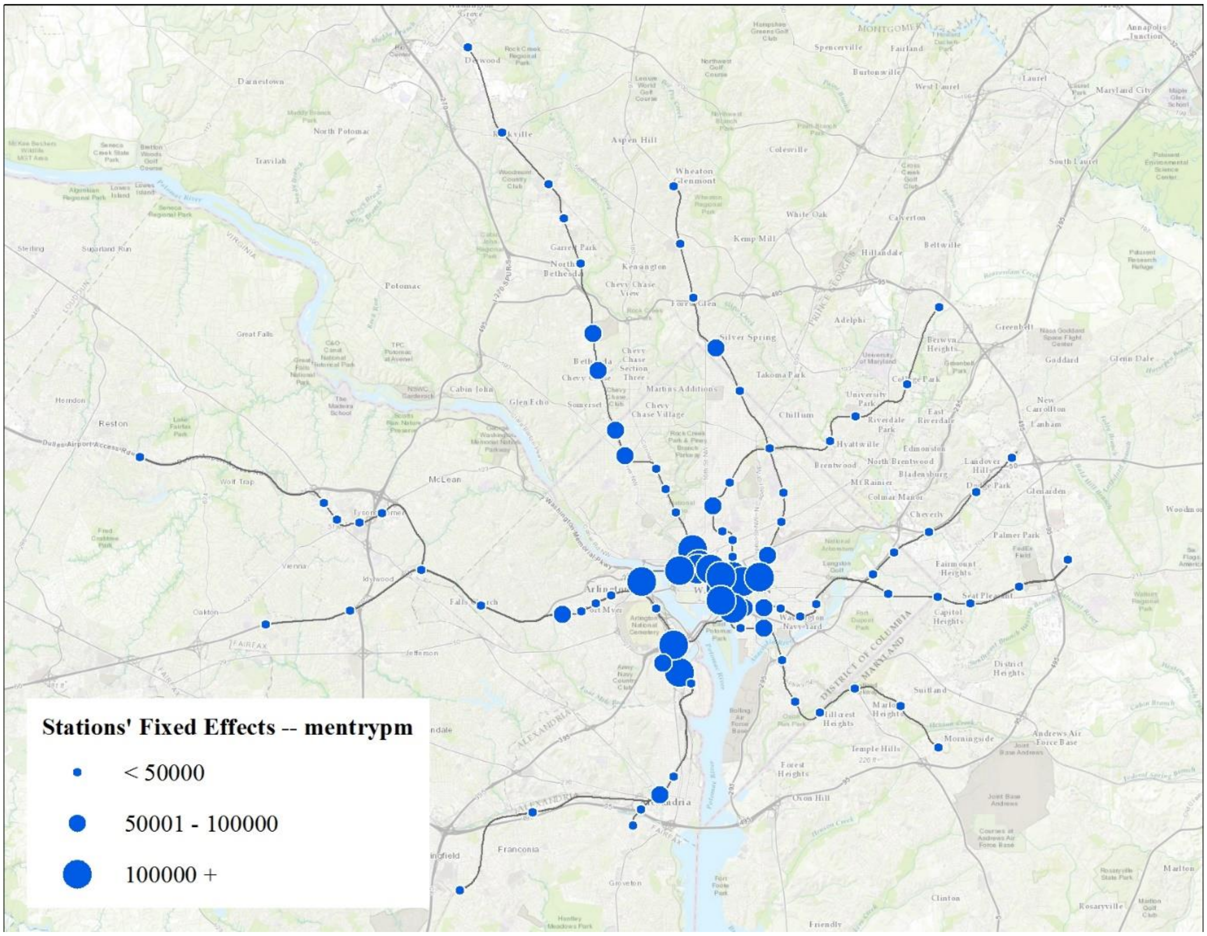
Year effects and month effects are found to be similar to results in 8.2.1 and 8.2.2. Mentrypm increased slightly and insignificantly in 2011, and declined in the years after. The 2015 level is 5,881.7 less than the 2010 level. Seasonality is confirmed by coefficients of month dummies. Again, July, April, and June are the top three months. Each shows more than 7,000 monthly PM entries.

Very similar to results of SSD with mexitam, stations with the largest ridership are those located in downtown D.C. Stations in residence-heavy peripheral neighborhoods, such as Forest Glen and Landover, have the smallest numbers of PM peak entries. This spatial pattern is illustrated in Figure 53.

Table 40 Selected Results of SSD with *mentrypm* as the Dependent Variable

mentrypm					
	Coef.	P		Coef.	P
King Street (base)	59,189.0*	0.000	Metro Center	268,757.1*	0.000
CaBi core	-4,886.9*	0.000	Farragut North	261,316.2*	0.000
CaBi non-core	2,458.4*	0.000	Farragut West	225,669.8*	0.000
2011	541.6*	0.342	L'Enfant Plaza	212,256.5*	0.000
2012	-960.3*	0.098	Union Station	204,890.3*	0.000
2013	-2,071.2*	0.000	Gallery Place-Chinatown	194,572.3*	0.000
2014	-4,037.2*	0.000	Foggy Bottom	163,104.9*	0.000
2015	-5,881.7*	0.000	McPherson Square	143,681.5*	0.000
Feb	-2,926.9*	0.000	Dupont Circle	111,480.3*	0.000
Mar	5,217.7*	0.000	Smithsonian	104,045.0*	0.000
Apr	7,828.0*	0.000	Congress Heights	-51,131.9*	0.000
May	5,036.5*	0.000	Benning Road	-51,232.4*	0.000
Jun	7,043.6*	0.000	Naylor Road	-51,493.0*	0.000
Jul	7,940.5*	0.000	Addison Road	-51,823.7*	0.000
Aug	3,669.5*	0.000	Deanwood	-53,761.9*	0.000
Sep	1,344.2*	0.035	Forest Glen	-53,780.9*	0.000
Oct	3,342.1*	0.000	Capitol Heights	-54,208.6*	0.000
Nov	-2,594.3*	0.000	Morgan Blvd.	-55,328.8*	0.000
Dec	-5,319.5*	0.000	Landover	-55,366.8*	0.000
			Cheverly	-56,019.3*	0.000
					R2 = 0.986
* Statistically different from zero at 5% significance level					

Figure 53 Stations' Fixed Effects in SSD with *mentrypm* as the Dependent Variable



8.2.4 Results of the Regression with *mexitpm* as the Dependent Variable

Table 41 shows selected results for regression with *mexitpm* as the dependent variable. Results in this section are similar to those of the regression with *mentryam* as the dependent variable (Section 8.3.1). First, the base station, King Street, has 68,797.2 monthly exits in the weekday PM peak. Second, this number decreased each year between 2011 and 2015. In 2015, the number of passengers getting off the train was 6,825.9 less than that number in 2010. The loss was about 10% over six years.

CaBi has had positive impacts on the number of PM peak exits for all stations but the magnitude varies by location. CaBi increases *mexitpm* of core stations by 2,781.2 on average, and that of non-core stations by 1,336.4. Both impacts are statistically significant.

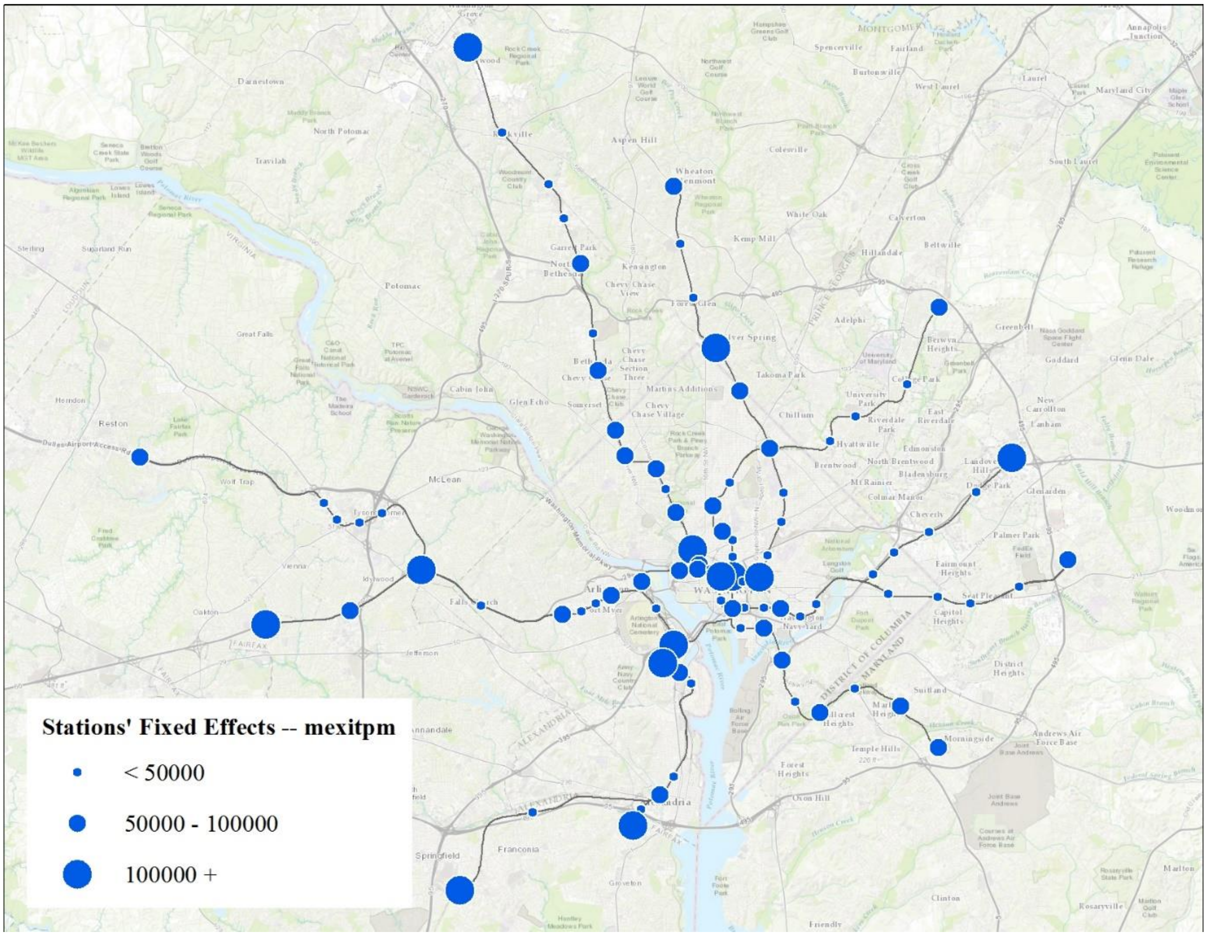
Month effects are similar to previous findings in that there are more trips between March and October, compared to other months.

Stations are unique. The small p values show that each station is statistically different from the King Street station. The spatial pattern of *mexitpm* is similar to that of *mentryam* in Section 8.2.1, that terminal stations and transit hubs have the largest number of exits in the PM peak. Interestingly, three Silver Line stations, McLean, Spring Hill and Greensboro, have the lowest exits in the PM peak. Figure 54 illustrates the spatial pattern.

Table 41 Selected Results of SSD with *mexitpm* as the Dependent Variable

mexitpm					
	Coef.	P		Coef.	P
King Street (base)	68,797.2*	0.000	*Union Station*	171,029.7*	0.000
CaBi core	2,781.2*	0.015	*Vienna*	91,888.9*	0.000
CaBi non-core	1,336.4*	0.018	*Shady Grove*	87,724.7*	0.000
2011	-221.7*	0.663	*Pentagon City*	80,555.9*	0.000
2012	-1,649.0*	0.002	*Gallery Place-Chinatown*	79,934.7*	0.000
2013	-2,699.7*	0.000	*Dupont Circle*	64,426.8*	0.000
2014	-4,444.4*	0.000	*Pentagon*	49,680.0*	0.000
2015	-6,825.9*	0.000	*Silver Spring*	42,688.1*	0.000
Feb	-2,849.9*	0.000	*New Carrollton*	40,474.1*	0.000
Mar	5,177.8*	0.000	*West Falls Church*	39,405.9*	0.000
Apr	7,926.6*	0.000	*Medical Center*	-52,196.6*	0.000
May	5,377.8*	0.000	*Eisenhower Avenue*	-52,842.2*	0.000
Jun	7,121.3*	0.000	*Deanwood*	-53,304.3*	0.000
Jul	7,844.7*	0.000	*Judiciary Square*	-54,090.2*	0.000
Aug	3,881.0*	0.000	*McLean*	-54,154.0*	0.000
Sep	1,458.3*	0.011	*Federal Triangle*	-55,301.3*	0.000
Oct	3,235.8*	0.000	*Spring Hill*	-56,357.2*	0.000
Nov	-2,267.5*	0.000	*Federal Center SW*	-60,062.1*	0.000
Dec	-4,694.3*	0.000	*Greensboro*	-60,335.1*	0.000
			Arlington Cemetery	-61,164.2*	0.000
					R2 = 0.961
* Statistically different from zero at 5% significance level					

Figure 54 Stations' Fixed Effects in SSD with *mexitpm* as the Dependent Variable



8.3 Summary and Discussion

Looking at the four regression results together, we can reach several interesting findings. First, regarding the yearly change, Metrorail lost ridership in four all measures, but in two different paths. The measure *mexitpm* started losing ridership immediately upon CaBi's program launch. The estimated ridership kept decreasing every year between 2010 and 2015. In 2015, *mexitpm* was about 6,825.9 smaller than their 2010 levels, about a 10% loss. On the other hand, the other three ridership measures, *mentryam*, *mexitam*, and *mentrypm*, experienced an initial increase followed by a steady decline. The increases between 2010 and 2010 varied, from *mentryam*'s 127.7 to *mexitam*'s 1,198.2. Since 2011, they began to decrease. In 2012, they decreased to below their 2010 levels. In 2015, they were about 5,000 smaller than they were in 2010, at a high statistical significance level.

The time effects found in this Station-Specific Dummy analysis are consistent with the effects found in the Difference-in-Difference analysis in the last chapter, as well as descriptive analysis results earlier in Chapter 3. They justify the importance of including a panel data in estimating a bike share program's impact on existing public transportation. If we fail to ignore the time effect, we might overestimate CaBi's positive impacts. From this perspective, the DID and the SSD are better suited the DRM.

Second, the results confirm the seasonality of Metrorail trips. Coefficients of month dummies indicate how Metrorail ridership fluctuates over seasons. Four Metrorail ridership measures share the same pattern—more trips made in the warmer seasons between March and October. The highest ridership takes place in April, June, or July, depending on the ridership measure. The highest ridership can take up to 13.4% of the estimated ridership of the base station. The lowest ridership happens in December, partly due to low temperatures, and partly due to the holiday season. The time impacts of months on Metrorail ridership are all statistically significant.

Third, Metrorail stations are unique and statistically significantly different from the base station, King Street. Using ArcGIS, I mapped the stations' fixed effects on each Metrorail station's ridership and identified spatial patterns. Stations with the largest numbers of *mentryam* and *mexitpm* tend to be terminal stations and transfer hubs, while stations with the largest number of *mexitam* and *mentrypm* are those located in downtown D.C. One likely explanation is the Washington metropolitan area's monocentric spatial structure that concentrates jobs in downtown D.C. and workers' homes in peripheral and suburban communities, thus generating AM inbound commuting flows and PM outbound flows. This residence-workplace segregation is a likely result of D.C.'s building height restriction and limited land supply.

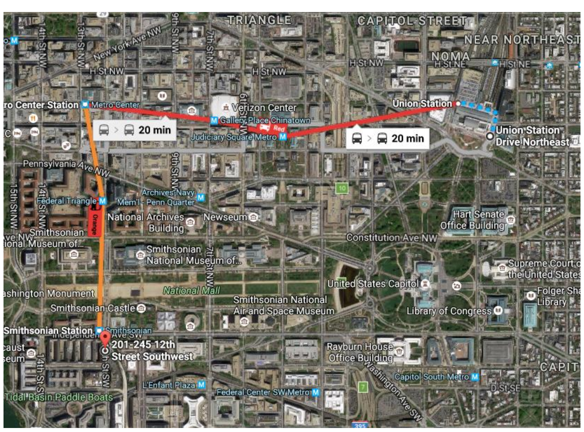
Finally, CaBi has statistically significant impacts on Metrorail ridership, after carefully controlling for time effects (by year and month) and stations' fixed effects. All CaBi variables are significant at a 95% confidence level. However, whether CaBi complements or substitutes Metrorail ridership varies by locations—whether a station is a downtown D.C. core station or a non-core station in peripheral and suburban communities. If a Metrorail station is one of the 23 core stations, its AM exits and PM entries are likely to be negatively affected by CaBi docking stations installed nearby. Conversely, CaBi has complementary effects on non-core Metrorail ridership, in all four measures.

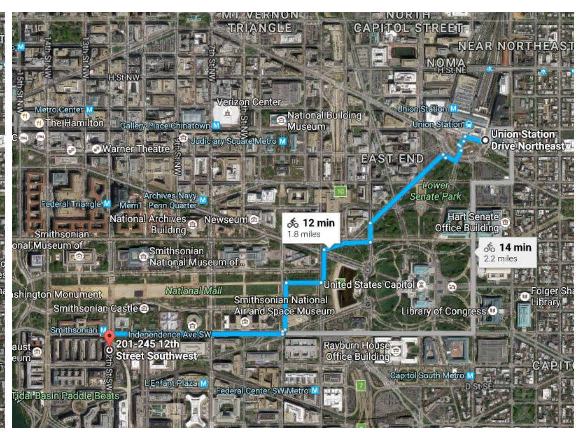
Regarding their magnitude, CaBi's substitute impacts are estimated to be 4,814.4 for *mexitam*, and 4,886.9 for *mentrypm* for core stations. Converted to a percentage, they are about 8-10% of the estimated system average ridership. CaBi's complementary impacts are slightly smaller, ranging from 1.8% to 4.5%.

I propose two theories explaining CaBi's different impacts on core and non-core stations—trip length and downtown job loss.

First, bike share activities consume a considerable amount of physical energy and thus people tend to bike within 1.5 miles. If the distance is longer, commuters are more likely to use rail transit. Development density in downtown D.C. results in many short-distance trips that can be covered by CaBi. What's more, Metrorail runs on fixed routes and stops at fixed stations requiring commuters to make transfers or walk after the train trip. One example is Union Station, discussed in Section 4.2.1. Suppose a commuter needs to travel from Union Station to Smithsonian. By Metrorail, they need to make one transfer at Gallery Place (Chinatown) or Metro Center, and the trip takes about 20 minutes, as illustrated in Figure 55 (the left). However, using CaBi, the commuter can bike across the National Mall, saving half the travel time. Therefore, for short-Euclidean-distance trips in downtown D.C., CaBi has the potential to replace Metrorail.

Figure 55 Travel Times by Metrorail and by CaBi between Union Station and Smithsonian





Left: by Metrorail Right: by CaBi

However, commute trips to downtown D.C. that originate in peripheral areas and in suburban communities usually are longer than a couple of miles. Commuters still have to rely on rail transit. CaBi may be able to solve the first-mile connection problem and make Metrorail stations accessible, but it can by no means replace Metrorail. Hence, CaBi is more likely to complement Metrorail trips originating or ending at stations in suburban areas.

Second, further ridership loss may be explained by omitted external factors. My Station-Specific Dummies analysis equation captures three contributing factors to Metrorail ridership: time effect, station location effect, and CaBi's impacts. However, there are several external elements that may boost or decrease Metrorail ridership, such as jobs in a station area. If downtown D.C. Metrorail station areas lost significantly more jobs than the other stations, the demands for rail transit commutes would decrease, bringing down the number of AM peak exits and PM peak entries. To test this, I pulled data from the Bureau of Labor Statistics and calculated job numbers for stations with negative CaBi impacts—including McPherson Square, Metro Center, Federal Triangle, Smithsonian, and L'Enfant Plaza. Table 42 lists each station's job numbers between 2010 and 2014, and the last row reports the average numbers of all 91 stations.[26] As we can see, except for McPherson Square, these stations each lost many jobs, ranging from 374 to 10,096, far more than the Metrorail system average, which is only 52. Therefore, jobs loss at Metrorail stations may explain why downtown D.C. lost more ridership than stations in peripheral areas.

[26] Data was accessed from the Longitudinal Employer-Household Dynamics (LEHD) 2010 – 2014.

Table 42 Jobs at Metrorail Station Area by Year

Station	2010	2011	2012	2013	2014	2014-2010 Change
McPherson Square	39,405	46,590	42,914	39,003	42,176	2,771
Metro Center	45,391	55,994	45,742	40,985	45,017	-374
Federal Triangle	31,220	33,121	21,915	24,057	21,124	-10,096
Smithsonian	9,499	12,783	4,060	4,050	4,260	-5,239
L'Enfant Plaze	26,066	21,904	26,612	15,572	19,006	-7,060
System Average	7,091	7,210	6,872	7,045	7,039	-52

However, neither trip length data or high-quality job data is available at the time of writing. I discuss the possibility conducting future research when data are available in the next chapter.

Chapter 9: Summary, Conclusions, and Suggestions

9.1 Summary and Conclusions

This dissertation's overriding purpose is to determine the impacts of a bike share program on rail transit ridership. To accomplish that goal, I performed a case study of the Washington metropolitan area, focusing on its Capital Bikeshare and Metrorail systems. The interplay between the two modes has generated different opinions. Many find CaBi to be a convenient, affordable, and healthy transportation option, while others, such as WMATA, which operates Metrorail, is concerned that CaBi may replace Metrorail and reduce its ridership.

Previous researchers have studied the relationship between CaBi and Metrorail and reached interesting findings, but most studies rely on data from CaBi member surveys. Since only CaBi users would participate in the survey, the data is likely to be biased. Therefore, this dissertation is dedicated to improving the existing knowledge by using rigorous regression analysis with detailed trip data. Based on WMATA's concerns, I designed the research hypotheses as: CaBi trips have only a substitute effect, and that having CaBi installed near Metrorail stations reduces Metrorail ridership.

Bike share programs are new. So, a literature review helped develop a better understanding of its features and factors. In Chapter 2, I reviewed the research background and found that the emergence of bike share programs is a component of the bigger paradigm switch into an era of shared mobility. First seen in the 1960s, bike share programs can be divided into four generations, based on technologies applied. Most bike share programs today are the third generation, supported by credit card payment, GPS bike tracking, and smartphone reservation apps.

Regarding how shared bikes are used, we tend to see more trips in warmer weather, during commuting peaks, and trips tend to be short-distances. Bike share programs have multiple benefits, such as the potential to reduce car use and thus to reduce carbon emissions. Bike sharing also encourages a healthy life style and benefits local retailers. At the end of this chapter, I reviewed the literature on factors of bike share activities. Besides factors such as the distance between origin and destination, weather, and biking infrastructure, accessibility to rail transit was found to have a big influence. However, the impacts are mixed. Some found that being near rail transit reduces bike share activities, some found a positive impact, while others found them uncorrelated.

The Washington metropolitan area provides a good case study based on its Capital Bikeshare and Metrorail systems. In Chapter 3, I studied Metrorail and Capital Bikeshare programs' features and trip trends, preparing for the later regression analysis. Using survey data, I particularly analyzed how CaBi users change their use of other transportation modes, and found very mixed attitudes. As of 2014, 58% of survey respondents reported they made fewer Metrorail trips than before, while 42% said they used Metrorail more or maintained the same level of use. Also, 64% reported that their CaBi trips started or ended at Metrorail stations.

A closer look at CaBi trips also reveals the program's characteristics. CaBi trips have seasonality—there are more trips during the warmer weather and tourist season between May and October. Trips also follow the commuting peak hours as do other transportation modes. Regarding account type, weekday trips are mostly made by commuters, while on weekends there are more casual trips made by casual users. These CaBi characteristics have important implications for regression models, specifically that CaBi trips affected by extreme weather conditions and recreational trips need to be eliminated.

Metrorail ridership has been declining since 2010, despite the opening of the Silver Line stations in 2014. I charted Metrorail ridership and CaBi trip numbers between 2010 and 2015 in one graph and found that as CaBi trip numbers increased, Metrorail ridership declined, suggesting a possible correlation between the two.

Chapter 4 starts with a discussion on CaBi's potential complementary and substitute impacts on Metrorail ridership from the microeconomic perspective. On the one hand, the combination of CaBi and Metrorail may cost less than driving and parking, and thus increase the demand for Metrorail. On the other hand, CaBi may replace Metrorail for lower travel time and cost, and result in a decrease in Metrorail ridership.

Both theories are supported by empirical evidence. A comparison of routes and travel times by Metrorail and CaBi between Union Station and Smithsonian concludes that because CaBi saves half the travel time by enabling travel across the National Mall and by saving transfer time it is likely to substitute for Metrorail. CaBi's complementary effects were found at the Takoma Park station, which has many CaBi trips ending at the station area in the morning and starting in the evening, suggesting that commuters use CaBi to bridge the distance between Takoma Park Metrorail station and their homes.

WMATA's SafeTrack maintenance period involves temporarily shutting down Metrorail stations and is a good opportunity to observe CaBi's substitute effects. The number of CaBi trips during SafeTrack periods increased compared to the same days of the week right before a Metrorail station's shutdown. Also, CaBi's $2 trip fare, which was designed to help commuters affected by the single tracking and Metrorail shutdowns, sold 70,568, indicating an increased demand. Finally, an origin-destination map shows that the increased trips started or ended near closed Metrorail stations, demonstrating CaBi's substitute impacts.

A review of the extant literature shows that most studies of a bike share program's impacts on rail transit ridership rely on survey data. Analysis tools are mostly charts and graphs. Surveys provide good first-hand data, however, since only bike share program members were surveyed, there is a selection bias. Also, due to the low respondent rate, a survey may not be the most suitable method.

Regression analysis with detailed actual trip data is highly desirable for answering the question of CaBi's impacts on Metrorail ridership. In Chapter 5, I introduce three regression models that fit the research question and data availability—the Direct Ridership Model, the Difference-in-Difference model, and the Station-Specific Dummies model. To maximize the benefits of the high-resolution and high-frequency data, Metrorail and CaBi ridership are divided into four measures. For Metrorail, ridership measures are *mentryam*, *mexitam*, *mentrypm*, and *mexitpm*, and for CaBi, they are *cstartam*, *cendam*, *cstartpm*, and *cendpm*. Components *entry*, *exit*, *start*, and *end* indicate trip types, and *am* and *pm* indicate trip times. Additional predictors were included and transformations were made to meet various model requirements.

Chapter 6 reports methodology, data, and results of the Direct Ridership Model. The DRM is a common method of estimating rail transit ridership at the station level. The current DRM considers transit service features, socio-demographics of people living and working in station areas, and built environment characteristics. In this Chapter, I introduced the DRM model and extended it with bike share trip variables to analyze how CaBi influences Metrorail ridership.

Results are mixed. CaBi can complement and substitute for Metrorail, as suggested by the positive associations between the number of CaBi trips started at Metrorail stations and the number of AM station exits, and between the number of CaBi trips ended at station areas and the number of PM peak Metrorail entries. The former indicates that CaBi solves the last-mile connection gap between Metrorail stations and workplaces. The latter suggests that CaBi bridges the gap between workplaces and Metrorail stations and thus attracts more commuters switching to Metrorail. Thus, DRM findings rejected the research hypotheses that CaBi only competes with Metrorail for riders.

However, the DRM has its limitations. Coefficients are found to be larger than expected, which might be caused by omitted variables. Also, Metrorail stations that have CaBi installed nearby are not randomly assigned, violating the critical assumption for a BLUE OLS estimator. Finally, the DRM pooled the observations over time, thus failing to capture systemic variation in the variables and their impacts over time. Therefore, though the DRM provides useful insights, sophisticated regression models capable of handling panel data and the quasi-experimental research environment are highly desired.

In Chapter 7, I use the Difference-in-Difference approach, a quasi-experimental technique, to address the random-assignment assumption in the DRM. A standard DID establishes a treatment group and a control group, and measures their pre-intervention outcomes and post-intervention outcomes. The difference between the treatment group's after-before ridership change and the control group's change can therefore be ascribed to the CaBi program.

However, since CaBi expanded every year between 2010 and 2015, the two-group two-period format does not apply here. In fact, there is a control group, five treatment groups (for Metrorail stations with CaBi installed in different years), a pre-intervention period and five post-intervention periods. Therefore, a special multiple-group-and-multiple-period DID is introduced to capture all differences.

Signs of coefficients suggest that CaBi increases Metrorail AM entries and PM exits but decreases AM exits and PM entries, which indicates that CaBi's impacts might be related to station locations. However, large P values prevent me from drawing that conclusion. Therefore, in Chapter 8, I designed a Station-Specific Dummies model to estimate CaBi's impacts by location (core vs. non-core Metrorail stations), after controlling for the year effects and stations' fixed effect. SSD results confirm that CaBi's impacts vary by location. It decreases Metrorail AM exits by 4,818.4 per month and PM entries by 4,886.9 per month for core stations, but increases them for non-core stations and also increases AM entries and PM exits for all stations. Metrorail ridership increases that resulted from CaBi's complementary effects range between 1,111.8 and 2,781.2 per month.

Results for the year effects confirm the SSD results that every year between 2010 and 2015, Metrorail lost ridership systematically. In 2015, the total loss reached 10%. Month also matters to Metrorail ridership. Months between March and October tend to have higher ridership while December has the lowest.

Also, the spatial patterns of Metrorail stations' fixed effects were identified by regression results and maps. Stations in downtown D.C. have more AM exits and PM entries, while stations in peripheral and suburban areas, particularly terminal and multi-modal transit hub stations, have larger numbers of AM entries and PM exits. These patterns echo the area's monocentric spatial structure, which has resulted from D.C.'s building height restriction and tight land supply.

The trip length is a possible explanation for CaBi's negative impacts on core stations' Metrorail ridership measures *mexitam* and *mentrypm*. CaBi trips, according to prior literature, are usually less than 1.5 miles. The high density in downtown D.C. with street grid is suitable for short-distance CaBi trips. Also, CaBi can save commuters unnecessary transfers as Metrorail runs on fixed routes and stops at fixed stations.

However, commuting trips to downtown D.C. that originate in peripheral areas and suburban communities are usually longer than a couple of miles. Commuters still have to rely on rail transit. In these cases, CaBi may be able to solve the first-mile connection problem and make Metrorail stations accessible, but by no means can it replace Metrorail. Hence, CaBi is more likely to complement Metrorail trips originating or ending at stations in suburban areas.

CaBi's negative impacts on downtown stations may be explained by job changes at those stations. The Longitudinal Employer-Household Dynamics(LEHD) data shows that Metro Center, Federal Triangle, Smithsonian, and L'Enfant Plaza lost up to 10,000 jobs each. Therefore, the additional ridership loss at these stations may result from a decreased commuting demand, not the CaBi program. However, without available data, this can't be further tested.

To summarize findings from various analyses, Table 43 lists CaBi's complementary effects and Table 44 lists its substitute effects. In short, these alternative specifications yield the consistent conclusion that CaBi program has both complementary and substitute effects and may lead to an increase or decrease of Metrorail ridership. This finding rejects the research hypothesis that CaBi only poses negative impacts on Metrorail. What's more, CaBi tends to substitute for Metrorail at downtown D.C. core stations, while complementing it at stations in peripheral and suburban areas.

Table 43 Findings on CaBi's Complementary Effects by Method

Method 1: Direct Ridership Model
• **One CaBi *cstartam* is positively associated with 49.1 average daily Metrorail *mexitam*.** • **One CaBi *cendpm* is positively associated with 57.9 average daily Metrorail *mentryam*.**
Method 2: Difference-in-Difference
• Having CaBi in station area increases the average daily Metrorail *mentryam* by 217.4. • Having CaBi in station area increases the average daily Metrorail *mexitpm* by 196.2.
Method 3: Station-Specific Dummies Analysis
• **Having CaBi in station area increases ridership in four measures by up to 2,781.2 per month.**

Note: Bold font indicates statistically significant results.

Table 44 Findings on CaBi's Substitute Effect by Method

Method 1: Direct Ridership Model
• **One CaBi *cendam* is negatively associated with 16.789 Metrorail *mexitam*.** • **One CaBi *cstartpm* is negatively associated with 40.640 Metrorail *mentrypm*.**
Method 2: Difference-in-Difference
• Having CaBi in station area decreases Metrorail *mexitam* by 14.6. • Having CaBi in station area decreases Metrorail *mentrypm* by 51.8.
Method 3: Station-Specific Dummies Analysis
• **Having CaBi in station area decreases core station ridership by 4,814.4 per month for *mexitam* and by 4,886.9 per month for *mentrypm*.**

Note: Bold font indicates statistically significant results.

Putting the two tables together, we can see that CaBi has mixed impacts on Metrorail ridership. CaBi may complement some Metrorail trips, but substitute for others, depending on the type and time. More importantly, the SSD results found that CaBi's impacts vary by Metrorail station locations, whether at a downtown D.C. core station or a non-core station in peripheral and suburban communities. CaBi reduces core Metrorail station ridership by 4,814.4 per month for the number of AM peak exits and by 4,886.9 per month for the number of PM peak entries, but increases ridership at non-core stations by up to 2,781.2 per month, at a high statistical significance level.

Also, it is worthwhile to compare the three regression models. Table 45 summarizes model features, significances of coefficients of CaBi variables, and R-squared values. The DRM takes cross-sectional average weekday daily AM/PM ridership per year as the input. It controls for other Metrorail ridership factors such as transit service, socio-demographics, and built environment characteristics, though data were not time varying. Coefficients of CaBi variables estimated using DRM are statistically significant. R-squared values, ranging between 0.495 and 0.851, suggest that the DRM is moderately fitted. The DID overcomes the unrealistic assumption of random assignment and controls for the systematic difference in ridership between Metrorail stations without and with CaBi installed nearby. Though coefficients signal a possible relationship between station location and CaBi's impacts, results are not statistically significant. The low values of R-squared also fail to justify the DID as a good model for this study. The SSD model controls for time effect (by year and by month) and station fixed effect for each station. Also, it takes more detailed monthly AM/PM ridership data as input, increasing the number of observations to 5,316. Results are as expected and statistically significant at a high confidence level. What's more, the large R-squared values indicate a good fit. Therefore, the SSD is the best model to test CaBi's impacts on Metrorail ridership.

Table 45 Model Comparison

	Features	Significance	R2
DRM	Cross-sectional; Average weekday daily AM/PM ridership per year; 526 obs.; Controlling for transit service, socio-demographics, and built environment (time-invariant).	Significant	0.495-0.851
DID	Panel; Average weekday daily AM/PM ridership per year; 526 obs.; Controlling for the systematic ridership difference between the control and the treatment groups.	Not significant	0.026-0.318
SSD	Panel; Monthly; 5,316 obs.; Controlling for time effect, station fixed effect.	Significant	0.961-0.988

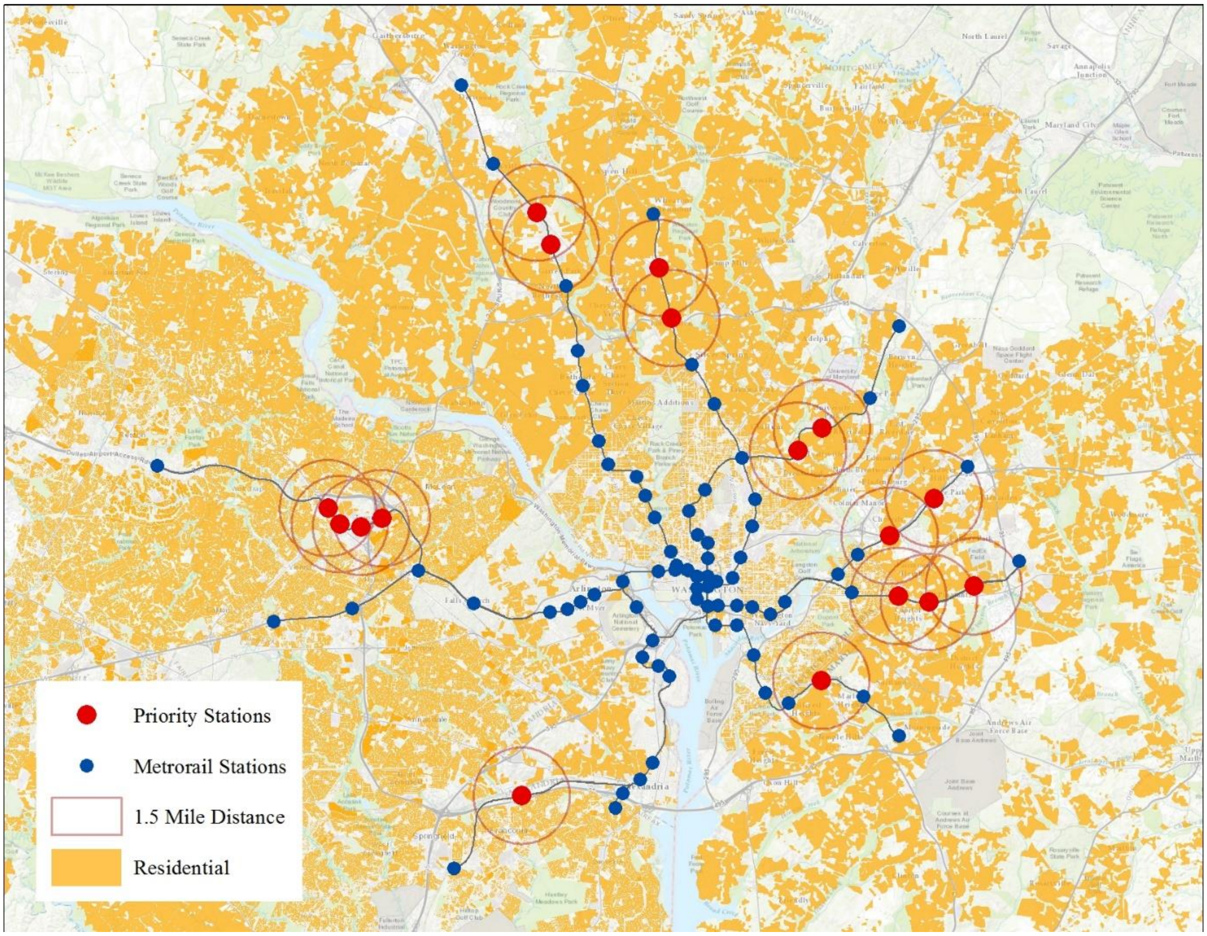
9.2 Policy Suggestions

Regression analysis results find that CaBi may substitute for Metrorail in some cases, but it also can complement Metrorail rides. This finding suggests that there is no need for WMATA to consider bike share programs as a challenge to Metrorail ridership. Instead, bike sharing's complementary effect has the potential to increase Metrorail ridership.

The SSD analysis results show that CaBi has complementary impacts on non-core stations suggest WMATA should work with CaBi to expand docks at Metrorail station areas in peripheral and suburban areas. CaBi stations should be installed in residential neighborhoods within 1.5-miles of Metrorail stations. These stations serve as the origins of morning CaBi trips and the destinations of PM peak trips. Together, these two groups of CaBi stations connect commuters' homes with Metrorail stations, and attract them to commuting via the CaBi-Metrorail combination.

I performed GIS analysis to identify priority Metrorail stations for CaBi installation using three criteria. First, I focus on the non-core stations in peripheral and suburban communities since CaBi has complementary effects on these stations. Second, I prioritize stations with relative smaller numbers of AM-peak entries. Third, I overlaid a land use GIS layer to identify stations in residential area since housing units are proxies for the commuting demand. After the process, the following stations are identified as the priorities: Addison Road, Capitol Heights, Cheverly, Forest Glen, Greensboro, Landover, McLean, Morgan Boulevard, Naylor Road, Prince George's Plaza, Spring Hill, Twinbrook, Tysons Corner, Van Dorn Street, West Hyattsville, Wheaton, and White Flint. Figure 56 shows these stations as red dots.

Figure 56 Priority Metrorail Stations for CaBi



CaBi stations should be installed as close to Metrorail station entrances as possible. A seamless transfer between CaBi and Metrorail helps to reduce the total travel time and thus improve the combined modes' attractiveness. Also, Metrorail stations may provide shelter to bicycle fleets, and thus keep bikes dry and clean.

Besides installing CaBi at non-core stations, other strategies may also help transfer riders between Metrorail and CaBi, and thus attract commuters using both. Integrating the CaBi and Metrorail payment systems would be an effective way to attract commuters to use both systems. Currently, bike share and rail transit payments are separate. Metrorail fares are paid using SmarTrip card or temporary pass ticket, while CaBi takes credit cards or CaBi ride keys. Experience in Europe and Asia suggest that integrating payments would benefit both modes.

There are two ways to integrate payments. One would allow the rail transit fare card to also pay for bike share use. Los Angeles has set a model for this approach. Metro (the rail transit system's name) users can check-out a shared bicycle at a docking station using a Metro TAP card (the system's pre-paid access card) that has been registered online for bike share access. The integration attracts commuters to take Metro by simplifying the transfer process.

Another way, which is more technology-forward, is mobile ticketing for both the Metrorail and CaBi systems. In 2016, the national smartphone penetration was higher than 80% (comScore, 2016) and Near Field Communication (NFC) technology is becoming more widespread; it enables payment by holding the smartphone a few centimeters from a receiving device. Several transit systems in the U.S.—Portland and Dallas—have adopted mobile ticketing supported by NFC. Passengers can pass a fare gate by scanning their cell phone at an NFC device. Transit tickets are charged to the bank account linked to the smartphone's NFC app.

WMATA's 2014 pilot project to test the use of NFC was not successful, leading WMATA to abandon the program after concluding that the market isn't ready for this technology. Now, three years later, people are more comfortable with contactless payment thanks to the popularity of D.C.'s mobile parking payment program. WMATA may re-consider NFC to keep its Metrorail system up-to-date (Duggan, 2014).

The bike share industry is also considering NFC-equipped smartphone payment. New dockless shared bikes are designed to carry a smartlock that enables smartphone checkout (Bluegogo, 2017). An NFC reader can be installed with smartlocks for mobile payment, which would create an opportunity to integrate bike share and rail transit payment using an NFC-equipped smartphone(Boegner et al., 2016).

Another strategy that to integrate bike share and rail transit use is the multi-modal trip planner mobile app. A trip planner tool is effective for providing schedule and fleet information for commuters' trip decisions. Currently, WMATA does not have an official mobile app though some train tracking tools have been developed by individuals. However, none have integrated Capital Bikeshare information. Given the fact people live and work in different places in Washington metropolitan area and use transportation services in more than one jurisdiction, a regional trip planner application with all public transportation choices is in great demand. Ideally, users could check train and bus schedules and make a Capital Bikeshare reservation 10 minutes before they exit Metrorail stations for a seamless travel experience.

Ridesourcing companies pioneered integrating information with rail transit agencies' mobile apps. For example, in Dallas, DART riders can access Uber via the agency's mobile ticketing app. Similar tools have been developed in Atlanta, Los Angeles, and Minneapolis (Jaffe, 2015b).

Besides integrating bike share information in mobile applications developed by transit agencies, another good platform is Google products. Currently, Google trip planner embedded in Google Maps provides estimated driving, bus and/or rail transit and walking time between two locations. A new ride-sharing tab was introduced to Google Maps Android and iOS app in March 2016 (Paul, 2016). North American Google Maps users can check Uber availability and estimated price from the tab. More recently, in September 2016, Lyft, Uber's main competitor, was integrated into the tab service (Nicas, 2016). For cyclists, there is a bicycling tab, showing the distance between input locations and estimated time based on speed assumptions. The bicycling tab should be upgraded to include bike share docking stations and bicycle availability. When users enter origin and destination, Google Maps would recommend bike share docking stations (one near the trip origin and the other near destination) to complete the trip via bike share. Google could also enable an online shared bicycle reservation. Ideally, rather than providing only single-mode estimated travel information, the next generation of trip planners should provide multi-modal travel options. The tool would enable commuters who use bike share to reach rail transit to estimate distance, time, cost, and availability of combined modes.

Technically speaking, one important step toward integrating bike share and rail transit information and schedule data is to standardize the format of open data. The General Transit Feed Specification (GTFS), a transit schedule open data format initiated by Google, has been widely used. A similar format for bike share, the General Bikeshare Feed Specification (GBFS), which included information on docking station locations, bike, and dock availability, and pricing information, has been under development under the North American Bikeshare Association's leadership (North American Bikeshare Association, 2015). Standardized open bike share data, will enable more bike share and multi-modal trip planner applications to help people choose the best transportation mode(s) to meet their needs.

In a nutshell, WMATA should take CaBi's complementary effects as an opportunity, and collaborate to increase commuters' accessibility to Metrorail. In terms of physical planning, WMATA should work with CaBi to add docks at non-core stations to fill commuters' last-mile gap between Metrorail stations and their homes. Also, emerging technologies may accelerate the integration of CaBi and Metrorail information, particularly payment via smartphone, to attract more millennium generation users to combining CaBi and Metrorail for commuting.

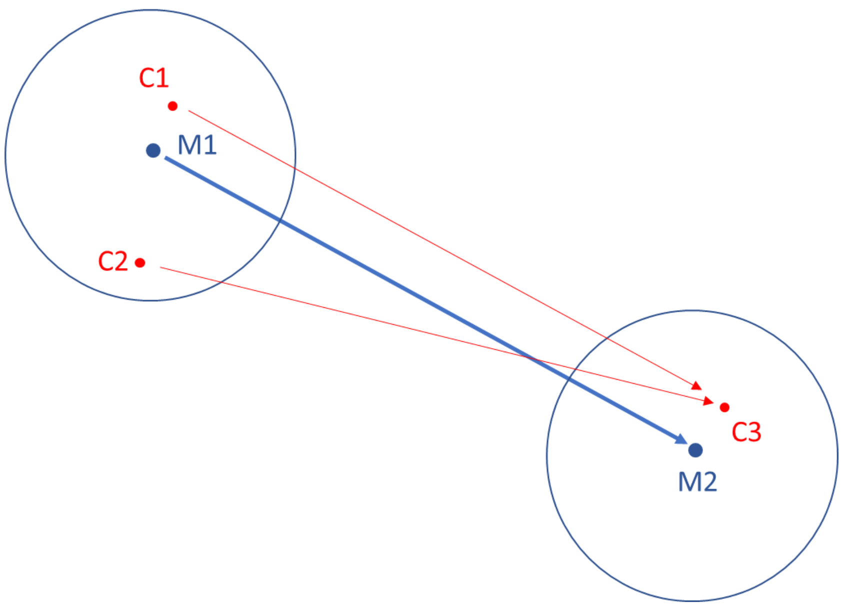
9.3 Further Research

While the regression results constitute robust evidence of bike share's impacts on rail transit ridership, there are additional dimensions in which future research could extend my analysis. Some of them rely on the availability of data and variables, and some would need more advanced econometric models to overcome methodological barriers.

First, it would be ideal to control DRM variables—transit service, socio-demographics of people living and working in the station area, and built environment characteristics should be time-variant. The Washington metropolitan area is one of the most dynamic places in the U.S. and we would expect to see neighborhoods redeveloping within a couple years. Failing to include time-variant data may lead to ascribing the ridership change to CaBi and overestimating the program's impact. However, Metrorail station areas are small, and the Census provides estimates at the block group level only in their American Community Survey (ACS) 5-year estimate. Therefore, annual data for socio-demographic variables are not available at the time of writing.

Second, the difference between CaBi's impacts on Metrorail core and non-core stations suggest that trip distance may play a role. Metrorail trips in downtown D.C. tend to be shorter-distance and more likely to be replaced by CaBi. One method of exploring the influence of trip distance on CaBi impacts would be to conduct a before-after comparison using O-D pairs. Figure 57 illustrates the method. Imagine two Metrorail stations, M1 and M2, which are the origin and the destination of a commuting trip. Imagine three CaBi stations, two of which, C1 and C2, are located near M1, and the third, C2, is near M2. If the distance between M1 and M2 is short, we would expect to see an increase of CaBi trips from C1 to C3 and from C2 to C3, and simultaneously a decrease of Metrorail trips from M1 to M2, resulting from CaBi's substitute effect. What's more, by performing regression analysis, we would expect to find that the decrease of Metrorail trips is statistically significantly associated with the increase of CaBi trips.

Figure 57 Illustration of Trip Distance Analysis



Another issue not addressed in my dissertation is the possibility of spatial correlation. It is reasonable to expect that the ridership of one Metrorail station is correlated with its neighboring station. Similarly, one could expect spatial correlation on Capital Bikeshare stations. Although spatial correlation is often ignored in applied work because correcting can be difficult, there are great benefits in addressing it.

Finally, self-selection generally refers to an agent making a choice depending on factors that are unobservable to the agent. Among users who combine CaBi and Metrorail, demographic features such as age, gender, and health may play an essential role. In particular, according to CaBi user surveys, the majority of CaBi members are young white men who are highly educated and in good shape. It is reasonable to assume that commuters who combine CaBi and Metrorail are very likely to be a small proportion of these white young male CaBi frequent users and thus we see the barrier of self-selection.

Appendices

Appendix A. Full Descriptive Statistics of the Station-Specific Dummies Model Input

Variable	Obs	Mean	Std. Dev.	Min	Max
mentryam	5,316	55735.5	40970.6	142.0	242376.0
mexitam	5,316	50593.1	71375.3	1205.0	340978.0
mentrypm	5,316	61343.4	76167.3	1574.0	381632.0
mexitpm	5,316	59526.9	41472.7	1004.0	289758.0
core	5,316	0.3	0.4	0.0	1.0
noncore	5,316	0.7	0.4	0.0	1.0
CaBi	5,316	0.5	0.5	0.0	1.0
CaBi core	5,316	0.3	0.4	0.0	1.0
CaBi noncore	5,316	0.2	0.4	0.0	1.0
2011	5,316	0.2	0.4	0.0	1.0
2012	5,316	0.2	0.4	0.0	1.0
2013	5,316	0.2	0.4	0.0	1.0
2014	5,316	0.2	0.4	0.0	1.0
2015	5,316	0.1	0.3	0.0	1.0
Feburary	5,316	0.1	0.3	0.0	1.0
March	5,316	0.1	0.3	0.0	1.0
April	5,316	0.1	0.3	0.0	1.0
May	5,316	0.1	0.3	0.0	1.0
June	5,316	0.1	0.3	0.0	1.0
July	5,316	0.1	0.3	0.0	1.0
August	5,316	0.1	0.3	0.0	1.0
September	5,316	0.1	0.3	0.0	1.0
October	5,316	0.1	0.3	0.0	1.0
November	5,316	0.1	0.3	0.0	1.0
December	5,316	0.1	0.3	0.0	1.0
Addison Road	5,316	0.0	0.1	0.0	1.0

Anacostia	5,316	0.0	0.1	0.0	1.0
Archives-Navy Memorial	5,316	0.0	0.1	0.0	1.0
Arlington Cemetery	5,316	0.0	0.1	0.0	1.0
Ballston	5,316	0.0	0.1	0.0	1.0
Benning Road	5,316	0.0	0.1	0.0	1.0
Bethesda	5,316	0.0	0.1	0.0	1.0
Braddock Road	5,316	0.0	0.1	0.0	1.0
Branch Avenue	5,316	0.0	0.1	0.0	1.0
Brookland	5,316	0.0	0.1	0.0	1.0
Capitol Heights	5,316	0.0	0.1	0.0	1.0
Capitol South	5,316	0.0	0.1	0.0	1.0
Cheverly	5,316	0.0	0.1	0.0	1.0
Clarendon	5,316	0.0	0.1	0.0	1.0
Cleveland Park	5,316	0.0	0.1	0.0	1.0
College Park-U of MD	5,316	0.0	0.1	0.0	1.0
Columbia Heights	5,316	0.0	0.1	0.0	1.0
Congress Heights	5,316	0.0	0.1	0.0	1.0
Court House	5,316	0.0	0.1	0.0	1.0
Crystal City	5,316	0.0	0.1	0.0	1.0
Deanwood	5,316	0.0	0.1	0.0	1.0
Dunn Loring	5,316	0.0	0.1	0.0	1.0
Dupont Circle	5,316	0.0	0.1	0.0	1.0
East Falls Church	5,316	0.0	0.1	0.0	1.0
Eastern Market	5,316	0.0	0.1	0.0	1.0
Eisenhower Avenue	5,316	0.0	0.1	0.0	1.0
Farragut North	5,316	0.0	0.1	0.0	1.0
Farragut West	5,316	0.0	0.1	0.0	1.0
Federal Center SW	5,316	0.0	0.1	0.0	1.0
Federal Triangle	5,316	0.0	0.1	0.0	1.0
Foggy Bottom	5,316	0.0	0.1	0.0	1.0
Forest Glen	5,316	0.0	0.1	0.0	1.0

Fort Totten	5,316	0.0	0.1	0.0	1.0
Franconia-Springfield	5,316	0.0	0.1	0.0	1.0
Friendship Heights	5,316	0.0	0.1	0.0	1.0
Gallery Place-Chinatown	5,316	0.0	0.1	0.0	1.0
Georgia Avenue-Petworth	5,316	0.0	0.1	0.0	1.0
Glenmont	5,316	0.0	0.1	0.0	1.0
Greenbelt	5,316	0.0	0.1	0.0	1.0
Greensboro	5,316	0.0	0.1	0.0	1.0
Grosvenor	5,316	0.0	0.1	0.0	1.0
Huntington	5,316	0.0	0.1	0.0	1.0
Judiciary Square	5,316	0.0	0.1	0.0	1.0
King Street	5,316	0.0	0.1	0.0	1.0
L'Enfant Plaza	5,316	0.0	0.1	0.0	1.0
Landover	5,316	0.0	0.1	0.0	1.0
Largo Town Center	5,316	0.0	0.1	0.0	1.0
McLean	5,316	0.0	0.1	0.0	1.0
McPherson Square	5,316	0.0	0.1	0.0	1.0
Medical Center	5,316	0.0	0.1	0.0	1.0
Metro Center	5,316	0.0	0.1	0.0	1.0
Minnesota Avenue	5,316	0.0	0.1	0.0	1.0
Morgan Blvd.	5,316	0.0	0.1	0.0	1.0
Mt. Vernon Square-UDC	5,316	0.0	0.1	0.0	1.0
Navy Yard	5,316	0.0	0.1	0.0	1.0
Naylor Road	5,316	0.0	0.1	0.0	1.0
New Carrollton	5,316	0.0	0.1	0.0	1.0
New York Ave	5,316	0.0	0.1	0.0	1.0
Pentagon	5,316	0.0	0.1	0.0	1.0
Pentagon City	5,316	0.0	0.1	0.0	1.0
Potomac Avenue	5,316	0.0	0.1	0.0	1.0
Prince George's Plaza	5,316	0.0	0.1	0.0	1.0
Reagan Washington National Airport	5,316	0.0	0.1	0.0	1.0

Rhode Island Avenue	5,316	0.0	0.1	0.0	1.0
Rockville	5,316	0.0	0.1	0.0	1.0
Rosslyn	5,316	0.0	0.1	0.0	1.0
Shady Grove	5,316	0.0	0.1	0.0	1.0
Shaw-Howard University	5,316	0.0	0.1	0.0	1.0
Silver Spring	5,316	0.0	0.1	0.0	1.0
Smithsonian	5,316	0.0	0.1	0.0	1.0
Southern Avenue	5,316	0.0	0.1	0.0	1.0
Spring Hill	5,316	0.0	0.1	0.0	1.0
Stadium-Armory	5,316	0.0	0.1	0.0	1.0
Suitland	5,316	0.0	0.1	0.0	1.0
Takoma	5,316	0.0	0.1	0.0	1.0
Tenleytown-AU	5,316	0.0	0.1	0.0	1.0
Twinbrook	5,316	0.0	0.1	0.0	1.0
Tysons Corner	5,316	0.0	0.1	0.0	1.0
U Street-Cardozo	5,316	0.0	0.1	0.0	1.0
Union Station	5,316	0.0	0.1	0.0	1.0
Van Dorn Street	5,316	0.0	0.1	0.0	1.0
Van Ness-UDC	5,316	0.0	0.1	0.0	1.0
Vienna	5,316	0.0	0.1	0.0	1.0
Virginia Square-GMU	5,316	0.0	0.1	0.0	1.0
Waterfront	5,316	0.0	0.1	0.0	1.0
West Falls Church	5,316	0.0	0.1	0.0	1.0
West Hyattsville	5,316	0.0	0.1	0.0	1.0
Wheaton	5,316	0.0	0.1	0.0	1.0
White Flint	5,316	0.0	0.1	0.0	1.0
Wiehle	5,316	0.0	0.1	0.0	1.0
Woodley Park-Zoo	5,316	0.0	0.1	0.0	1.0

Appendix B. Full Results of the Station-Specific Dummies Analysis

Table 46 Results of SSD with *mentryam* and *mexitam* as the Dependent Variables

mentryam			*mexitam*		
	Coef.	P		Coef.	P
CaBi core	2,471.0	0.013	CaBi core	-4,814.4	0.000
CaBi non-core	1,111.8	0.023	CaBi non-core	2,143.3	0.000
2011	127.7	0.771	2011	1,198.2	0.014
2012	-1,221.6	0.006	2012	-331.2	0.504
2013	-1,998.7	0.000	2013	-1,131.7	0.023
2014	-3,660.6	0.000	2014	-2,741.1	0.000
2015	-6,085.8	0.000	2015	-4,882.7	0.000
Feb	-1,634.6	0.001	Feb	-1,158.5	0.030
Mar	4,556.3	0.000	Mar	4,196.2	0.000
Apr	5,647.5	0.000	Apr	5,128.2	0.000
May	4,539.5	0.000	May	4,355.1	0.000
Jun	6,478.0	0.000	Jun	5,990.1	0.000
Jul	5,058.1	0.000	Jul	4,708.8	0.000
Aug	2,159.7	0.000	Aug	2,213.3	0.000
Sep	2,244.3	0.000	Sep	2,416.3	0.000
Oct	3,259.5	0.000	Oct	3,202.8	0.000
Nov	-2,083.9	0.000	Nov	-1,644.1	0.003
Dec	-5,992.4	0.000	Dec	-5,217.6	0.000
King Street (base)	60,968.5	0.000	King Street (base)	47,297.9	0.000
Addison Road	-17,647.8	0.000	Addison Road	-42,744.7	0.000
Anacostia	-1,461.9	0.369	Anacostia	-14,566.6	0.000
Archives-Navy Memorial	-55,234.4	0.000	Archives-Navy Memorial	62,279.3	0.000
Arlington Cemetery	-60,504.7	0.000	Arlington Cemetery	-44,095.2	0.000
Ballston	32,059.8	0.000	Ballston	18,116.6	0.000
Benning Road	-28,855.1	0.000	Benning Road	-44,943.5	0.000
Bethesda	5,637.2	0.000	Bethesda	13,776.9	0.000

Braddock Road	-7,646.4	0.000	Braddock Road	-35,515.4	0.000
Branch Avenue	36,654.3	0.000	Branch Avenue	-41,140.0	0.000
Brookland	-17,827.1	0.000	Brookland	-14,015.5	0.000
Capitol Heights	-35,857.5	0.000	Capitol Heights	-45,423.3	0.000
Capitol South	-45,141.0	0.000	Capitol South	41,916.1	0.000
Cheverly	-40,785.3	0.000	Cheverly	-45,407.2	0.000
Clarendon	-23,389.9	0.000	Clarendon	-34,712.1	0.000
Cleveland Park	-15,243.1	0.000	Cleveland Park	-44,573.8	0.000
College Park-U of MD	-20,363.4	0.000	College Park-U of MD	-32,295.2	0.000
Columbia Heights	25,169.8	0.000	Columbia Heights	-9,012.2	0.000
Congress Heights	-33,082.2	0.000	Congress Heights	-44,059.5	0.000
Court House	7,442.1	0.000	Court House	-15,073.8	0.000
Crystal City	22,777.7	0.000	Crystal City	44,112.1	0.000
Deanwood	-42,800.6	0.000	Deanwood	-44,311.9	0.000
Dunn Loring	-2,792.0	0.035	Dunn Loring	-33,391.0	0.000
Dupont Circle	20,519.0	0.000	Dupont Circle	91,639.5	0.000
East Falls Church	-7,664.0	0.000	East Falls Church	-42,884.1	0.000
Eastern Market	-17,911.3	0.000	Eastern Market	-21,195.7	0.000
Eisenhower Avenue	-43,681.3	0.000	Eisenhower Avenue	-40,229.2	0.000
Farragut North	-37,728.9	0.000	Farragut North	252,908.0	0.000
Farragut West	-34,051.9	0.000	Farragut West	251,839.7	0.000
Federal Center SW	-53,807.6	0.000	Federal Center SW	32,007.6	0.000
Federal Triangle	-59,009.1	0.000	Federal Triangle	75,252.6	0.000
Foggy Bottom	-10,712.1	0.000	Foggy Bottom	157,149.8	0.000
Forest Glen	-27,500.5	0.000	Forest Glen	-45,114.6	0.000
Fort Totten	16,114.3	0.000	Fort Totten	-30,031.1	0.000
Franconia-Springfield	57,178.5	0.000	Franconia-Springfield	-35,861.7	0.000
Friendship Heights	5,670.1	0.000	Friendship Heights	-8,808.5	0.000
Gallery Place-Chinatown	-26,758.9	0.000	Gallery Place-Chinatown	154,546.5	0.000
Georgia Avenue-Petworth	-8,693.4	0.000	Georgia Avenue-Petworth	-34,001.2	0.000
Glenmont	26,615.7	0.000	Glenmont	-43,801.1	0.000
Greenbelt	22,924.4	0.000	Greenbelt	-37,156.7	0.000

Greensboro	-53,103.0	0.000	Greensboro	-38,165.8	0.000
Grosvenor	16,502.1	0.000	Grosvenor	-41,683.5	0.000
Huntington	63,804.9	0.000	Huntington	-40,141.5	0.000
Judiciary Square	-52,753.1	0.000	Judiciary Square	78,926.4	0.000
L'Enfant Plaza	-4,641.8	0.004	L'Enfant Plaza	204,653.1	0.000
Landover	-30,767.9	0.000	Landover	-45,206.6	0.000
Largo Town Center	6,315.7	0.000	Largo Town Center	-40,734.4	0.000
McLean	-45,076.6	0.000	McLean	-37,625.9	0.000
McPherson Square	-29,817.8	0.000	McPherson Square	159,432.8	0.000
Medical Center	-41,904.8	0.000	Medical Center	24,228.7	0.000
Metro Center	-28,687.5	0.000	Metro Center	238,956.0	0.000
Minnesota Avenue	-37,252.5	0.000	Minnesota Avenue	-36,615.9	0.000
Morgan Blvd.	-34,191.1	0.000	Morgan Blvd.	-44,787.1	0.000
Mt. Vernon Square-UDC	-39,045.6	0.000	Mt. Vernon Square-UDC	-17,533.9	0.000
Navy Yard	-42,299.0	0.000	Navy Yard	29,667.1	0.000
Naylor Road	-24,885.1	0.000	Naylor Road	-43,755.9	0.000
New Carrollton	64,817.0	0.000	New Carrollton	-29,653.3	0.000
New York Ave	-22,808.7	0.000	New York Ave	20,586.7	0.000
Pentagon	68,256.8	0.000	Pentagon	87,273.7	0.000
Pentagon City	54,469.9	0.000	Pentagon City	-11,547.9	0.000
Potomac Avenue	-21,826.9	0.000	Potomac Avenue	-36,686.3	0.000
Prince George's Plaza	-15,020.3	0.000	Prince George's Plaza	-36,634.2	0.000
Reagan Washington National Airport	-44,634.4	0.000	Reagan Washington National Airport	-13,085.8	0.000
Rhode Island Avenue	-11,922.3	0.000	Rhode Island Avenue	-31,450.2	0.000
Rockville	-13,382.8	0.000	Rockville	-32,188.1	0.000
Rosslyn	29,342.8	0.000	Rosslyn	72,504.4	0.000
Shady Grove	129,093.1	0.000	Shady Grove	-31,929.8	0.000
Shaw-Howard University	-32,414.8	0.000	Shaw-Howard University	-28,493.2	0.000
Silver Spring	61,896.8	0.000	Silver Spring	-2,570.4	0.072
Smithsonian	-56,658.2	0.000	Smithsonian	63,234.9	0.000
Southern Avenue	12,161.8	0.000	Southern Avenue	-41,448.2	0.000
Spring Hill	-48,803.0	0.000	Spring Hill	-38,349.4	0.000

Stadium-Armory	-39,382.5	0.000	Stadium-Armory	-33,127.4	0.000
Suitland	9,635.0	0.000	Suitland	-29,635.8	0.000
Takoma	5,715.6	0.000	Takoma	-37,369.2	0.000
Tenleytown-AU	-23,217.5	0.000	Tenleytown-AU	-9,672.2	0.000
Twinbrook	-14,053.7	0.000	Twinbrook	-33,066.6	0.000
Tysons Corner	-48,221.1	0.000	Tysons Corner	-29,166.9	0.000
U Street-Cardozo	-20,070.3	0.000	U Street-Cardozo	-26,674.9	0.000
Union Station	136,184.9	0.000	Union Station	179,529.3	0.000
Van Dorn Street	-14,402.0	0.000	Van Dorn Street	-42,465.3	0.000
Van Ness-UDC	-6,038.6	0.000	Van Ness-UDC	-26,353.5	0.000
Vienna	127,068.3	0.000	Vienna	-34,522.8	0.000
Virginia Square-GMU	-24,125.6	0.000	Virginia Square-GMU	-33,730.8	0.000
Waterfront	-36,507.3	0.000	Waterfront	-24,901.9	0.000
West Falls Church	57,760.1	0.000	West Falls Church	-23,579.8	0.000
West Hyattsville	-16,503.4	0.000	West Hyattsville	-43,752.5	0.000
Wheaton	-16,278.8	0.000	Wheaton	-41,224.2	0.000
White Flint	-27,720.6	0.000	White Flint	-26,269.3	0.000
Wiehle	39,215.2	0.000	Wiehle	-27,944.8	0.000
Woodley Park-Zoo	-6,184.1	0.000	Woodley Park-Zoo	-32,895.1	0.000

Table 47 Results of SSD with *mentrypm* and *mexitpm* as the Dependent Variables

mentrypm			*mexitpm*		
	Coef.	P		Coef.	P
CaBi core	-4,886.9	0.000	CaBi core	2,781.2	0.015
CaBi non-core	2,458.4	0.000	CaBi non-core	1,336.4	0.018
2011	541.6	0.342	2011	-221.7	0.663
2012	-960.3	0.098	2012	-1,649.0	0.002
2013	-2,071.2	0.000	2013	-2,699.7	0.000
2014	-4,037.2	0.000	2014	-4,444.4	0.000
2015	-5,881.7	0.000	2015	-6,825.9	0.000
Feb	-2,926.9	0.000	Feb	-2,849.9	0.000
Mar	5,217.7	0.000	Mar	5,177.8	0.000
Apr	7,828.0	0.000	Apr	7,926.6	0.000
May	5,036.5	0.000	May	5,377.8	0.000
Jun	7,043.6	0.000	Jun	7,121.3	0.000
Jul	7,940.5	0.000	Jul	7,844.7	0.000
Aug	3,669.5	0.000	Aug	3,881.0	0.000
Sep	1,344.2	0.035	Sep	1,458.3	0.011
Oct	3,342.1	0.000	Oct	3,235.8	0.000
Nov	-2,594.3	0.000	Nov	-2,267.5	0.000
Dec	-5,319.5	0.000	Dec	-4,694.3	0.000
King Street (base)	59,189.0	0.000	King Street (base)	68,797.2	0.000
Addison Road	-51,823.7	0.000	Addison Road	-29,121.6	0.000
Anacostia	-19,426.2	0.000	Anacostia	-10,822.3	0.000
Archives-Navy Memorial	66,940.7	0.000	Archives-Navy Memorial	-48,371.1	0.000
Arlington Cemetery	-47,414.4	0.000	Arlington Cemetery	-61,164.2	0.000
Ballston	19,937.6	0.000	Ballston	21,950.1	0.000
Benning Road	-51,232.4	0.000	Benning Road	-43,166.5	0.000
Bethesda	17,724.8	0.000	Bethesda	7,940.7	0.000
Braddock Road	-42,745.5	0.000	Braddock Road	-20,161.5	0.000
Branch Avenue	-47,736.2	0.000	Branch Avenue	16,440.5	0.000

Brookland	-14,589.2	0.000	Brookland	-22,519.7	0.000
Capitol Heights	-54,208.6	0.000	Capitol Heights	-47,419.5	0.000
Capitol South	38,730.7	0.000	Capitol South	-43,601.8	0.000
Cheverly	-56,019.3	0.000	Cheverly	-51,607.6	0.000
Clarendon	-38,687.5	0.000	Clarendon	-20,266.9	0.000
Cleveland Park	-46,089.2	0.000	Cleveland Park	-26,214.8	0.000
College Park-U of MD	-34,183.1	0.000	College Park-U of MD	-29,369.1	0.000
Columbia Heights	9,471.3	0.000	Columbia Heights	28,876.3	0.000
Congress Heights	-51,131.9	0.000	Congress Heights	-45,733.3	0.000
Court House	-17,079.9	0.000	Court House	-7,560.5	0.000
Crystal City	44,899.2	0.000	Crystal City	15,182.2	0.000
Deanwood	-53,761.9	0.000	Deanwood	-53,304.3	0.000
Dunn Loring	-39,358.6	0.000	Dunn Loring	-17,493.8	0.000
Dupont Circle	111,480.3	0.000	Dupont Circle	64,426.8	0.000
East Falls Church	-46,618.8	0.000	East Falls Church	-20,537.1	0.000
Eastern Market	-21,706.1	0.000	Eastern Market	-17,315.3	0.000
Eisenhower Avenue	-48,697.6	0.000	Eisenhower Avenue	-52,842.2	0.000
Farragut North	261,316.2	0.000	Farragut North	-10,594.1	0.000
Farragut West	225,669.8	0.000	Farragut West	-14,618.0	0.000
Federal Center SW	23,364.6	0.000	Federal Center SW	-60,062.1	0.000
Federal Triangle	78,903.8	0.000	Federal Triangle	-55,301.3	0.000
Foggy Bottom	163,104.9	0.000	Foggy Bottom	30,663.8	0.000
Forest Glen	-53,780.9	0.000	Forest Glen	-41,926.8	0.000
Fort Totten	-29,604.7	0.000	Fort Totten	540.3	0.719
Franconia-Springfield	-39,241.7	0.000	Franconia-Springfield	36,051.6	0.000
Friendship Heights	-1,780.5	0.288	Friendship Heights	8,935.5	0.000
Gallery Place-Chinatown	194,572.3	0.000	Gallery Place-Chinatown	79,934.7	0.000
Georgia Avenue-Petworth	-33,213.2	0.000	Georgia Avenue-Petworth	-26,713.5	0.000
Glenmont	-48,050.0	0.000	Glenmont	1,698.3	0.268
Greenbelt	-39,663.1	0.000	Greenbelt	6,374.9	0.000
Greensboro	-48,010.3	0.000	Greensboro	-60,335.1	0.000
Grosvenor	-43,787.8	0.000	Grosvenor	-6,006.2	0.000

Huntington	-42,334.8	0.000	Huntington	35,328.0	0.000
Judiciary Square	66,371.5	0.000	Judiciary Square	-54,090.2	0.000
L'Enfant Plaza	212,256.5	0.000	L'Enfant Plaza	-11,610.8	0.000
Landover	-55,366.8	0.000	Landover	-42,702.8	0.000
Largo Town Center	-47,648.9	0.000	Largo Town Center	-5,502.3	0.000
McLean	-47,115.3	0.000	McLean	-54,154.0	0.000
McPherson Square	143,681.5	0.000	McPherson Square	-19,821.5	0.000
Medical Center	10,905.2	0.000	Medical Center	-52,196.6	0.000
Metro Center	268,757.1	0.000	Metro Center	31,607.1	0.000
Minnesota Avenue	-44,123.9	0.000	Minnesota Avenue	-44,348.3	0.000
Morgan Blvd.	-55,328.8	0.000	Morgan Blvd.	-44,301.5	0.000
Mt. Vernon Square-UDC	-23,695.1	0.000	Mt. Vernon Square-UDC	-43,620.4	0.000
Navy Yard	25,748.0	0.000	Navy Yard	-16,183.1	0.000
Naylor Road	-51,493.0	0.000	Naylor Road	-36,247.5	0.000
New Carrollton	-35,932.8	0.000	New Carrollton	40,474.1	0.000
New York Ave	21,631.2	0.000	New York Ave	-34,185.9	0.000
Pentagon	72,107.1	0.000	Pentagon	49,680.0	0.000
Pentagon City	27,470.3	0.000	Pentagon City	80,555.9	0.000
Potomac Avenue	-41,827.9	0.000	Potomac Avenue	-37,713.0	0.000
Prince George's Plaza	-36,261.3	0.000	Prince George's Plaza	-21,081.6	0.000
Reagan Washington National Airport	-18,741.1	0.000	Reagan Washington National Airport	-28,784.9	0.000
Rhode Island Avenue	-34,985.7	0.000	Rhode Island Avenue	-20,202.8	0.000
Rockville	-38,477.6	0.000	Rockville	-24,097.3	0.000
Rosslyn	75,188.1	0.000	Rosslyn	16,863.2	0.000
Shady Grove	-29,657.7	0.000	Shady Grove	87,724.7	0.000
Shaw-Howard University	-28,744.5	0.000	Shaw-Howard University	-39,533.9	0.000
Silver Spring	5,129.3	0.002	Silver Spring	42,688.1	0.000
Smithsonian	104,045.0	0.000	Smithsonian	-41,643.8	0.000
Southern Avenue	-47,814.6	0.000	Southern Avenue	-5,447.4	0.000
Spring Hill	-48,515.9	0.000	Spring Hill	-56,357.2	0.000
Stadium-Armory	-39,868.3	0.000	Stadium-Armory	-49,083.2	0.000
Suitland	-36,725.9	0.000	Suitland	-7,538.0	0.000

Takoma	-40,778.9	0.000	Takoma	-9,350.9	0.000
Tenleytown-AU	-8,443.6	0.000	Tenleytown-AU	-14,914.6	0.000
Twinbrook	-38,677.7	0.000	Twinbrook	-27,854.0	0.000
Tysons Corner	-32,038.4	0.000	Tysons Corner	-44,542.3	0.000
U Street-Cardozo	-24,161.7	0.000	U Street-Cardozo	-12,659.5	0.000
Union Station	204,890.3	0.000	Union Station	171,029.7	0.000
Van Dorn Street	-50,425.4	0.000	Van Dorn Street	-27,539.0	0.000
Van Ness-UDC	-24,945.4	0.000	Van Ness-UDC	-17,474.9	0.000
Vienna	-30,812.7	0.000	Vienna	91,888.9	0.000
Virginia Square-GMU	-39,760.2	0.000	Virginia Square-GMU	-34,723.0	0.000
Waterfront	-28,102.7	0.000	Waterfront	-41,477.9	0.000
West Falls Church	-29,733.7	0.000	West Falls Church	39,405.9	0.000
West Hyattsville	-47,687.1	0.000	West Hyattsville	-32,317.5	0.000
Wheaton	-44,102.0	0.000	Wheaton	-25,571.1	0.000
White Flint	-33,420.0	0.000	White Flint	-38,520.7	0.000
Wiehle	-26,653.3	0.000	Wiehle	22,066.6	0.000
Woodley Park-Zoo	-20,481.8	0.000	Woodley Park-Zoo	-10,519.8	0.000

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