The Land Use and Built Environment Factors Impacting Where Women are Using Bikeshare in Boston

By

Laura Krull

BA in Economics
Cornell University
Ithaca, New York (2012)

Submitted to the Department of Urban Studies and Planning
in partial fulfillment of the requirements for the degree of

Master in City Planning

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

June 2018

Author ______________ Signature redacted
Department of Urban Studies and Planning
May 29, 2018

Certified by ______________ Signature redacted
Professor P. Christopher Zegras
Department of Urban Studies and Planning
Thesis Supervisor

Accepted by ______ Signature redacted
Professor of the Practice, Ceasar McDowell
Chair, MCP Committee
Department of Urban Studies and Planning

The Land Use and Built Environment Factors Impacting Where Women are Using Bikeshare in Boston

by

Laura Krull

Submitted to the Department of Urban Studies and Planning on May 29, 2018 in Partial Fulfillment of the Requirements for the Degree of Master in City Planning

ABSTRACT

In the last 10-15 years, many cities across the U.S. have worked to create cities that are not just for motor vehicles. Even with these monetary and physical infrastructure investments, a very low percentage of people in the U.S. primarily use bicycles as a form of transportation, and a large gender gap exists in bicycling. Research suggests the gender gap is due to factors such as risk aversion, bicycling being less convenient to female household responsibility, and women having a stronger preference for safety than men. The objective of this thesis is to analyze built environment and land use factors related to bikeshare usage and investigate if these factors differ for men and women. Exploring how different factors might affect male and female ridership can reveal how gender differences manifest themselves in biking, and can lead to insights into why women bike at such low rates compared to men.

In this thesis, I estimate direct ridership models for Boston's bikeshare system, Hubway, to predict trip origins based on a 14 demographic, safety, bicycle infrastructure, safety and transit explanatory variables. I find that many variables impact men and women similarly, particularly land use and demographic factors. The one variable that was significant in all models for women but not in any models for men was distance to separated bicycle facilities. This result indicates that for women, there are more trip origins at stations closer to separated bicycle facilities. I discuss the implication of these findings for city planners and Hubway or other bikeshare systems. The results point to the need for additional research on how experience level may also influence bikeshare usage.

Thesis Supervisor: P. Christopher Zegras

Title: Associate Professor of Transportation and Urban Planning

Acknowledgement

I would like to thank my advisor Chris Zegras for his thorough feedback, thoughtful advice and guidance. I appreciated that you pushed me to make this thesis better. I also would like to thank my reader Eric Huntley for providing a sounding board throughout the process, as well as support and smiles. Additionally, Professor Joe Ferraira and Mike Foster were instrumental over the last two years, teaching me the array of technical skills that I needed for this analysis.

A special thanks to Dorothy Mitchell, Erin Aigner, and Tarani Duncan, three women in the transportation field who encouraged me about the importance of this topic, during the very early stages of this thesis.

Finally, I would like to thank the late night CRON crew (especially Hannah and Louis) for making me feel more normal during stressful times, the amazing fellow MCP2 students I look up to and I am lucky to call friends, and my amazing roommates Talia and Tamara for the coffee and laughs along the way.

Table of Contents

LIST OF FIGURES

LIST OF TABLES

1 INTRODUCTION

1.1 Motivation

In the last 10-15 years, many cities across the U.S. have worked to create cities that are not just for motor vehicles. Movements such as Complete Streets and Vision Zero indicate an increased interest in creating streets that are safe and usable for bicycling and walking. Still, even with these monetary and physical infrastructure investments, a very low percentage of people in the U.S. primarily use bicycles as a form of transportation, with less than one percent (0.6%) of commuters biking to work at least once a week (ACS, 2016). According to the American Community Survey (ACS), there was a 3.8% decline in people who use a bicycle as the primary form of transportation to work in 2015, although over half of the largest cities saw an increase in people biking to work (ACS, 2015). Even though bicycling makes up a small percentage of transportation mode choice in the U.S., it has gained increased attention as cities have focused on healthy forms of transportation. Additionally, biking is not equally spread across demographics; gender shows a large disparity in usage. Men are more than twice as likely to bike to work than women, 0.8 percent of men commute by bike while only 0.3 percent of women commute by bike (ACS, 2012).

There is emerging research into the social and cultural factors impacting why women bike at lower rates than men, but less research focuses on women's bicycle preferences and factors that impact why they are choosing to or not to ride a bike. Additionally, there is limited quantitative data on bicycle usage in cities, particularly related to gender and this varies significantly from city to city. Cities such as Portland and Boston do yearly or monthly bicycle counts, but those are often manually done and limited to a few locations.

This thesis explores the factors related to ridership on Boston's bikeshare system, Hubway, and how these factors compare for men and women. I built a dataset of station-area and station specific characteristics to estimate regression models predicting station-level usage. The findings suggest that land use factors effect men's and women's usage similarly, but some safety factors impact men's and women's usage differently. The results suggest where higher ridership stations are located, how the physical environment at stations can be improved to increase ridership, and how these differ between men and women.

1.2 Theoretical framework

Travel behavior is usually analyzed using utility maximization theory to explain transportation mode choice. Individuals choose a transportation option among a set of available alternatives, that maximizes their utility, which tends to focus on cost of travel (in monetary and time costs). In this theory, researchers in the field of active transportation have recognized the importance of the quality of the environment as a determinant of behavior (Krizek et al, 2009). The framework I use focuses on physical environment characteristics related to choosing bike share as a transport mode. An additional framework, not used here, includes individual characteristics and interpersonal characteristics as causal factors in active transportation route choice. This thesis focuses on the physical environment characteristics, recognizing that there are other factors that are also contributing to individuals' mode choice. From the literature review, five categories of factors emerged as impacting bike usage; land use, safety, bicycle infrastructure, transit and demographics.

Knowing behaviors of individuals is a hurdle in bike research. Three types of measurements tend to be used for measuring relevant behaviors: self-reporting (e.g. ,travel diary), observation (in person or sensors) and instrumentation (motion detectors such as GPS) (Troiano ,2005). Using observation can capture number of trips and intensity well, but does not capture trip purpose or who is or is not cycling. From these types of measurement possibilities, observation using bikeshare data provides a large amount of readily available data to capture usage by gender, but the results cannot illuminate who is or is not captured within that usage, nor why individuals may choose to bike, or not.

1.3 Research Questions

My objective is to analyze factors related to usage of bikeshare and investigate if these factors differ for men and women. Exploring how different factors effect men and women ridership can reveal how gender differences manifest themselves in biking, and can lead to insights into why women bike at such low rates compared to men. While numerous hypotheses exist explaining the gender gap in biking – such as risk aversion, bicycling being less convenient, or women having family roles that do not encourage bicycle usage – more granular understanding of women's preferences is needed.

As cities continue to move toward more non-motorized modes of transportation, biking may go from a fringe mode to a more normalized form of transportation. Accordingly, planners should understand the gender gap in biking, and assess what factors can be used to address this gap, so that as biking increases as a mode it does not continue to have a large gender equity gap. Planners will need more tools, data and insights to serve the needs of cyclists and to address this gender gap in biking. My goal is to provide more insight into factors affecting where women choose to ride, to help planners plan bicycle facilities more equitably. I will explore three questions around bike share usage:

- Does women's usage of bike share differ from men's (in trends such as time of day, day of week etc.)?
- What are the major factors that are effecting bike share usage?
- Do these factors differ for men and women?

1.4 Overview of Methods

To answer these questions, I estimate direct ridership models, which predict Hubway station trip origins based on a variety of explanatory variables. The period of analysis is April–October 2017, and the dependent variable is the number of trips that start at a station (trip origins). The trip origin data is grouped by gender and broken up into four different periods of the day. The explanatory variables are within five categories; demographics, bicycle infrastructure, safety, land use, and transit.

I construct a dataset of station-level and station-area variables at each Hubway station in the Boston region, using a street network distance of a quarter mile define the catchment area for the station-area variables.

I estimate the models using the statistical software R. First, I remove correlated variables and use the Chow Test to test if different models are justified for male and female usage and for different times of day. Next, I run a base OLS model for total trip origins, before running OLS models on the grouped data to compare the results between men and women by time period. Finally, after identifying spatial autocorrelation, I run spatial lag and spatial error models to account for spatial autocorrelation in seven of the eight models.

1.5 Structure

This thesis includes six chapters. After this introduction, the second chapter presents a literature review on bicycling and gender differences in transportation. The following chapter describes the study area's land use and transportation, and the Hubway System. The fourth chapter explains the data sources, overview of the dependent and explanatory variables, and analytic methods. The fifth chapter presents the model output and analyzes the results. A final chapter concludes with implications, limitations, and areas for future research.

2 LITERATURE REVIEW

When trying to dissect why women have lower bikeshare usage rates than men, it is important to look into existing literature in many disciplines, including broadly factors impacting why people bike, gender specific reasons, and factors specific to bike share. Accordingly, I review three areas: general factors related to decisions to bicycle, gender and travel behavior, and bikeshare usage.

2.1 Factors Affecting Cycling

2.1.1 Land Use and Built Environment

Many studies have researched the impact of built environments on motorized vehicles (Ewing, Cervero, 2001), (Crane, 2000). Studies have shown that, all else equal, neighborhood built environment characteristics impact how much residents drive, with factors like land-use mix, transit accessibility and pedestrian friendliness leading to lower vehicle miles travelled. Cervero and Duncan (2003) found that urban design and land-use diversity factors were positively associated with the decision to ride a bike. Factors such as well-connected streets, small city blocks, mixed land uses, and close proximity to retail activities were shown to induce non-motorized transport (Cervero & Duncan, 2003). Many studies suggest that denser urban areas lead to higher cycling share (Pucher & Buehler, 2006, Parker et al., 2008). These higher density areas tend to have lower levels of vehicle ownership (Litman, 2007) which can have a positive effect on cycling. Density has also been shown to increase cycling frequency. Dill and Voros (2007) found that people living closer to city centers take more utilitarian bike trips.

Distance is another factor that and individual takes into account when deciding on a transport mode, generally (Keijer and Rietveld 2000). This can also have larger impact for cycling since a longer distance typically means a higher travel time than for other modes such as automobiles or transit. For cycling, longer trip distances tend to represent a much lower share of trips (Moritz, 1998; Zacharais, 2005; Pucher & Buehler, 2006). Some of this is probably due to the increased physical effort required for longer trips (Van Wee et al., 2006). Trip distance is also linked to land use. Residents living in city centers use bicycles as a transportation mode more than residents in the suburbs (Witlox & Tindemans, 2004).

2.1.2 Infrastructure

Studies have indicated the importance of bicycle infrastructure – that well-connected neighborhood streets and a network of bicycle-specific infrastructure can encourage more bicycling among adults (Dill, 2009). Dill and Carr (2003) found that the number of bike lanes per square mile explains a large share of the variation in bicycle commuting rates. Continuous and non-interrupted cycle lanes and paths have also been identified as influencing the decision to cycle (Wang et al., 2011, Heinen et al., 2009). Network continuity represents a safety concern for cyclists, as they may have to reintegrate into vehicular traffic when facilities suddenly terminate (New Zealand Transport Agency, 2011).

Research has shown that bicycle infrastructure improves safety of bicycling. A longitudinal study of sharrows[1] in Chicago found when looking at crashes before and after infrastructure installation, bicycle crashes went down (Ferenchak & Wesley, 2016). However, less literature compares different types of bicycle facilities, such as conventional bike lanes, buffered bike lanes[2], sharrows or parking buffered lanes. The factors analyzed have tended to be route characteristics (such as turn frequencies) or environmental factors (such as traffic conditions) rather than specific bike infrastructure. This is likely due to a lack of detailed bike infrastructure

[1] Sharrows are defined as roads with shared lane marking, and are used to raise awareness of bicyclists' presence and move cyclists toward the center of the travel lane, away from parked cars (Ferenchak & Marshall, 2016).

[2] NACTO guidelines define a buffered bike lane as a conventional bike lane with a designated buffer space separating the bike lane from motor vehicle travel lane or parking late.

inventory data or a lack of enough varied facility types to do meaningful analysis.

One study, using GPS data in San Francisco, found bike lanes were preferred to other bike facilities especially by infrequent cyclists (Hood et al., 2011). Yet, another study using bicycle mounted GPS units in Portland, Oregon found that cyclists placed relatively high value on off-street bike paths, enhanced neighborhood bikeways (bicycle boulevards) and bridge facilities (Broach et al., 2012). Additional research has studied the effect of bicycle facilities separated from traffic. Proximity to trails was one of three significantly environmental variables for respondents cycling at least once a week in a survey in the state of Washington (Moudon et al, 2005). Krizek and Johnson (2006) found that only close distance to separated bike facilities were statistically significant predictors of choosing to cycle.

2.1.2.1 Bicycle Route Choice and Infrastructure

Broadly, there has been a lot of research on overall bike route choice preferences. Existing research has found that cyclists' route choice depends on distance, safety, turn frequency, slope, intersection control, and traffic volumes (Broach et al., 2012; Broach et al., 2009; Ehrgott, Wang, Raith, & Van Houtte, 2012; Hood et al., 2011; Winters et al., 2011). When looking at environmental factors, research reveals similar results, with both men and women reporting that perceived environmental factors related to traffic conditions, motorist aggression and safety are main concerns. (Heesch et al., 2012).

2.1.3 Safety

A main determinant of whether people chose to bike or not is how safe they perceive bicycling to be (Geller, 2009; Gatersleben & Appleton, 2007; Pucher & Buehler, 2008). Bike infrastructure can improve the safety of cyclists, but this varies by the experience level of the cyclist. Some studies have shown that riding in vehicular traffic is safer than riding on a cycle tracks (Pedler & Davies 2000). Comparing sharrows to bike lanes and no infrastructure, a longitudinal study found that sharrows saw the smallest decrease in bicycle injuries, suggesting that sharrows have limited effectiveness in terms of safety (Ferenchak & Wesley 2016). Krizek et al. (2009) note that separated bicycle facilities are perceived as being safer than regular bicycle facilities, although they are not necessarily safer, specifically at intersections with vehicular traffic. This perception of increased safety may help less confident cyclists decide to ride a bike and lead to higher levels of ridership (Krizek et al, 2009).

A study of facility safety in Canada found that rates of incidents were lowest per kilometer on vehicular roads, followed by off-road paths, then sidewalks (Aultman-Hall, 2000). However, this could be due to the experience levels of the cyclists using different facility types. For example, confident, regular cyclists may ride in vehicular traffic, where inexperienced cyclists use separated bike facilities, but may be more accident prone due to inexperience (and/or in reality, these facilities may be less safe). Additionally, there is a difference between how cyclists perceive safety and actual safety (Heinen et al., 2010). Therefore, different bike infrastructure may be more attractive to different populations, from a safety perspective.

To better understand the different perceptions of safety, Roger Geller, the bicycle coordinator for the Portland (Oregon) Bureau of Transportation created a categorization of "the four types of cyclists" in an effort to better plan for all types of cyclists (Geller, 2006). Geller divided the population in Portland into the four types. The 'strong and fearless' make up the smallest portion (<1%), and are riders who will ride anywhere, regardless of the conditions. The 'enthused and confident' generally prefer bike-specific facilities but are comfortable riding with traffic, and make up 7% of the population. The 'interested but concerned' are curious about cycling but have safety concerns that may prevent them from riding and make up 60% of the population. The 'no way, no how' have no interest in cycling, no matter the circumstances and make up 33% of the population. Geller's typologies were not initially well documented, but Dill and McNeil (2013) attempted to verify Geller's typologies through a phone survey in Portland. They categorized respondents based on stated comfort level on a variety of facility types, their interest in cycling as a mode of transportation and their physical ability to bicycle (Dill & McNeil, 2013). Their resulting population estimates for each category were: 'strong and fearless' 4%, 'enthused and confident 9%, 'interested but concerned' 56%, and 'no way no how' 31%.

Perceptions of safety also vary by how many other cyclists are on the road. The concept of "safety in numbers" means that more cyclists implies increased perception of safety, which then increases cycling. Bauman et al. (2008) found evidence that as more cyclists are on the road, the safer it becomes, because motorists and cyclists get used to interacting with one another. Evidence suggests that in areas with higher levels of ridership, cycling is safer. Analysis of data from cities in 68 cities California, 14 cities in Europe, and 47 towns in Denmark found that collision rates declined with increases in the number of people walking or bicycling (Jacobsen, 2003). Communities with higher rates of bicycle use have fewer crashes per capita.

Another factor in safety perceptions relates to vehicle infrastructure. Studies have shown that cyclists prefer two lane roads to four lane roads (Petritsch et al, 2006; Shankwiler 2006). Additionally, cyclists have a negative perception of roads with high traffic (Dill & Voros, 2007).

Safety can have a large impact on individuals deciding to bicycle, and often depends on bicycle infrastructure, number of cyclists on the road and automobile infrastructure. However, these preferences for safety vary depending on experience level and other demographics, and there can be differences in perceived safety versus actual safety.

2.1.4 Trip Types

Trip purpose can impact mode choice and temporal travel decisions. In a study analyzing bike usage in five North American cities, the researchers categorized trips and bicycle facilities as utilitarian and recreational to examine differences. Utilitarian networks had higher usage during the workweek, with a peak during morning commute and a larger peak during evening commute. Recreational systems had a broad peak from late morning to mid-afternoon, with more traffic on weekends (Miranda-Moreno et al., 2013).

2.2 Travel Behavior and Gender

In order to understand gender differences in bicycling travel behavior, it is important to first explore how travel behavior generally differs for men and women. Three key sub topics of travel behavior and gender are outlined next including: gender and social cultural norms, gendered space in transportation, and gender and biking.

2.2.1 Gender and Social Cultural Norms

Research has shown that women would have lower rates of cycling than men due to social factors impacting travel behavior. Women tend to have more household responsibilities, such as childcare duties, and errands (Collins & Tisdell, 2002). Such responsibilities do not lend themselves easily to biking (Gordon & Richardson, 1998). Additionally, cycling is known as being a risky transportation mode (Noland, 1995), and women tend to be more risk averse than men (Weber et al., 2002) which would imply lower rates of adoption. However, women are more likely than men to cycle for shopping and errands or visiting friends, and these trips lend themselves more easily to using a bicycle (Krizek et al., 2005). These shorter, non-commuting trips tend to be less time-constrained and can be more easily taken by bike, if the infrastructure and socio-cultural norms allow for usage. For example, dropping off children at school can be difficult without a cargo bike or facility that feels safe. There are also stigmas and societal norms that can keep women from biking. Norms such as women being expected to show up "presentable" to places can be a deterrent, or that cyclists are associated with being 'sporty' (Aldred, 2013).

Historically, women had very different travel patterns than men, and the differing travel patterns and access to transport modes impacted where they worked, among other things (Cichocki, 1980). Women tend to take more, shorter trips, likely due to differing responsibilities. Even today, women's travel behavior and transport needs are not fully understood or properly provided for in cities (Coleman, 2000). Bikeshare programs can be a way to lower the bar to cycling by allowing women to take shorter trips and not having to worry about maintaining a bike (Anzilotti, 2017).

2.2.2 Gendered Spaces in Transportation

Moving in urban spaces is also experienced differently by women and men (Schmucki, 2012). City transport systems have been planned by men, who have a predominant view of how men will use this infrastructure, with the assumption that women have the identical needs as men (Hamilton & Jenkins, 1992). How women move through urban spaces has received less attention than other areas on gender in the city. Trench et al. (1992) found that many women would not use public transportation due to personal safety reasons, and others felt concerned about car garages.

There exists a large gap between the consultant knowledge that has grown as an area of transport policy and planning on gender patterns in specific transport locations and academic analytical frameworks in the understanding of transport (Grieco, & McQuaid, 2012). Gendered transport in cities reveals what different spaces and places women used, experienced and how such a specific experience has promoted the construction of gendered social and economic identities (Schmucki, 2012).

2.2.3 Gender and Biking

Gender differences in cycling is a growing area of research. Men cycle for at least twice as many trips as females do, across all trip types in the U.S. (Emond at al., 2009). Over the past 20 years, women's commuting trips have varied. In 2010, women's bicycle commute trips made up a quarter of all bicycle commute trips, which was a decrease from 2001, where woman were one-third of all commute trips by bike (Census 2010, Pucher et al., 2011)

Krizek et al. (2005) found that in Minneapolis, men were more than twice as likely to take a trip by bike than women, 0.66% versus 0.25%. In the survey results, women were more likely to rate paved shoulders and lighting on bicycle paths as very important to commuting by bicycle. Perceptions of safety also revealed gender differences, with four main areas: lack of bicycle paths, unsafe driver behavior, unsafe cyclist behaviors, and unsafe road conditions. Women reported lack of paths and poor road conditions more than men did. Much of the work surrounding gender, cycling and travel behavior suggests that the different built environment, facility or route choice decisions made by women are likely to have implications for the different approaches to cycling infrastructure taken by planners and policy makers.

2.2.3.1 Biking Infrastructure and Safety

Preferences for bike infrastructure vary by demographic group, and by experience level. Women as well as inexperienced and younger cyclists tend to report bicycle facilities as being more important (Stinson & Bhat, 2003; Krizek et al., 2005; Stinson & Bhat, 2004; Gerrard et al., 2008). In United Kingdom, Australia, the U.S., and Canada 30% or less of cyclists are women, while in Germany, Denmark and the Netherlands 45% or higher of cyclists are women (Pucher & Buehler, 2008). The countries and cities with high-cycling rates for women also had high-quality cycling infrastructure (Heinen & Handy, 2012). As shown in stated-preference studies, women perceive risks differently than men (Weber et al., 2001) and show a stronger preference for cycling infrastructure that offers more safety (Akar et al., 2013). Research of commuters in Australia found, consistent with gender differences in risk aversion, that female commuter cyclists showed a preference for routes with maximum separation from vehicle traffic (Garrard et al., 2008). Additionally, women demonstrate a stronger preference for safer forms of cycling infrastructure (Krizek et al., 2005). Female commuter cyclists prefer to use routes with maximum separation from motorized vehicles, therefore improving cycling infrastructure in the form of bicycle paths and lanes that provide a high degree of separation from motor traffic is likely to be key for increasing transportation cycling in under-represented groups such as women (Garrard et al., 2008). A qualitative study of barriers to bike share usage in Brisbane found that lack of contiguous bicycle infrastructure was a barrier to bicycling (Fishman et al., 2012).

2.2.3.2 Land Use and Built Environment

Gender differences regarding the role of land use in cycling have been less studied. One study of male and female students found that neighborhood built environment-related factors are noticeably different between female and male students (Mitra & Nash, 2017). The study of post-secondary students in Toronto found that for post-secondary students, access to dedicated cycling infrastructure and high business density were associated with higher odds of cycling to school but only among female commuters. Yet these built environment factors did not impact female cycling for non-commute purpose (Mitra & Nash, 2017).

2.2.3.3 Conclusions of Gender and Biking

Cultural norms and differences in preferences may be related to a large portion of the gender gap. Cycling in its current state in the U.S. does not always lends itself easily to female household responsibilities. Additionally, safety and bicycle infrastructure are two areas that research has shown to be related to female ridership. Improvements in infrastructure and safety are correlated to increases in ridership. Other factors related to bicycle ridership are less studied.

2.3 Bikeshare Systems

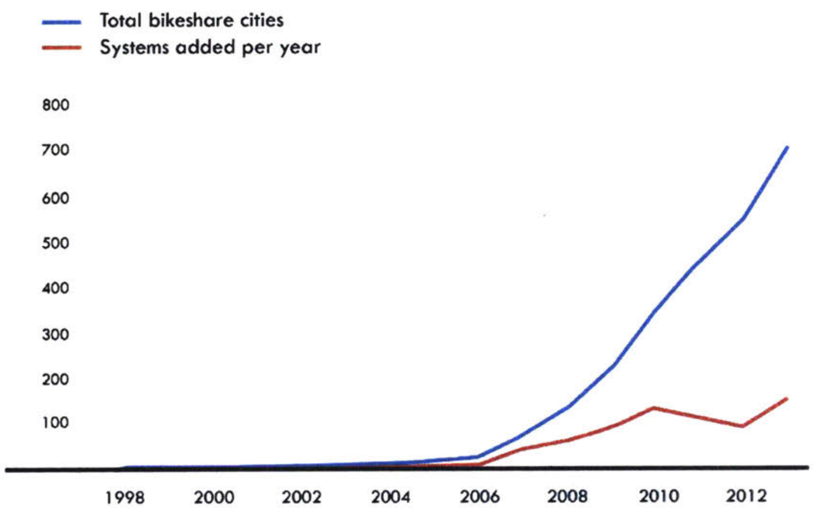
2.3.1 Introduction

Bike share is a service where individuals have access to a fleet of bicycles for a fee. Bicycles can typically be rented from a dock or station in the network and returned to any other dock, with pricing and time limits varying from city to city. Bikeshare programs (BSP) first began in the 1960s but have seen an acceleration in the last 10 years. Researchers have categorized bikeshare history into four 'generations' (Parkes et al., 2013). The first generation bikeshare system, Witte

Fietsen (White Bikes), was launched in Amsterdam in 1965 (Davis, 2014). The system was completely free for anyone to use. The lack of security and incentives for users to treat bikes responsibly led to theft and the end of the system. Bikeshare systems did not come back until 1995, the second generation of bikeshare systems, when a program launched in Copenhagen. The coin-operated systems also lacked accountability and the system was also plagued with theft (DeMaio, 2009). The third generation of bikeshare systems learned from the mistakes of the previous two and generally use dedicated docking stations, automated credit card payment, and GPS units to track bicycles. Fourth generation bikeshare systems, currently emerging, include characteristics such as dockless sytstems and transit smartcard integration (Parkers et al., 2013).

Bikeshare has been growing at a significant rate in the last five years in the U.S., as shown in **Error! Reference source not found.**. In 2010 there were only four systems, and in 2016 there were 55 systems in the US. Boston has the sixth largest bike share system in the country, following New York City, Chicago, Washington DC, San Francisco, and Minneapolis (NACTO, 2018).

Figure 2-1 Bikeshare Over Time, 1998-2013



Data Source: Adapted from Fishman, 2014

Shaheen et al. (2010) summarized six key benefits of bike share programs: flexible mobility, emissions reductions, individual financial savings, reduced congestion and fuel use, health benefits, and support for multimodal transport connections by being a first/last-mile connection.

2.3.2 Bikeshare and Other Modes

A growing number of studies have investigated what mode bike share users used before the systems were in place, and how bike share programs influence transport choice. This research can help planners better understand how people are substituting modes, and how transit and bike share can coexist. Many of the benefits Shaheen et al. (2010) list assume substitution from modes like automobiles. However, research does not necessarily show a strong a substitution from automobiles. Shaheen , Martin, Cohen, and Finson (2012) conducted an online survey in Montreal, Toronto, Washington DC, and Minneapolis/St. Paul and found that mode substitution from cars to bike share is low. A survey in China found that around 80% of bike share users would have walked, used public transport or their own bike, if the system was not available (Yang et al., 2010). One limitation the authors noted from these results is that China has a low proportion of trips by private vehicle, but that the shift from private automobiles was still disappointing. Additional research using survey methods in Dublin, London, and Washington, DC reported low substitutions rates from car to bike share (LDA Consulting 2012; Murphy, 2010; Transport for London, 2010). Car ownership is related to trip substitutions. Shaheen, Zhang, Martin and Guzman (2011) saw different transportation shifts depending on vehicle ownership in China. In their survey of Hangzhou bike share users, a majority of non-car owners shifted from public transport (80%) compared to 50% for car owners. Additionally, 78% of car owners said they used bike share for trips they otherwise would have done by car.

Research indicates that many of the bike share trips are not substitutions away from automobiles but are rather substitutions away from other active transportation modes such as walking and transportation. However, for car owners who are using bike share, a majority of these trips are substitutes for automobile trips.

2.3.3 Preferences and Trip Purposes

Studies have looked at how various land use and built environment factors, transportation infrastructure, and bicycle facilities affect bike share usage. Wang et al. (2015) found that stations closer to jobs resulted in higher usage of the bike share system, as did food-related businesses near stations. Fuller et al. (2011) found, in Montreal, a correlation between proximity of residential address to bike share usage. Transit also has been shown to affect usage. Bachland-Marleau et al. (2012) found that the more bicycle facilities near a bike share station, the more usage the station had.

Additional studies found bicycle infrastructure impacting usage. Buck and Buehler (2011) found a statistically significant relationship between bike share activity and presence of bike lanes when controlling for population and retail opportunities around docking stations. Also, Rixey (2013) and Wang et al. (2015) found that the presence of a paved trail or bikeway in the surrounding area of the station increased bike share usage.

A common benefit cited for bike share systems is the so-called first-mile last-mile connections, but research has been varied. The first-mile last-mile problem is the gap between transit station and origin or destination. Bikeshare can be a compliment to transit because it decreases this gap in transit service. A study of Capital Bikeshare in Washington, D.C. found that public transit ridership was positively associated with bikeshare ridership at the station level (Ma et al., 2015). Proximity to transit station can also be a key factor for ridership of a bike share station (Daddio, 2012). Campbell et al. (2016) found that it is unclear if bike share is an attractive "first-and-last-mile solution." Additionally, in China the interaction with transit has been shown to be both a competitor and a complement to transit (Shaheen et al., 2011).

Studies have analyzed trip purpose of bike share users. Trip purpose was mainly work or education related (70%) (Murphy 2010). Bikeshare members in Hangzhou, China indicated that they frequented the station closest to work (40%) or home (40%) most (Shaheen et al., 2011). Similarly, a member survey of the Washington DC bike share system found that the most common trip purpose was work, followed by social/entertainment (although education was not an option for trip type) (LDA Consulting, 2012). Shaheen et al. (2012) also found that among North American's largest bike share programs, commuting (including to school) was the most common trip purpose.

2.3.4 Demographics

Many researchers have found that the demographics of bike share users is different from the general population (LDA Consulting, 2012; Lewis, 2011; Ogilbie & Goodman, 2012). An analysis of the bike share system in Washington, DC found that the bike share members had significantly higher employment rates and education levels, lower average age, and were more likely to be male than the general population (LDA Consulting, 2012). Ogilvie and Goodman

(2012) compared registered users in London's bike share system to the general population examining usage levels to understand socio-demographic factors impacting bike share usage. They found gender was a large predictor of use, with the model estimating that women took 60% fewer trips than men.

2.4 Conclusions

Women and men have different preferences and therefore different travel behaviors when choosing to bike. Additionally, women experience the built environment in different ways than men do, and therefore have different preferences and needs when traversing the city. Lack of availability of data with gender or other demographic factors, has prevented substantial analysis of bicycle use and differences between women and men. Little research has looked at large samples of quantitative data, such as usage data, to analyze what factors affect use. Parsing the data by gender allows for analysis into gender differences that may exist. Analyzing gender differences can produce more useful insights for city governments and bicycle planners on how to create physical environments to best attract users and create more gender equal cities.

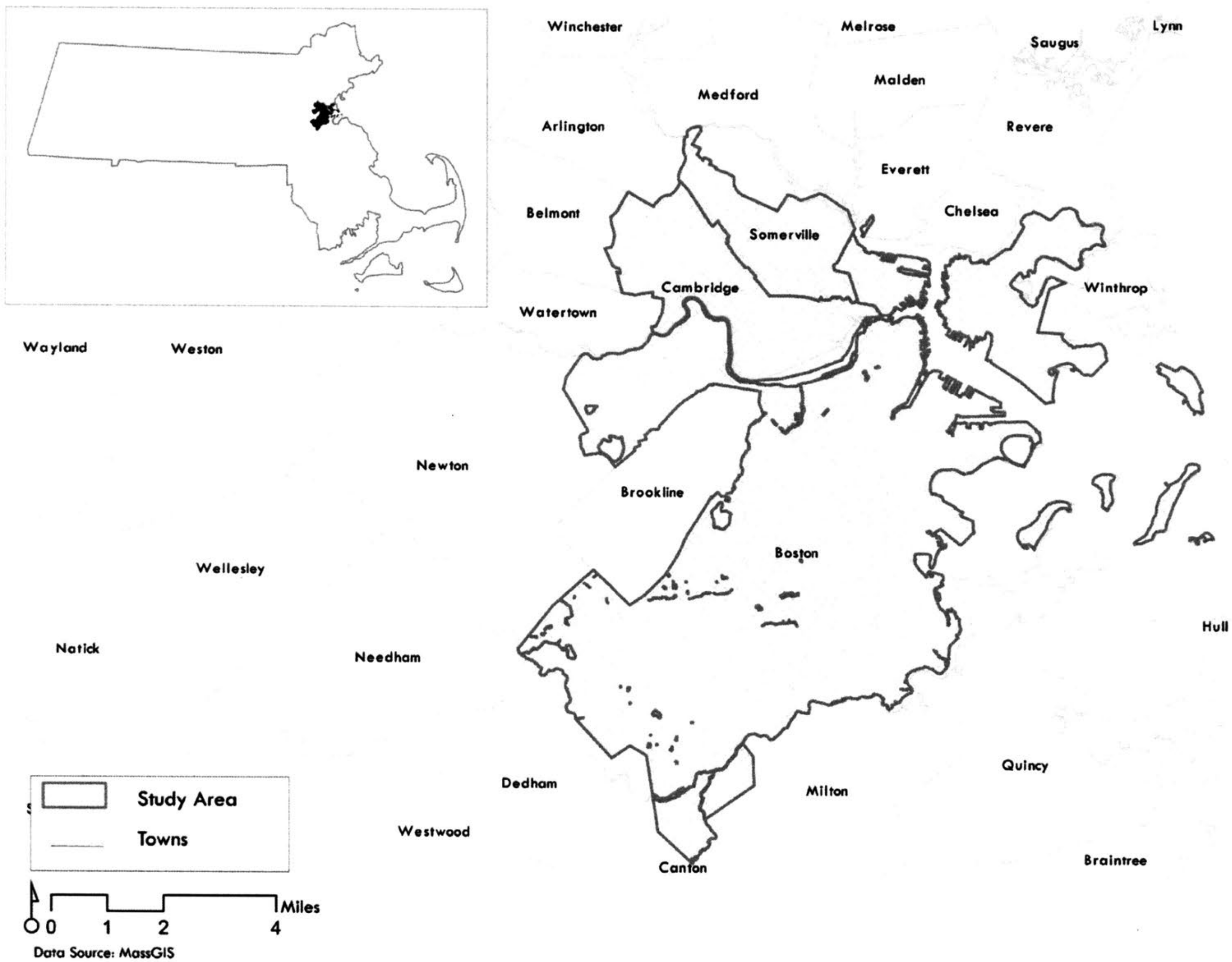
3 BACKGROUND

3.1 Study Area

The study area for this analysis is the Hubway service area, which serves the cities of Boston, Brookline, Cambridge and Somerville, as shown in Figure 3-1 Study Area Context. All cities are within the greater Boston region. For this analysis stations in the city of Brookline were omitted due to data limitations, described in the next section.

Cambridge and Somerville abut Boston to the north and northwest. All three are historic towns. Boston and Cambridge were established as towns in the mid-1600s, and Somerville was settled in the mid-1600s. Topographical limitations in the study area include the Atlantic Ocean to the east, and the Charles River between Boston and Cambridge. The study area is relatively flat at close to sea level. Somerville has some small elevation gains around Winter Hill, and Prospect Park, as does the southern portion of Boston (Dudley Square, Roxbury, and Dorchester).

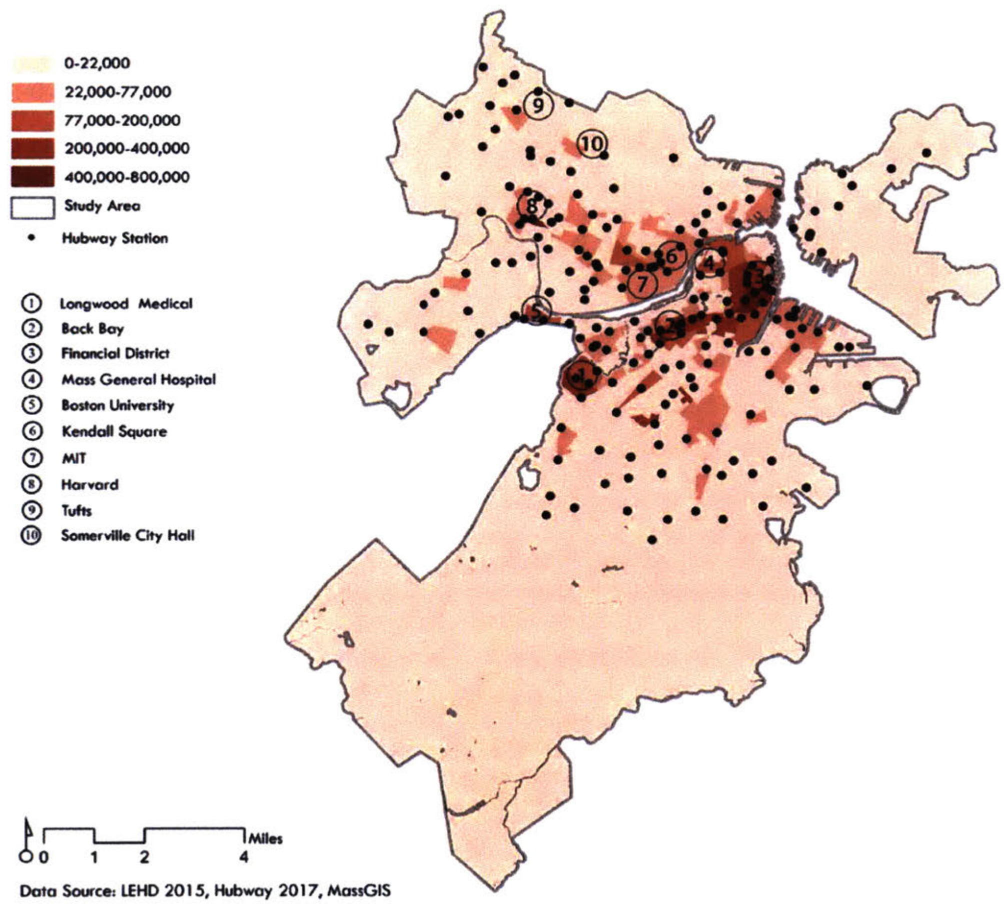
Figure 3-1 Study Area Context



3.1.1 Jobs

Most of the jobs in the study area are clustered around Boston's Longwood Medical Area, Back Bay, the Financial District, Mass General Hospital, and Northeastern, as shown in **Error! Reference source not found.**. In Cambridge, jobs are clustered around Kendall Square, MIT, and Harvard. Somerville has one job cluster around the city's government center.

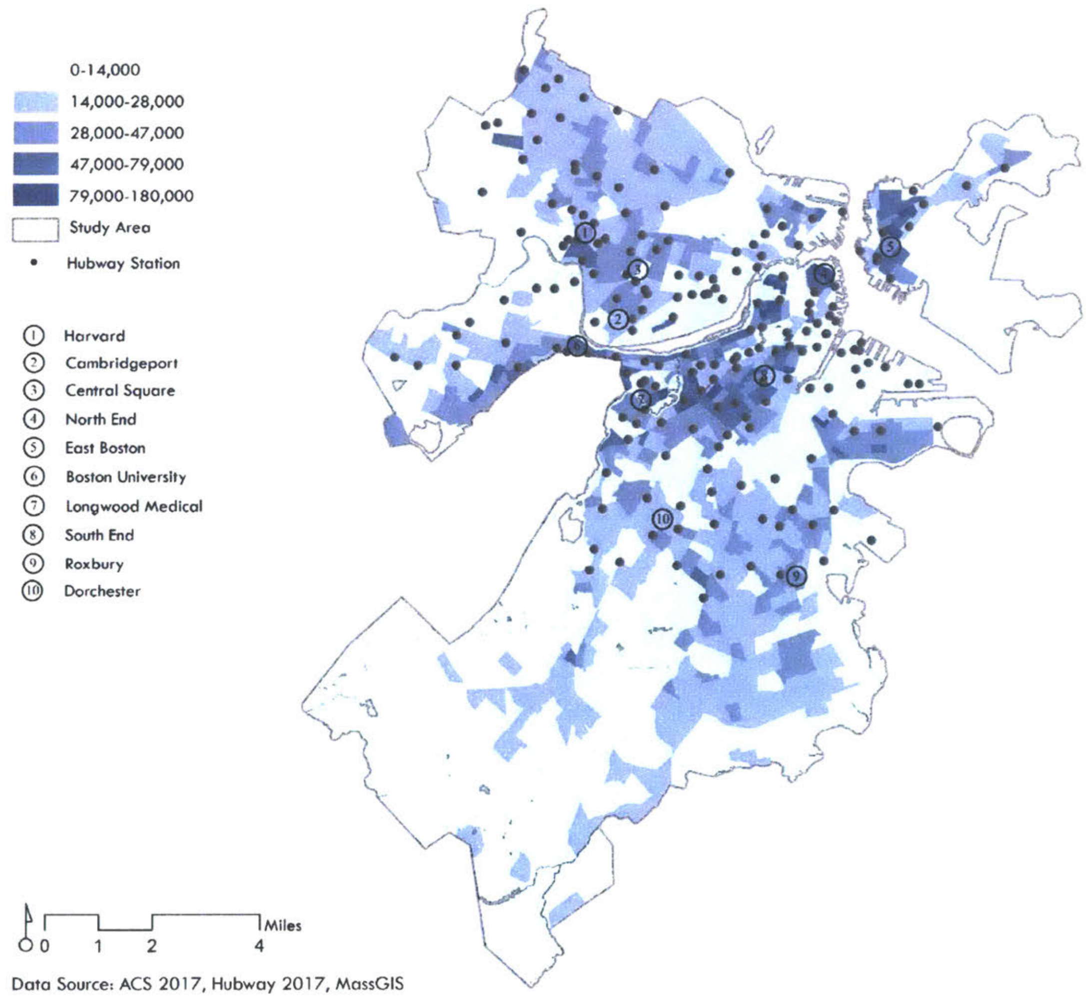
Figure 3-2 Study Area Job Density (per sq. mi)



3.1.2 Population

The study area has a population of 856,941. As shown in Figure 3-3, population is dispersed throughout all three cities. Somerville has a relatively consistent population density throughout the city, while Cambridge has higher population density around Harvard, Cambridgeport, and Central Square. Boston has population density clustered in the North End, East Boston, around Boston University, Longwood, and the South End. Population density is also spread further away from the core in Roxbury and Dorchester.

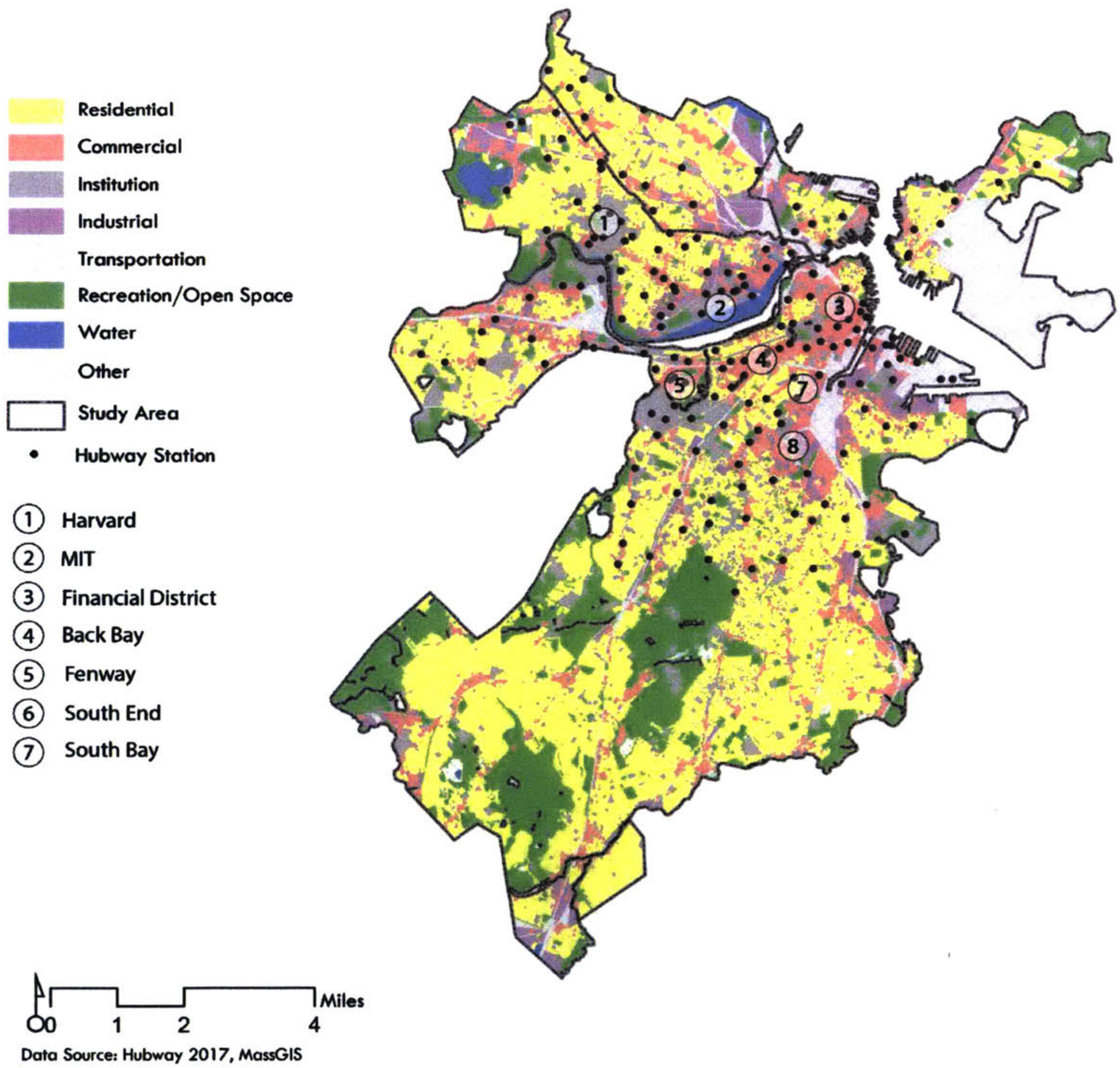
Figure 3-3 Study Area Population Density (per sq. mi)



3.1.3 Land Uses

The study area has varied land uses, as shown in Figure 3-4. Cambridge and Somerville are mainly residential, with a number of commercial corridors in the cities. Cambridge has two large public institutions (Harvard and MIT), while Somerville has two large areas of industrial land. Boston has a larger amount of commercial area in the Financial District, Back Bay, Fenway, South End, and South Bay.

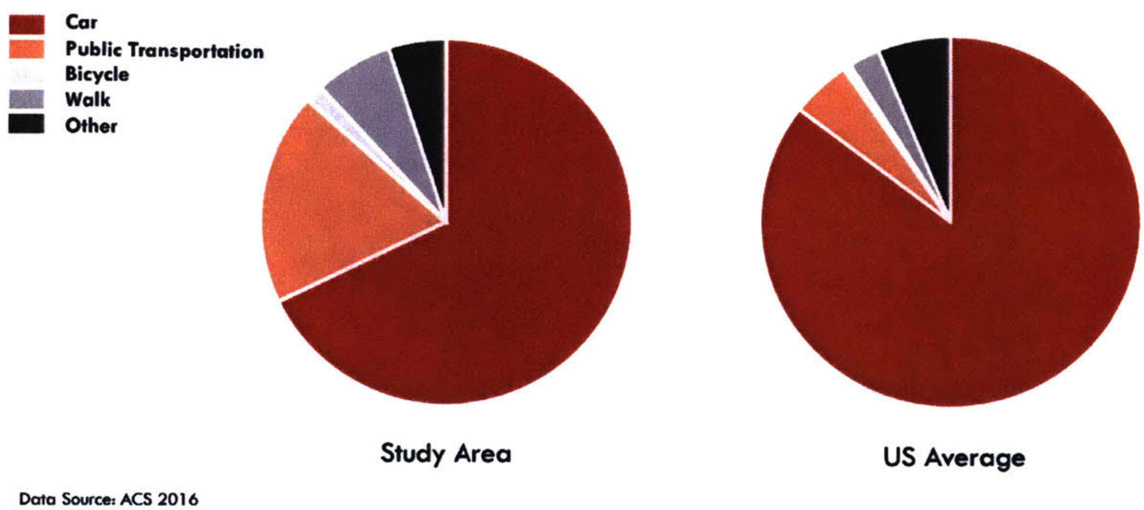
Figure 3-4 Study Area Land Use



3.1.4 Transportation

The study area has a multimodal transportation system that connects the greater Boston region internally as well as throughout New England. Land use and transportation are interconnected, and as shown in the previous maps, the city of Boston spans a large amount of area, much of which has low population density. As such, commuting modes are impacted by where people can live and work. On average 67% of workers commute by car in the study area, 19% by public transportation, 7% by walking, and 1% by biking[3]. As shown in Figure 3-5 , the study area is more multimodal than the U.S. as a whole.

Figure 3-5 Study Area Commute Mode, 2016

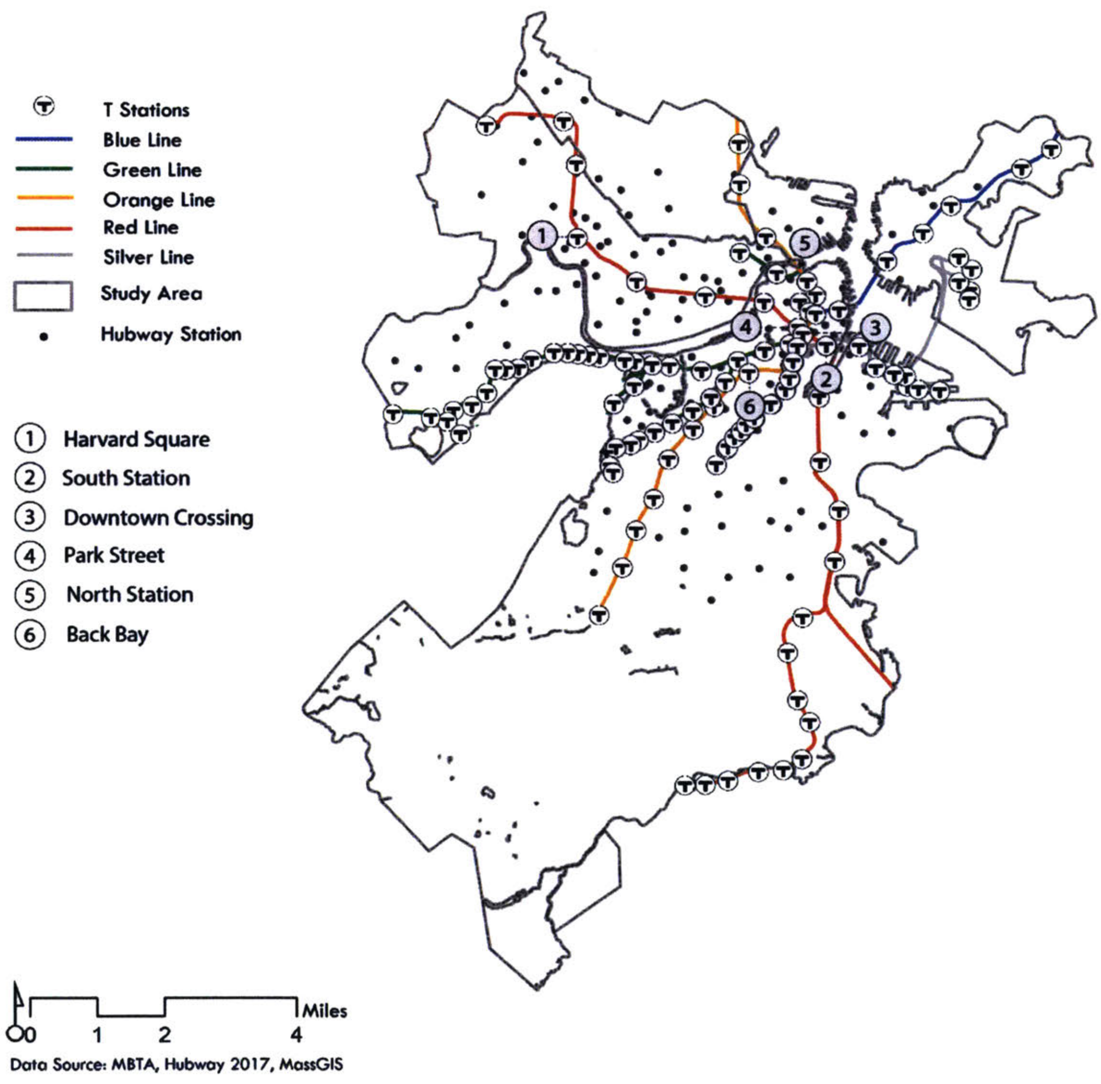


[3] An additional 5% of workers use other modes, including working from home.

3.1.4.1 Public Transportation

The Massachusetts Bay Transportation Authority (MBTA) serves the study area via urban rail (heavy and light rail), commuter rail, ferries, buses, and paratransit. Figure 3-6 shows the regional connectivity of the urban rail network ("the T"). The top five stations by weekly ridership, in order, are Harvard Square, South Station, Downtown Crossing, Park Street and North Station. South Station, North Station and Back Bay Station connect to regional trains.

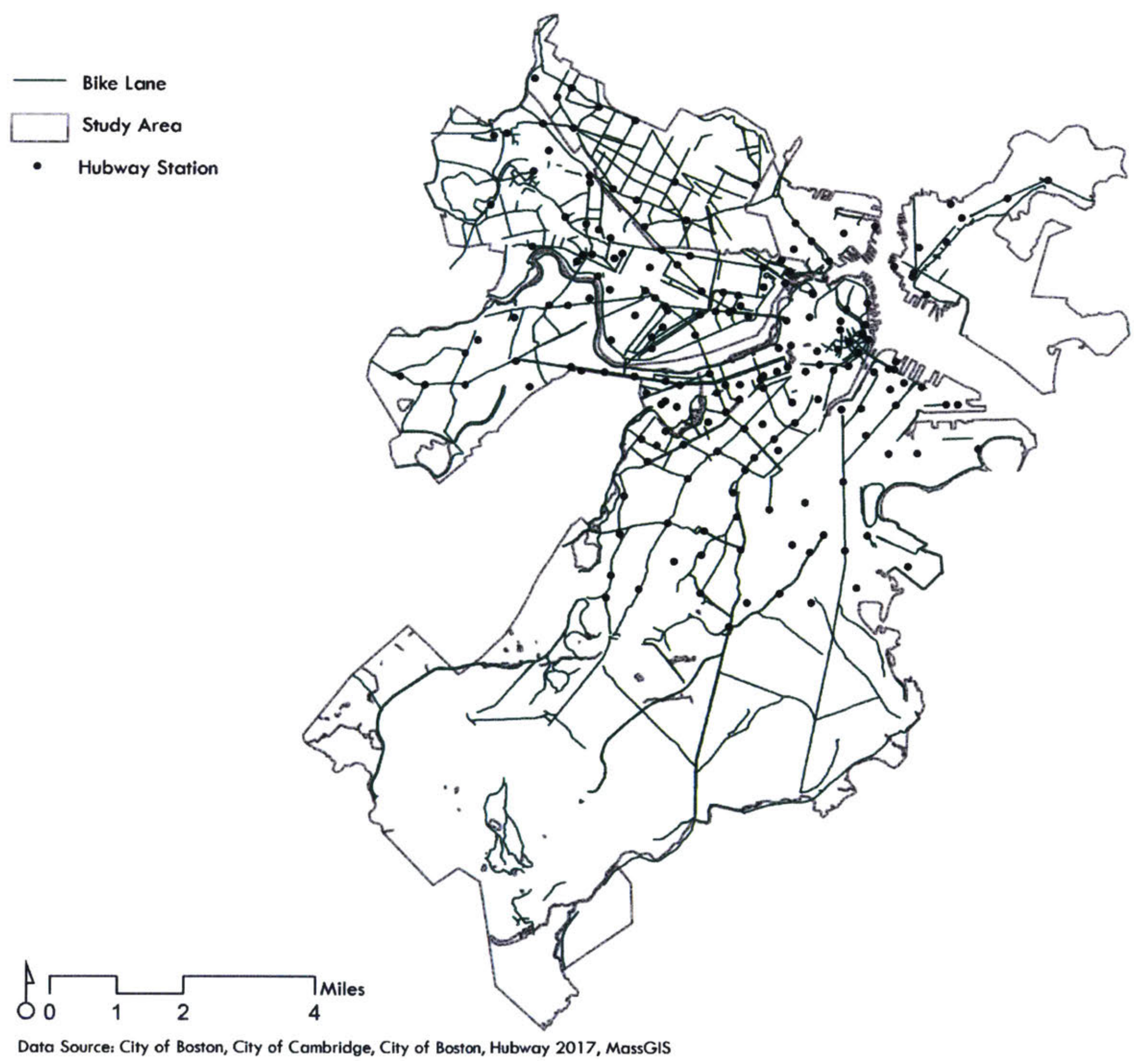
Figure 3-6 Study Area T Stations and Lines



3.1.4.2 Biking

Bicycle infrastructure varies across the region. One factor that limits the regional connectivity of the network is that each town is responsible for developing its own infrastructure. The regional land use planning agency, the Metropolitan Area Planning Council (MAPC), does not hold any jurisdictional power. MAPC has worked to encourage regional bike planning through a 1997 Regional Bicycle and Pedestrian Plan, and updating it as a 2007 Regional Bicycle Plan for the greater Boston area. MAPC also was a key player in the founding of Hubway, leading the bidding process for the initial launch in 2007. Figure 3-7 shows study area bicycling network.

Figure 3-7 Study Area Bike Network



Boston, Cambridge, and Somerville have received accolades for being good cities for bicycling. The League of American Bicyclists awarded Boston a silver standard, Cambridge a gold standard, and Somerville a gold standard as Bicycle Friendly Communities (BFC). According to the League of American Bicyclists, the BFC program attempts to set standards for what constitutes a real bicycling culture and environment. Bicycling Magazine does its own ranking, working with organizations, bike advocates, and riders, and analyzing data from departments of transportation to rank top cities. According to Bicycling Magazine, key statistics include population, miles of bicycle facilities, bicycling-friendly business score, people per bike-share, and median home value. In 2016, Cambridge was ranked 8th for small cities, and Boston was ranked 26th for large cities. People for Bikes also has city ratings, based on five factors: ridership, safety, network, reach and acceleration. The cities in the study area received scores, on a five-point scale, of: Boston 2.6, Cambridge 2.3, and Somerville 1.7.

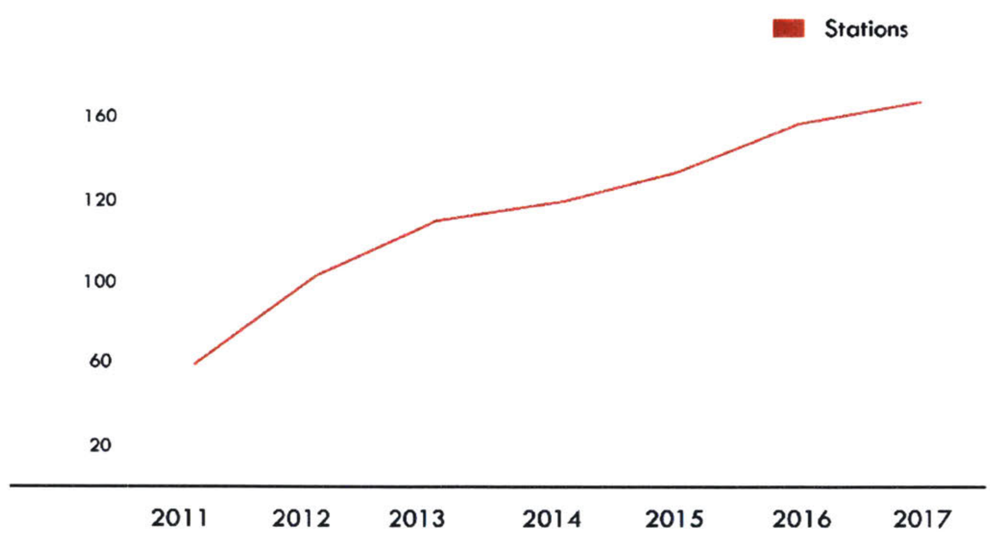
3.2 Regional Bike Share System: Hubway

The City of Boston began planning for bike share in 2007, founding its Boston Bikes program. Expecting the bikeshare system to be region wide, the city enlisted the help of the Metropolitan Area Planning Council (MAPC) to lead the process of selecting a company to operate the system. Alta Bicycle Share, which since a change of ownership has changed its name to Motivate, was selected as a full-service bike share operator and technology innovator.

Hubway launched July 18, 2011, at first only in Boston. The system began with 61 stations and 610 bicycles. The system was funded by a $4.5 million grant from the Federal Transit Administration and local organizations. At the end of 2011 Brookline, Cambridge, and Somerville signed contracts with Alta Bike Share to expand to their cities. The system has steadily grown each year. By the end of 2012 the system had added 45 new stations and 540 bicycles. At the end of 2013 the system had expanded to 130 stations and 1,200 bikes. Currently there are stations serving every T line, commuter rail and ferry. There are 192 stations in total, with 1800 bikes. Figure 3-8 and Figure 3-9, below, show how the number of stations and membership has grown over the years, with over 14,000 annual members in 2017.

In May 2018, Mayor Walsh announced that Hubway would add more than 70 new stations over the next two years, for a total of 245 stations and 2400 bikes. The City also announced a new sponsorship with Blue Cross Blue Shield, which would pay nearly $20 million to change Hubway into Blue Bikes. This will also expand the system to over 1,000 new bikes and add 100 new stations in the region (Graham, 2018). The municipalities of Boston, Brookline, Cambridge, and Somerville own the system. Figure 3-10 shows a map of the Hubway stations in Boston, Brookline, Cambridge and Somerville.

Figure 3-8 Growth in Stations, 2011-2017



Data Source: Hubway 2017

Figure 3-9 Growth in Annual Members, 2011-2017

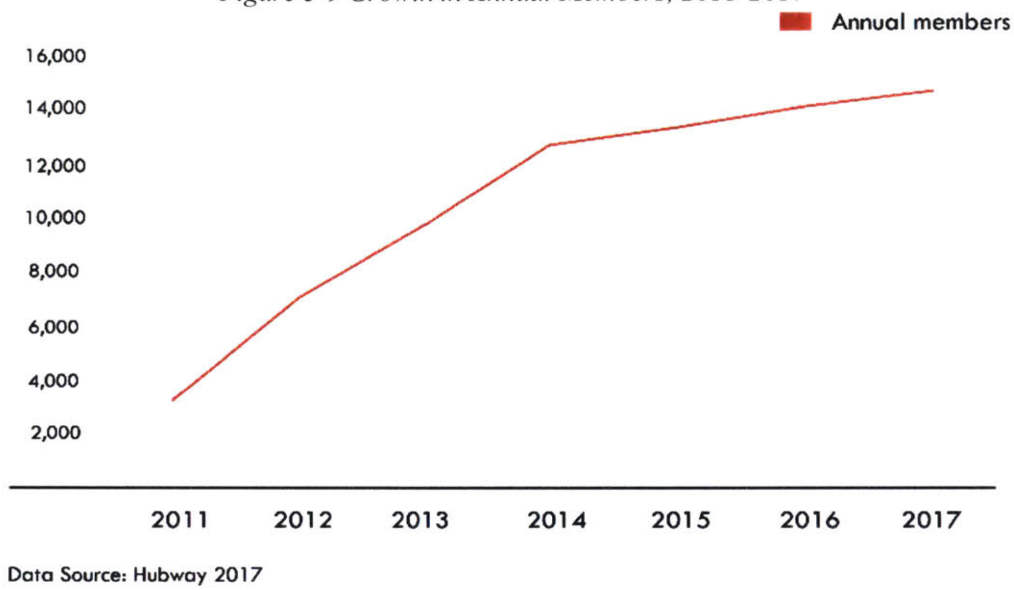
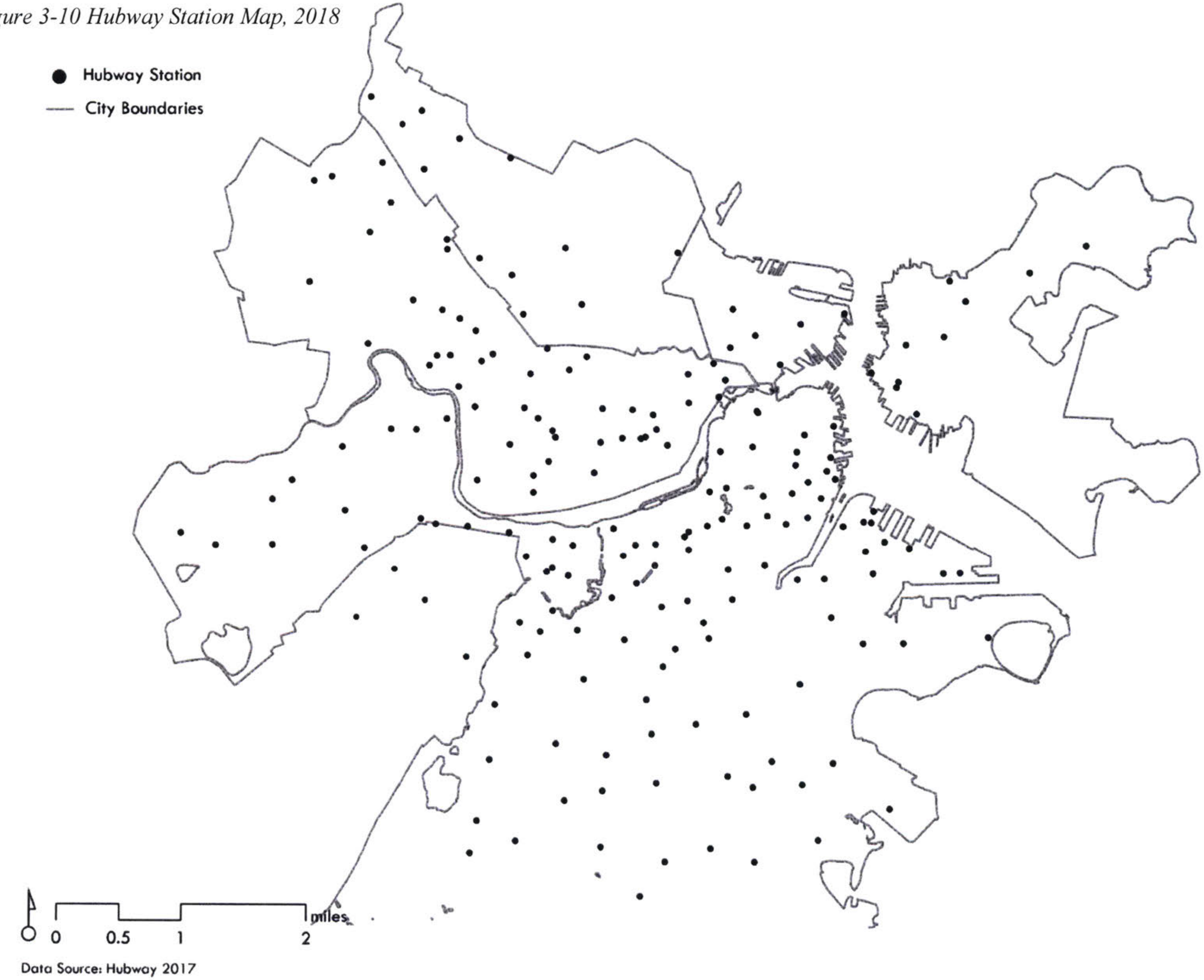


Figure 3-10 Hubway Station Map, 2018



3.2.1 System Details

Hubway offers three membership types; a 24-hour pass, a 72-hour pass or an annual pass. Annual memberships cost $99 upfront, or $10/month with an annual commitment. For annual and monthly members, 30 free minutes per use are included in the membership price. It costs $1.50 for an additional 30 minutes, $3 for the next 30 minutes and $6 beyond that. Hubway groups annual members and monthly members into the general category of 'subscribers'. The growth in annual members since launching has roughly matched the expansion of stations, as shown in Figure 3-8 and Figure 3-9.

4 DATA AND METHODS

The dataset for this analysis includes land use, built environment, transit, and demographic variables. I construct the dataset from various publicly available data sets from the City of Boston, City of Cambridge, City of Somerville, and MassGIS. Some variables, identified in Section 4.2, are counted manually due to limitations of data access across all three cities. Station-specific and station area variables were calculated for the 192 Hubway Stations in the study area, with some stations later removed, using GIS, R, and Excel. I aggregated trip origins by station from publicly available Hubway trip data for 2017. This chapter discusses the construction of the dataset and methods for analysis.

4.1 Dependent Variable

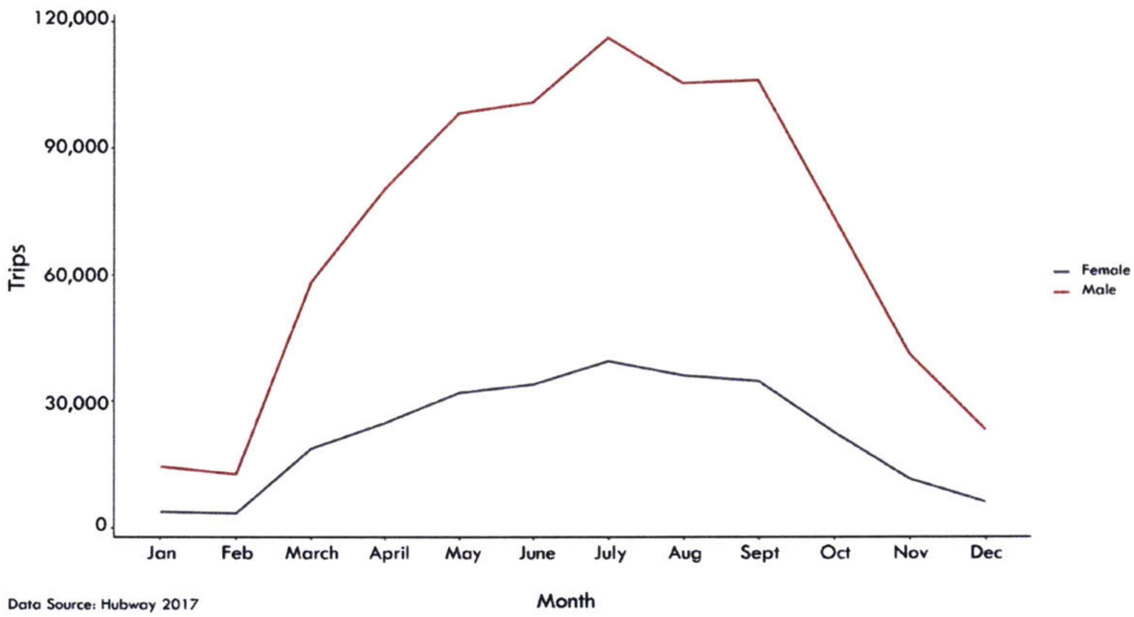
4.1.1 Hubway Usage

The dependent variable for this analysis is Hubway trip origins. Factors contributing to trip origins differ from factors contributing to trip attractions (Krykewycz et al, 2011). My analysis is limited to trip origins because I am interested in relating factors to where trips start, to understand if physical environment factors might influence the choice of using bike share. Due to limitations in scope for my analysis, I could not include an analysis for destination trips.

Hubway publishes data by trip for each month. The trip data includes the origin station, start time, destination station, end time and trip duration, as well as customer data that includes member id, area code, gender (for subscribers), and age. The data does not include the route the user takes. Casual riders (members who register for a 24-day or a 72-hour pass) are not included in the analysis since these riders' gender cannot be identified.

The dataset includes over 1,313,774 trip origins for the whole year, with August seeing the highest number of trips. Figure 4-1 shows the distribution of trips per month, by gender[4] for subscribers.

Figure 4-1 Hubway Trip Origins by Time of Year



4.1.1.1 Filtering

My analysis focuses on origin trips for April-October 2017 for Hubway stations. I only analyzed data from April to October because, until winter 2017, stations in Boston, Brookline and Somerville were closed during the winter months, generally starting in late November or early December, and returning in the first week of April. In winter 2017-2018, 35 of the 192 stations closed during the winter months. Cambridge, however, does not close stations in the winter, therefore I removed the months of November-March so that all stations are in operation during the analysis time period. Additionally, stations in Brookline were also removed because the city

[4] When monthly and yearly members register, they have three gender options; male, female and other, there is no write in option. Other makes up 0.61% of subscriber origin trips.

did not have data available for many explanatory variables. After this process, 188 stations remained.

Additional observations were removed based on relative anomalies, including trips that started and ended at the same location, trips that were less than two minutes, and trips that were over 60 minutes. This removed outliers and errors and also increased the likelihood of focusing on utilitarian instead of recreational trips. Additionally, weekend trips were removed. My analysis focuses on utilitarian trips because I am interested in understanding factors related to non-leisure trips. Individuals using bicycles for commuting and leisure or sport are sensitive to different factors (Stinson & Bhat, 2005). Additionally, recreational trips have a different temporal distribution than utilitarian trips; recreation trips tend to have a broad peak that runs from late morning to midafternoon and on weekends (Miranda-Moreno et al., 2003). Accordingly, I removed weekend trips and long trips to limit the number of leisure trips. That said, it is not possible to determine trip type in the Hubway trip origins data, so I do not attempt to make explicit claims about utilitarian trips.

The trips were further grouped into time periods: AM Peak (6-10AM), Midday (11-3PM), PM Peak (4PM-8PM), and Late Night (9PM-1AM). Overnight trips (2-5AM) (0.99% of observations) were excluded. Table 4-1 shows the percent of total trips during each time period.

Table 4-1 Percent of Trip Origins by Time Period

Time Period	*Gender*	*Percent of Total Trips*
Overnight	Male	0.76%
	Female	0.23%
AM	Male	24.54%
	Female	8.13%
Mid	Male	15.18%
	Female	4.94%
PM	Male	30.26%
	Female	9.64%
Late	Male	5.02%
	Female	1.31%

After this data cleaning, 692,475 trip origins remained. Of these, men accounted for a much larger share than women: 524,387 versus 168,088 trips. Figure 4-2 shows the distribution of trips in the dataset by hour, and Figure 4-3 shows the distribution of trips by time period. Clear morning and evening peaks appear for both men and women, around 8AM and 5PM, with a small bump also around noon.

Figure 4-2 Trip Origins by Gender and Hour, April-October 2017

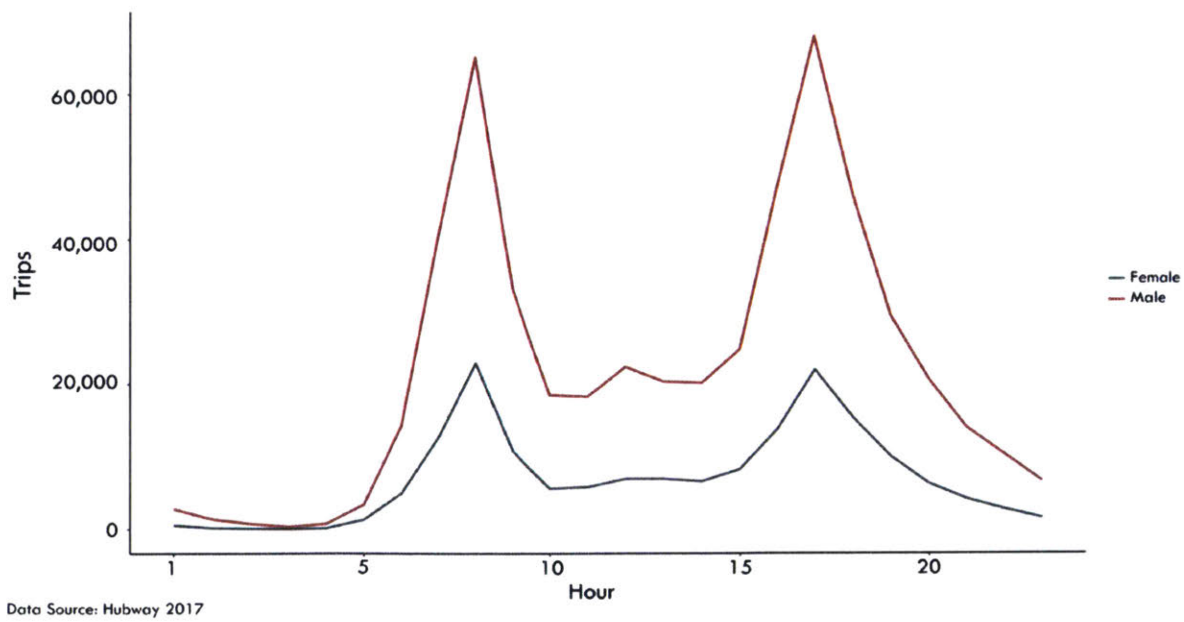
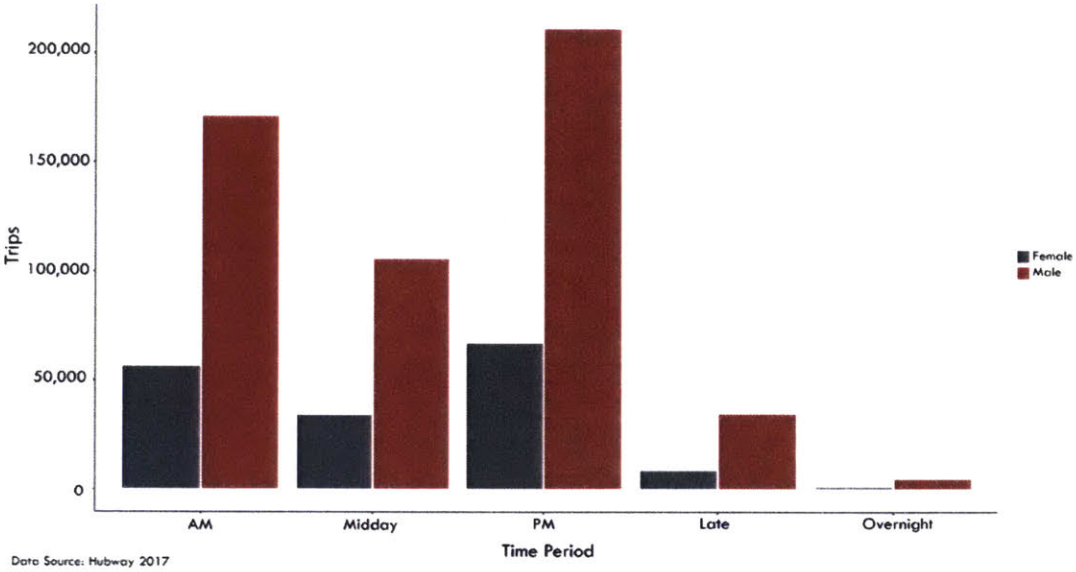


Figure 4-3 Trip Origins by Gender and Time Period, April-October 2017



4.1.1.2 Relative Usage

To more easily compare differences in relative usage, I examine usage by gender as a share of total trips by that gender. As shown in Figure 4-4., women start a relatively higher share of their total trips at 8 AM. Number of trips and percentage of trips over a day shows that men and women exhibit similar temporal patterns over a day. Figure 4-5 shows that the relative shares of total usage by women and men are almost identical across the day, with women having a slightly higher share of usage during the AM Peak and slightly lower share of usage during late night, differences of around one percentage point in each case.

Figure 4-4 Share of Trips by Gender and Hour, April-October 2017

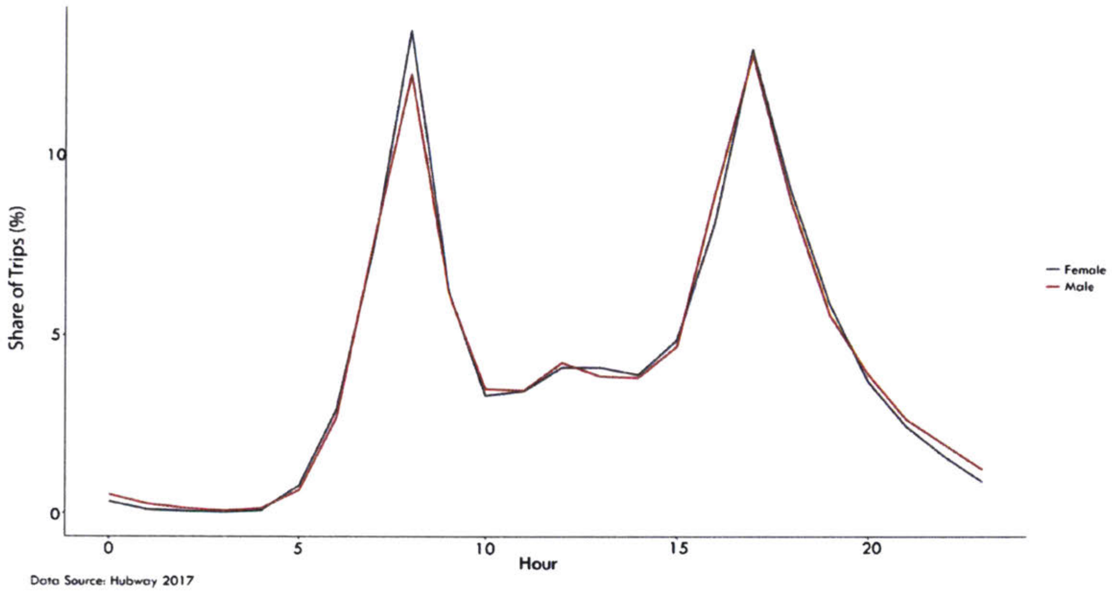
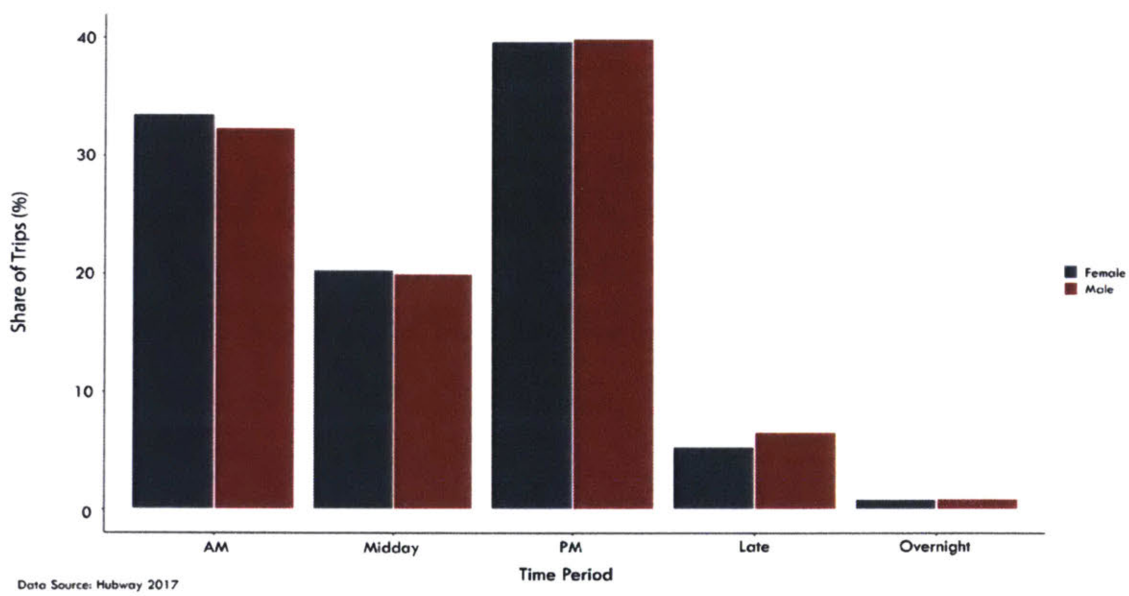


Figure 4-5 Share of Trips by Gender and Time Period , April-October 2017



4.1.1.3 Spatial Distribution

Spatially representing where users start their trips can help give an idea of spatial patterns that exist in the data. During AM peak, women have a large share of trips in Back Bay West, along the Green Line to Longwood, at Mass General Hospital, and around Central and Inman Squares. Men however, have a large share of their trips near Long Wharf North and the Financial District, at North and South Station, in Back Bay, and in Cambridgeport/Central Square. Long Wharf North, North and South Station are key transit and ferry nodes where last-mile connections may happen.

Midday trips show very similar spatial patterns for men and women, and most trips are more concentrated. Clusters of trips occur at Kendall/MIT, Financial District, Central Square and Back Bay for both genders. These are main areas of employment, so these clusters could indicate midday trips starting from work.

PM trips also show very similar spatial patterns. Clusters of trip origins for both males and females occur in Kendall/MIT and Back Bay with smaller clusters at Harvard Square and South Station. Additionally, a large share of female trip origins occur around Mass General Hospital. In addition, male trip origins see a larger share of trips in the Financial District. This spatial distribution for when many workers leave work could be due to clustering of female workers in the health care industry and male workers in the finance industry.

Late night trip origins are more concentrated, but vary between male and female. Male shares of trips cluster around the Financial District, Kendall/MIT, Central Square and Harvard. Female shares of trips cluster around Government Center, the Theatre District, Central Square and Kendall/MIT.

Figure 4-6 Female Share of Origin Trips by Station, 6AM-11AM

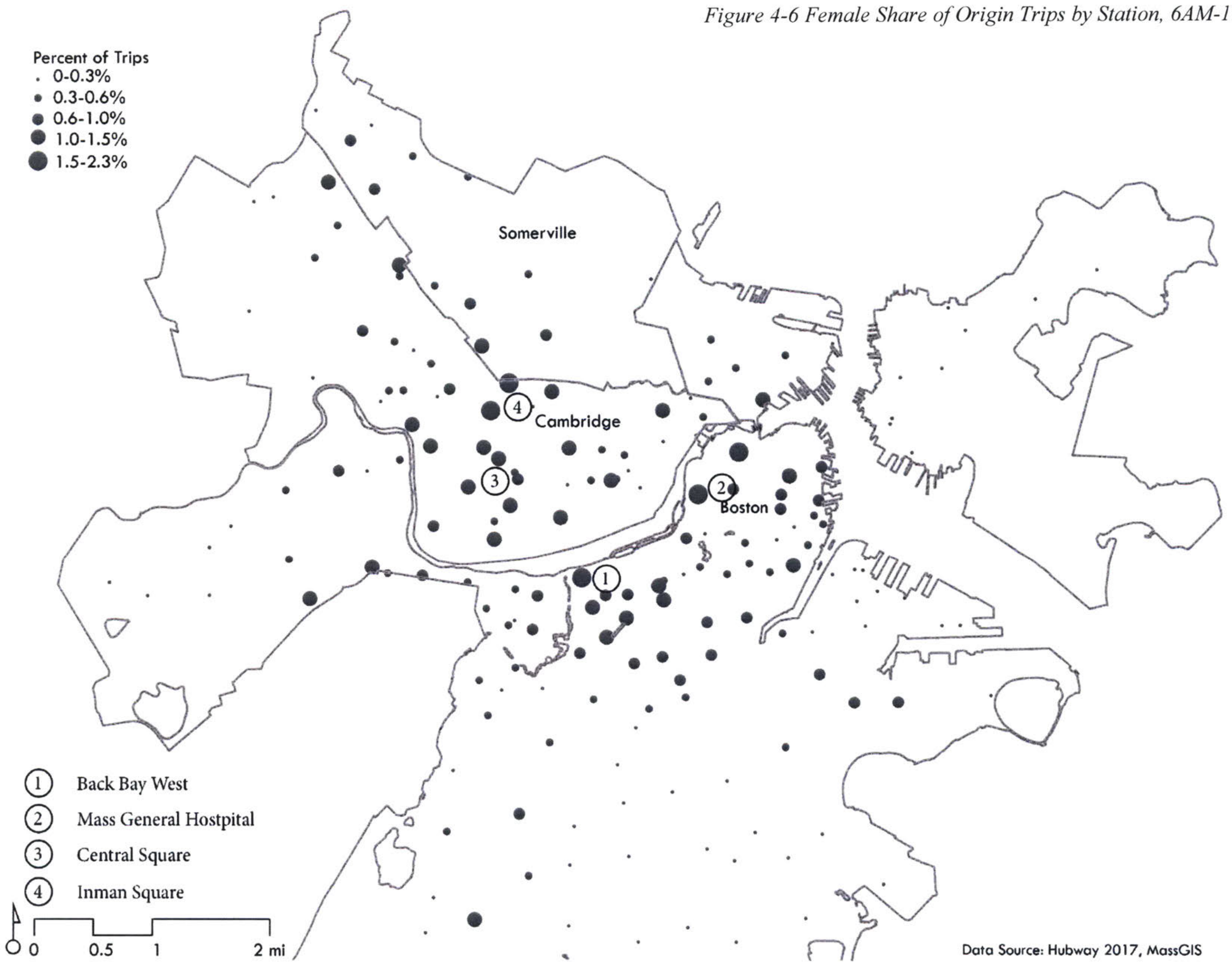


Figure 4-7 Male Share of Origin Trips by Station, 6AM-11AM

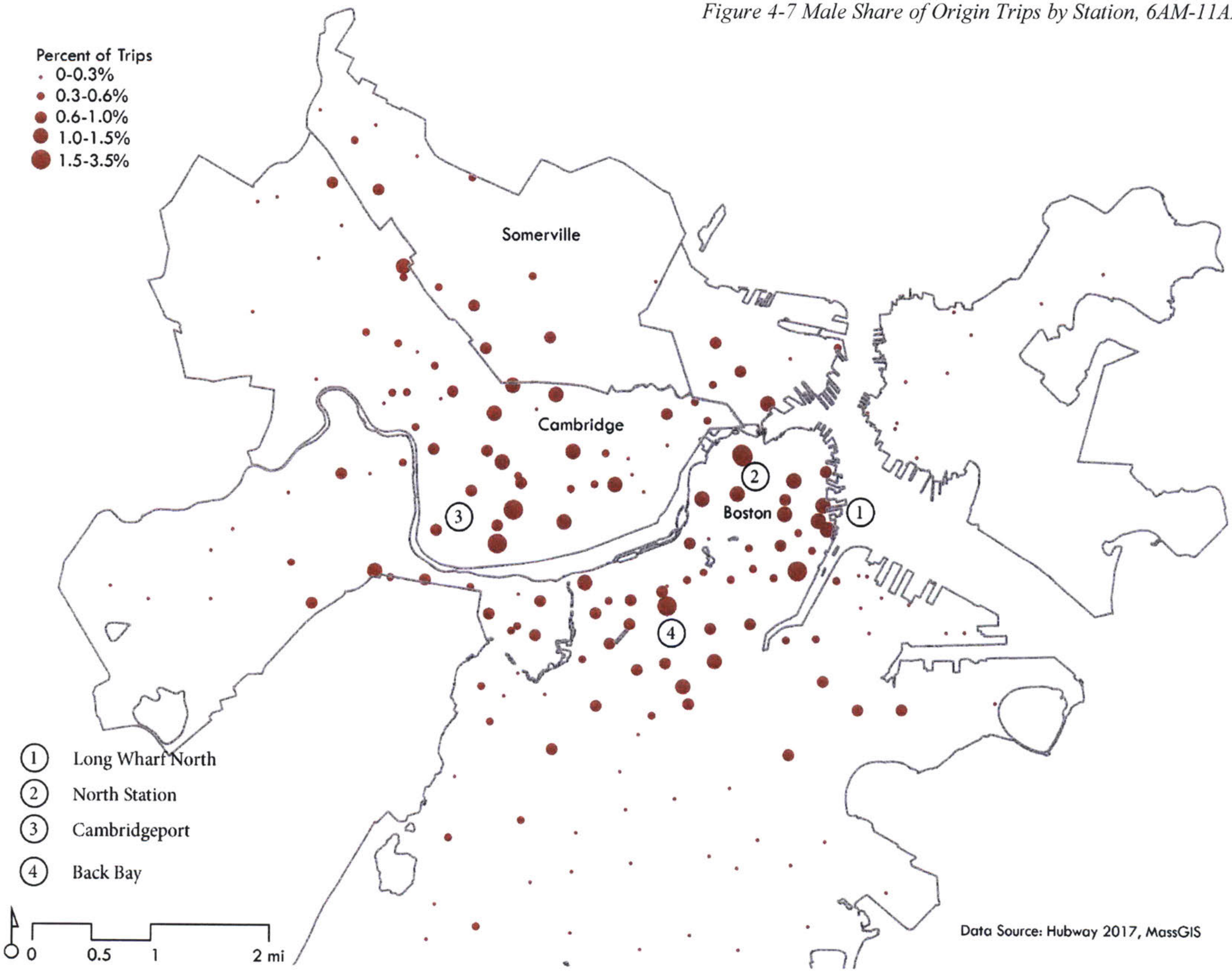


Figure 4-8 Female Share of Origin Trips by Station, 11AM-4PM

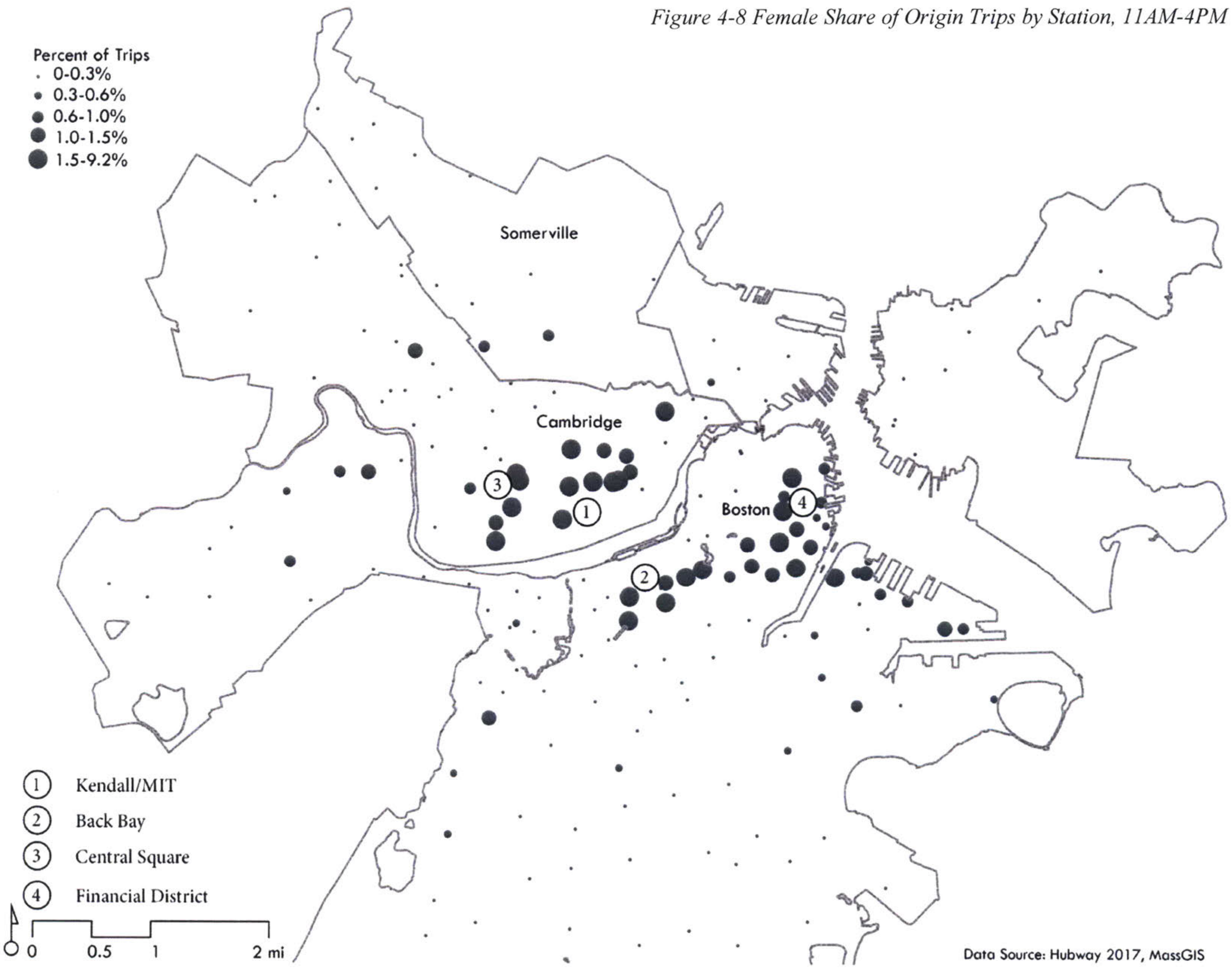


Figure 4-9 Male Share of Origin Trips by Station, 11AM-4PM

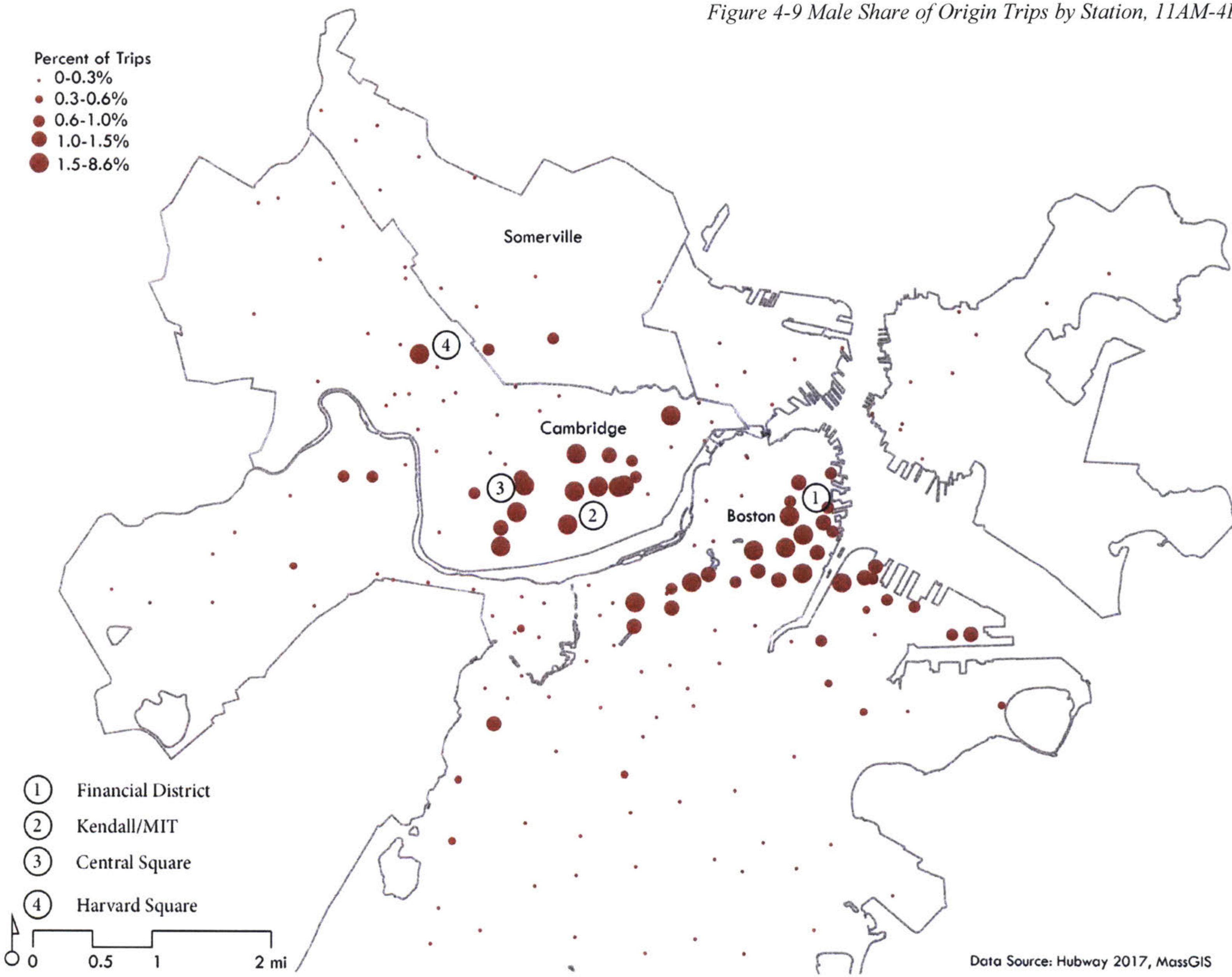


Figure 4-10 Female Share of Origin Trips by Station, 4PM-9PM

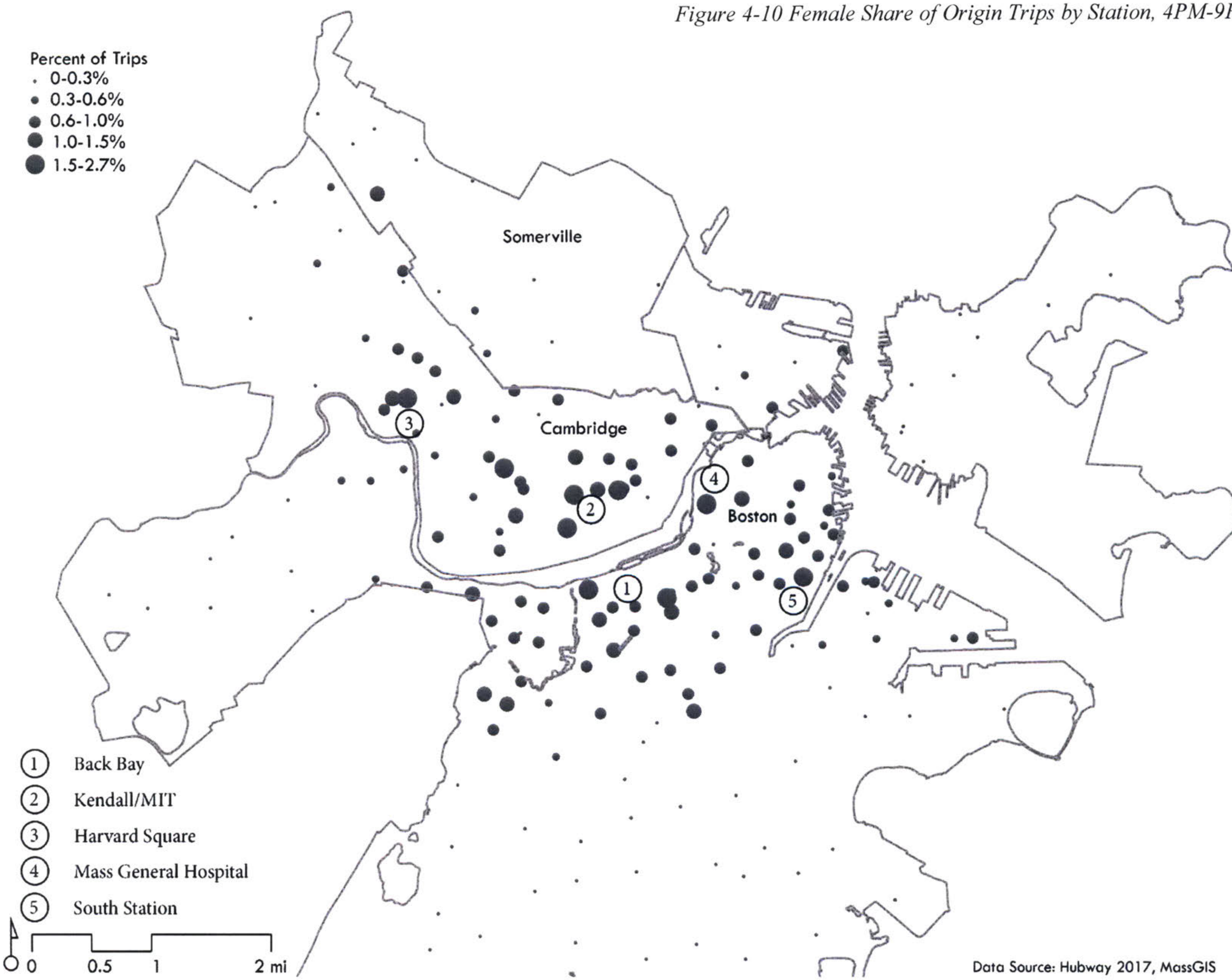


Figure 4-11 Male Share of Origin Trips by Station, 4PM-9PM

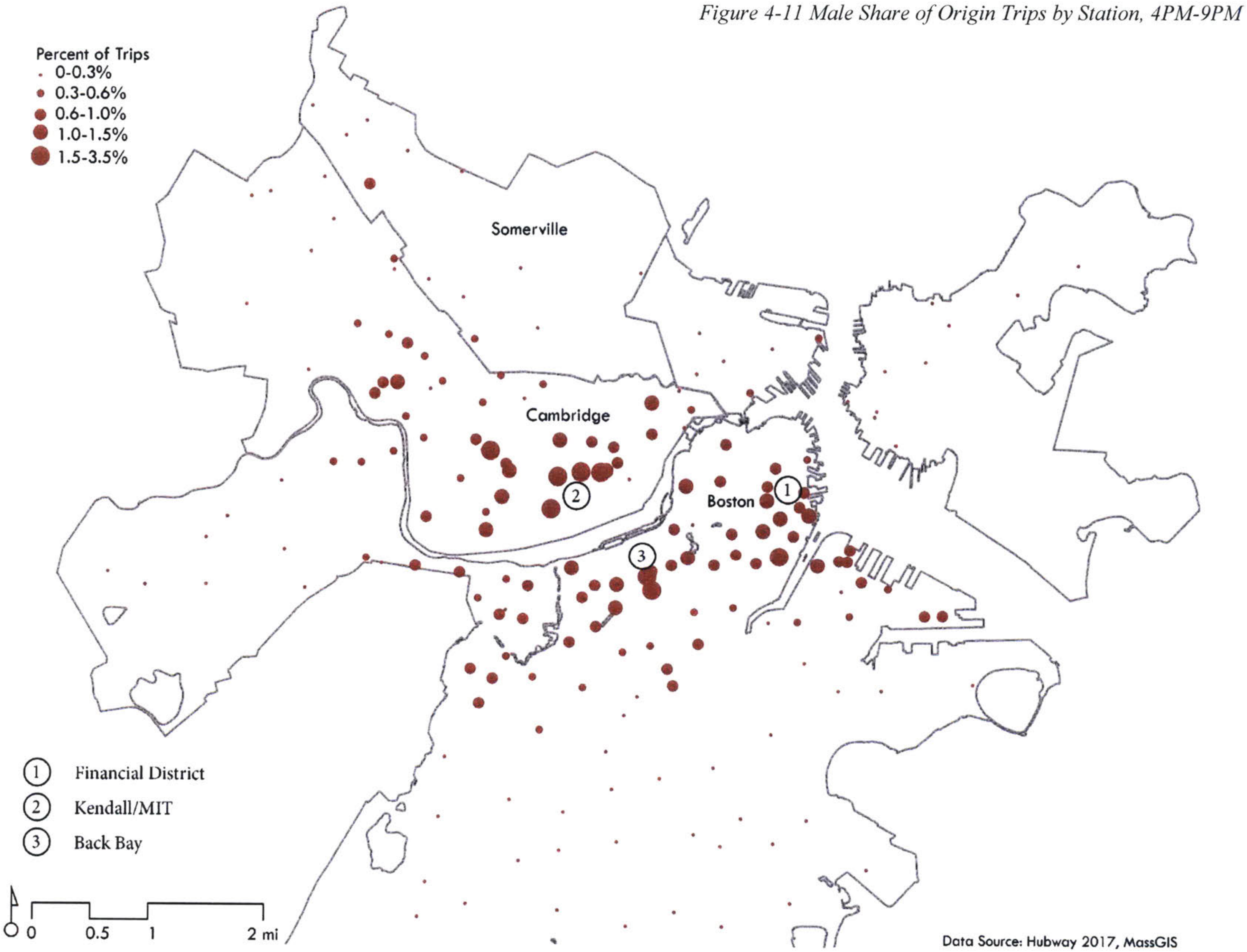


Figure 4-12 Female Share of Origin Trips by Station, 9PM-2AM

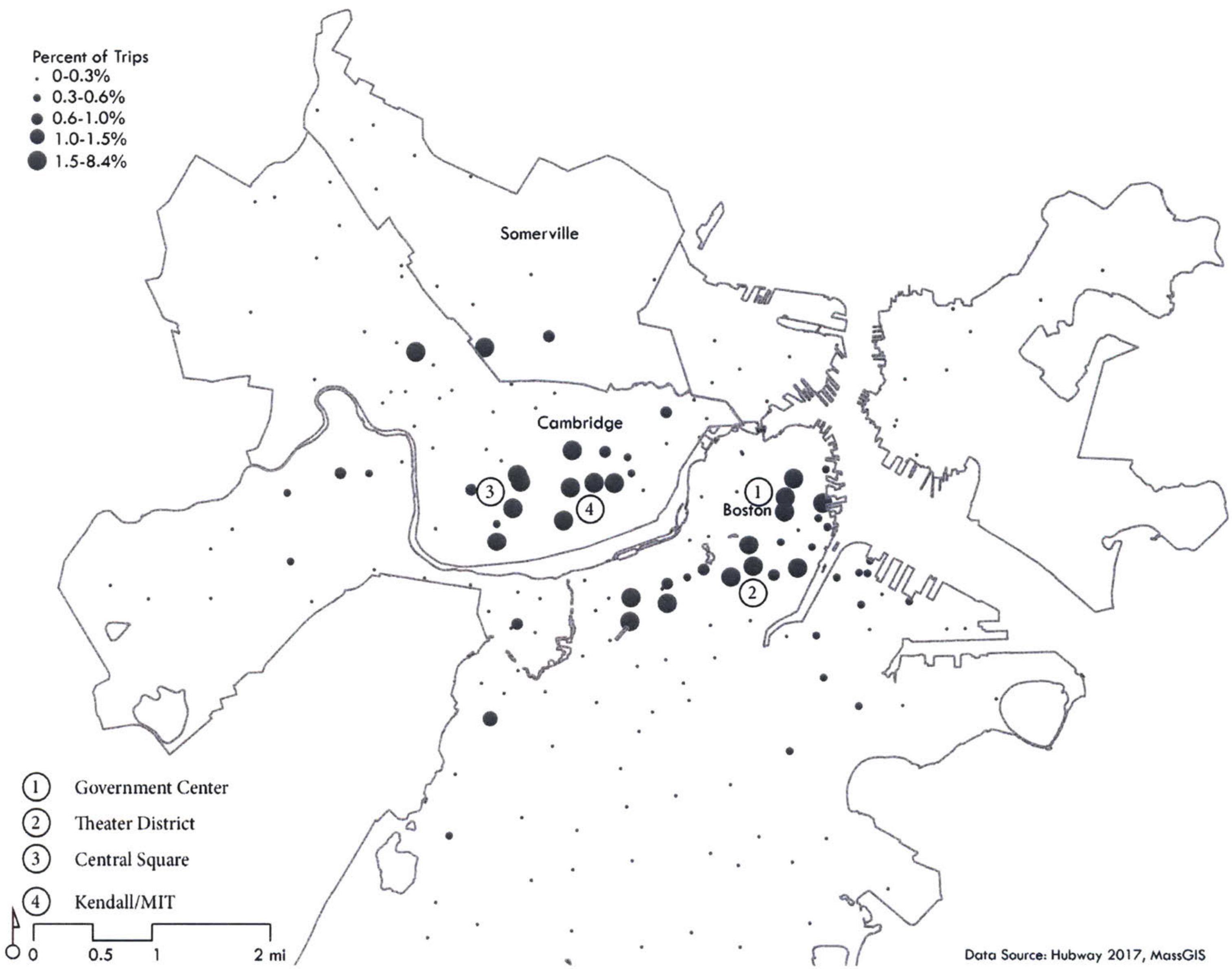
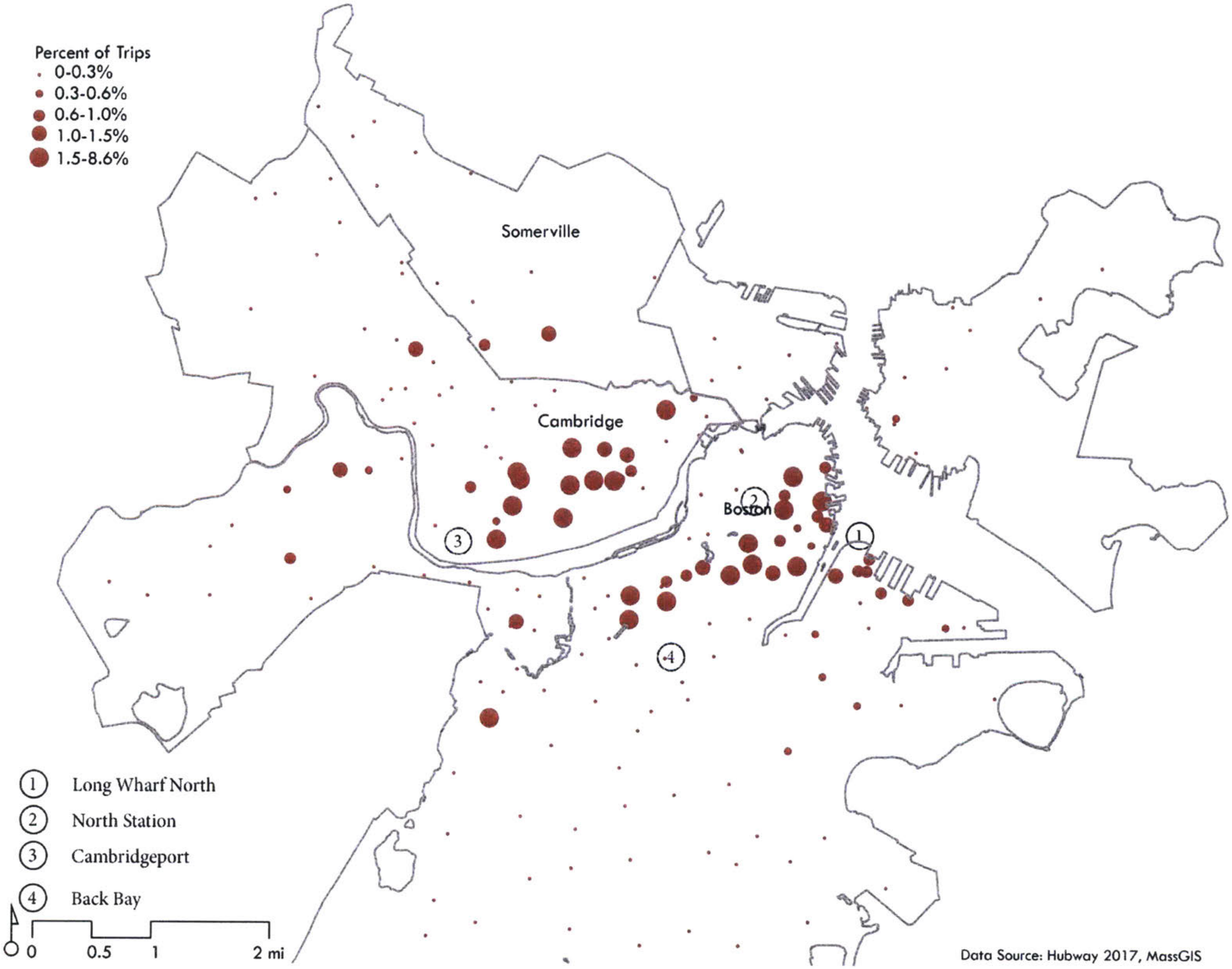


Figure 4-13 Male Share of Trip Origins by Station, 9PM-2AM



4.1.1.4 Descriptive Statistics

The descriptive statistics of trip origins by station, shown in

Statistic	N	Mean	St. Dev.	Min	Max
Female 6AM-11AM	188	301.12	250.32	1	1,254
Female 11AM-4PM	188	182.98	181.90	1	1,421
Female 4PM-9PM	188	357.04	328.87	2	1,773
Female 9PM-2AM	188	48.49	55.86	0	303
Male 6AM-11AM	188	909.01	870.15	8	6,998
Male 11AM-4PM	188	562.44	635.31	6	5,078
Male 4PM-9PM	188	1,121.26	1,193.94	11	7,252
Male 9PM-2AM	188	185.97	217.22	0	1,309

, illustrate the large range in station usage, and differences between average number of trip origins for men and women. The PM peak time period has the highest mean value for men and women, and the late night time period has the lowest mean value for both men and women. The data was highly skewed left, so a square root transformation was used to transform the data to be closer to a normal distribution for modeling. Histograms of trip origins and the transformation are shown in Appendix A and B.

Table 4-2 Explanatory Variable Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Female 6AM-11AM	188	301.12	250.32	1	1,254
Female 11AM-4PM	188	182.98	181.90	1	1,421
Female 4PM-9PM	188	357.04	328.87	2	1,773
Female 9PM-2AM	188	48.49	55.86	0	303
Male 6AM-11AM	188	909.01	870.15	8	6,998
Male 11AM-4PM	188	562.44	635.31	6	5,078
Male 4PM-9PM	188	1,121.26	1,193.94	11	7,252
Male 9PM-2AM	188	185.97	217.22	0	1,309

Table 4-3 Top 20 Stations (by total trip origins)

Station	*Total Trips*	*Female AM*	*Male AM*	*Female Mid*	*Male Mid*	*Female PM*	*Male PM*	*Female Late*	*Male Late*
MIT at Mass/Amherst St	19085	688	2093	1421	5078	1509	6572	276	1309
South Station - 700 Atlantic Ave	19016	763	5826	513	2259	1773	7252	98	429
Central Square at Mass Ave	13271	731	2316	664	1700	1690	4695	303	1115
MIT Stata Center at Vassar St	13046	130	607	796	3349	1269	6330	75	465
Kendall T	12760	593	1834	768	3166	1035	4715	102	526
Nashua Street at Red Auerbach	11722	1154	6998	222	756	550	1658	40	296
Beacon St at Massachusetts Ave	11197	1254	2137	528	1551	1133	3008	266	1128
MIT Vassar St	10184	667	3176	304	2057	523	2768	96	539
MIT Pacific St at Purrington St	10034	696	2569	489	2032	700	2422	154	878
Charles Circle - Charles/Cambridge	9702	1092	2139	471	1088	1130	2997	116	567
Ames St at Main St	9479	260	962	709	2425	807	3655	102	520
One Kendall Square	9417	610	1714	628	1819	773	3106	103	577
Back Bay T Stop	9289	701	2766	261	883	901	3257	120	323
Copley Square	8927	582	1372	496	1231	1262	3387	153	400
Harvard Square at Mass/Dunster	8529	294	885	564	1536	1135	3032	244	801
Boston City Hall	8300	529	1873	350	1541	660	2963	53	282
University Park	7686	475	1589	267	1335	552	2455	177	805
Lechmere Station	7219	676	1499	280	1117	576	2775	35	233
Boylston St at Fairfield St	7029	495	1217	368	1162	615	2717	73	345
Christian Science Plaza - Mass Ave	6985	750	1428	334	811	811	1958	151	595

A full list of trip origins by station, with station rank, illustrates that the highest stations for men and women are very similar. The top 20 stations for total trip origins are shown in Table 4-3. Many of the top 20 stations are near T stations or landmarks in the city.

4.2 Explanatory Variables

I categorized the explanatory variables into five categories: demographics, safety, bicycle infrastructure, land use and transit. Variables related to the area surrounding stations were aggregated to a quarter mile catchment area. The data come from a variety of sources, including MassGIS, American Community Survey (ACS), the Longitudinal Employer Household Dynamics (LEHD), City of Boston, City of Somerville and City of Cambridge. Variables were chosen based on availability from all three cities, literature on factors affecting bikeshare usage, and literature on factors related to where or why women bike. I used ArcMap to calculate variables and R, SQL, and Excel to analyze the results. Some factors, such as distance, are shown in the literature to vary between men and women but were not included in this analysis due to its focus on physical environment characteristics, and focus on trip origins rather than origin-destination pairs. All variables are briefly outlined next, with descriptive statistics and histograms in Appendix C and D.

Variables related to the area surrounding the station were calculated for the station catchment area, which was estimated as the quarter mile street network distance from a Hubway station. Using the street network distance rather than Euclidean distance provides a better representation of human accessibility to the station distance because it follows the street network and accounts for network connectivity rather than distance as the crow flies. Figure 4-14 shows an example of the difference between using a Euclidean distance-based versus a street network-based catchment area. Due to station proximity, many catchment areas were not exclusive, with varying amounts of catchment area overlaps across the study area. Figure 4-15 shows each station and its catchment area. There was significant overlap in areas such as inner downtown Boston and Central Square, Kendall Square and Harvard Square in Cambridge.

Figure 4-14 Quarter Mile Catchment Area

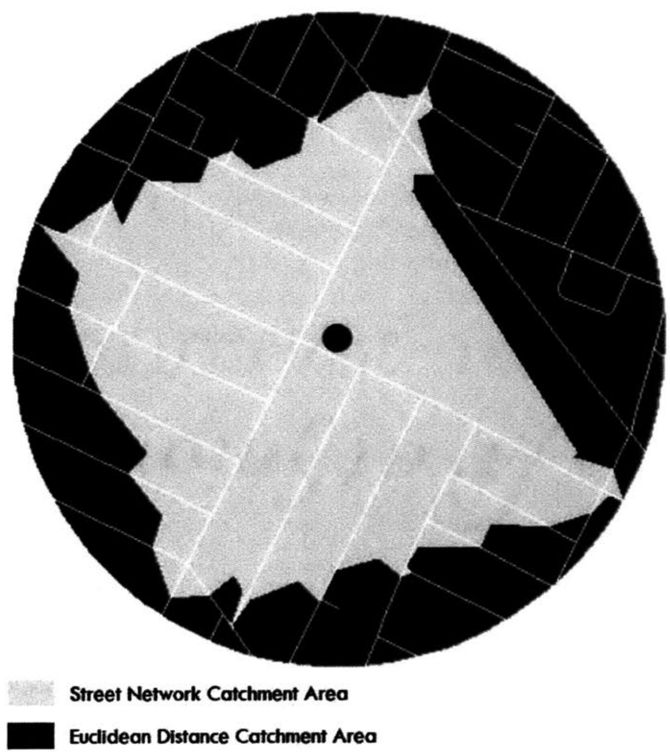


Figure 4-15 Station Catchment Areas

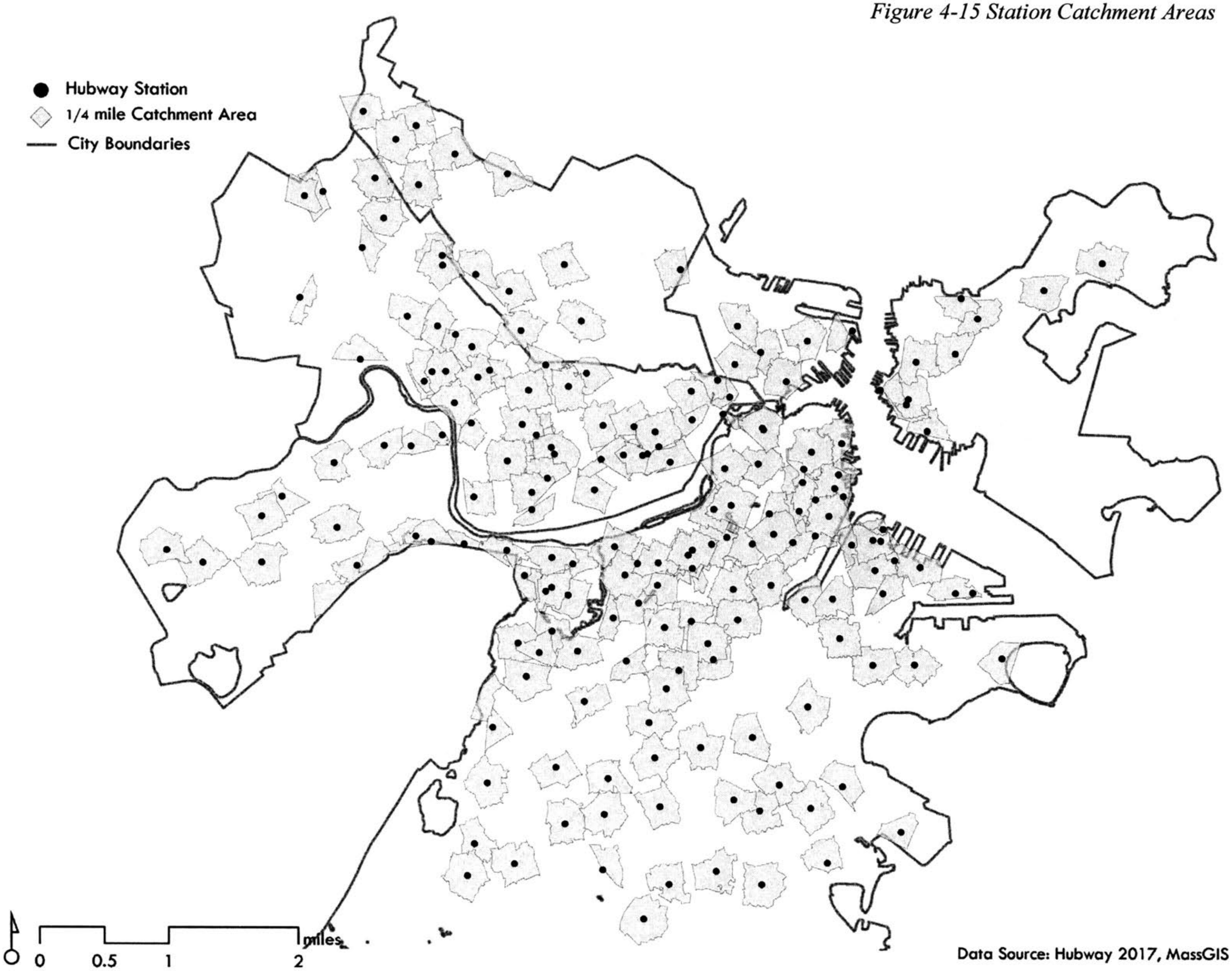


Table 4-4 shows an overview of the 17 variables initially included in the model. The next section describes the variables in more detail, including methods when variables were calculated.

Table 4-4 Explanatory Variable Overview

	Explanatory Variable	***Expected Sign***	***Reason for the expected sign***	***Source***
Demographics	Jobs	+	Jobs attract trips	1
	Population	+	Population produces trips	2
	Density	+	Higher density areas produce and attract more trips	2
Land Use	Distance to CBD	-	More activity closer to CBD so more destinations are in closer proximity	3
	Major University	+	Universities are trip producers	3,4
	Commercial Area	+	Commercial areas attract trips	5, 6, 7
Bicycle Infrastructure	Docks	+	Hubway supplies docks where there is more demand	8
	Distance to Separated Bike Facility	-	More inexperienced cyclists prefer to be closer to separated bike facilities	5, 6, 7
	Distance to Bike Facility	-	Bicycle infrastructure increases perceived safety	5, 6, 7
	Length of Bike Network	+	Bicycle infrastructure increases perceived safety	5, 6, 7
Safety	Average Number of Lanes	-	Fewer lanes mean less traffic and/or narrower streets	4, 9
	Average Annual Daily Traffic	-	More traffic flow decreases perceived safety	9
	Bike Activity	+	Areas with more cyclists have higher perceived safety	6, 7, 10
	Length of Truck Route	-	Large trucks feel unsafe so are avoided	6
	Streetlights	+	More visibility is desired for safety	6, 7, 8
Transit	T Station	+	Transit can attract riders for first or last mile connections	4, 11
	Number of bus stops	+	Transit can attract riders for first or last mile connections	12

1: LEHD Data, US Census Bureau 2015; 2: American Community Survey (ACS) 2012-2016; 3: Manual calculation; 4: MassGIS; 5: City of Boston; 6: City of Cambridge; 7: City of Somerville; 8: Motivate; 9: MassDOT; 10: Boston Area Research Initiative; 11: MBTA; 12: BetterBus

4.2.1 Demographics

4.2.1.1 Population

I calculated population for men and woman separately, using the American Community Survey (ACS) 2012-2016 (5-year estimates) at the census block level. For census blocks that were not completely contained within a catchment area, I calculated the population proportional to the area within the catchment area. Additionally, for overlapping catchment areas, population was split among the overlapping catchment areas, so that population would not be double counted. For example, if three catchment areas overlapped, the overlapping population within the overlapping polygon was divided by three. I used this method assuming that population in, say, two stations with overlapping catchment areas has an equal likelihood of using either station. I expect population to have a positive effect on trip origins because a large portion of transportation trips begin at home (for example, home-based-work or home-based-other). I also calculated the density of catchment area as people per square foot. Density can capture population as representing clusters of people, which could indicate other amenities. I expect density to have a positive effect on trip origins because higher density of population indicates more trip production.

4.2.1.2 Jobs

I aggregated jobs data from LEHD data and the Employment Statistics (LODES) Dataset. Jobs can be an indicator of demand for travel from work. The data is from the most recent year available, 2015, at the block level, and includes number of female workers, and number of male workers. For census blocks that were not completely contained within a catchment area, I calculated the jobs proportional to the area within the catchment area[5]. I expect jobs to have a positive effect on trip origins.

4.2.2 Safety

4.2.2.1 Average Annual Daily Traffic

Average annual daily traffic (AADT) is an estimate of the number of vehicles that use a roadway during the year. AADT effects the perceived safety in an area, which impacts a potential user's comfort in the surrounding area when departing or arriving. AADT is captured by MassDOT for a limited number of

[5] Unlike population, Jobs were only calculated as proportional to the area within the catchment area, so jobs were double counted for overlapping catchment areas.

streets. I calculated an average of the AADT for roads within the catchment area. Some areas, especially newer developments like the Seaport, may have underestimated AADT because the data was captured between 2009-2012. I obtained the data from MassGIS, as sourced from the MassDOT road inventory. I expect AADT to have a negative relationship with trip origins because an area with more vehicle traffic would decrease how safe and comfortable it feels to bike in that area.

4.2.2.2 Number of Lanes

To capture road width, number of lanes is used to estimate how pleasant it is in the area surrounding the station. More lanes can make it difficult for cyclists to navigate through the traffic. For each street in the catchment area, I summed the total number of lanes on each street to calculate the average total number of lanes in the catchment area. This would show, on average in the surrounding area, how pleasant a street is to bike on, with fewer lanes indicating a more pleasant street. The number of lanes is likely correlated with average annual daily traffic, since lanes are usually added to accommodate more traffic. I obtained the data from MassGIS, and sourced from MassDOT road inventory. I expect number of lanes to have a negative relationship with trip origins.

4.2.2.3 Parking Meters

Parking meters are generally located in retail and entertainment areas, where short term parking is needed. Therefore, parking meters are included to identify areas of high activity. Parking areas are also dangerous for cyclists, with vehicles crossing into bicycle lanes while parking, or drivers/passengers opening their car doors into cyclists when they exit vehicles. The data was aggregated to the catchment area. Parking meters data was obtained from the City of Boston, Cambridge, and Somerville. I expect this variable could have two impacts on bikeshare usage: 1) decrease ridership due to parking activity often meaning more potential conflicts with cyclists or 2) parking representing commercial areas which will increase ridership due to commercial corridors being destinations or origins for trips.

4.2.2.4 Truck Routes

Truck activity can have adverse impacts on noise and safety, so some cities limit the streets where heavy vehicles can drive. Trucks are permitted on most streets in the region, but are encouraged to use a system of Posted Truck Routes for a majority of their trips. I obtained a truck route map for the region from the City of Cambridge and manually geocoded it. Then I calculated the total length of the truck route within each catchment. I expect stations with a higher amount of truck routes to have lower trip origins because large vehicles decrease perceived safety for cyclists.

4.2.2.5 Number of Bus Stops

On most streets bus stops are in or adjacent to the bike lane. Navigating around a stopped bus, or a bus pulling into a bus stop can leave cyclists exposed to traffic and can feel unsafe. Additionally, buses are large vehicles, and getting passed by a bus can feel unsafe. I calculated the number of bus stops in the catchment area to indicate another safety metric. I expect bus stops have a negative relationship with origin trips. I calculated the data using the Better Bus ArcMap tool, which utilizes the MBTA general transit feed specification (GTFS).

4.2.2.6 Streetlights

Lighting can increase perceived safety, particularly for women. Women have indicated in previous studies that they tend to prefer well-lit areas. Streetlights can increase this perceived safety, but also tend to be in areas where pedestrians or drivers may also need them, such as commercial corridors or major intersections. Streetlights can also increase actual safety by decreasing pedestrian, bike and vehicle accidents with appropriate lighting of streets (Lutkevish et al, 2012). Light can increase surveillance and deter potential crime (Haans and de Kort, 2012). This could however, indicate that streetlights are placed in areas where there is more crime and/or had more accidentss. Given that most streetlights have been on streets for many years, the reduction in accidents would likely outweigh any initial crime or unsafe conditions, so I expect streetlights to have a positive relationship with trip origins in the PM peak and night time periods. I obtained streetlight data from the City of Boston, and Cambridge. The data did not exist for Somerville, so I manually counted streetlights using Street View in Google Earth. To normalize the data, I divided the total number of streetlights by length of road network in the station area catchment area.

4.2.3 Bicycle Factors

4.2.3.1 Length of Bike Network

Availability of bicycle infrastructure can increase usage, as cyclists feel safer. The length of the bike network was calculated for each catchment area, in feet. All bike facility types were included. I expect length of bike network to positively affect trip origins. Bicycle network data was obtained from City of Boston, Cambridge, and Somerville. The data was combined to create a bike network for the entire study area.

4.2.3.2 Distance to Bike Facility

Research has indicated that bike infrastructure increases bike usage. Distance to bike facility is used to indicate how close the station is to bike infrastructure. The distance to a bike facility was calculated for each Hubway station, as the distance to the closet bike facility. All bike facility types were included. I expect stations closer to bike facilities to have more trip origins. I obtained bicycle network data from City of Boston, Cambridge, and Somerville.

4.2.3.3 Distance to Separated Bike Facility

Facilities separated from traffic tend to be preferred by cyclists, and for women in particular. I expect that the closer a station is to a separated bike facility, the higher the number of trips that will start at that station. Each city had different designations for the facilities. Separated facilities included: major shared use path, cycle track, mixed use path, bike path/multi-use path, parking separated bike lane, and separated bike lane. I calculated the distance to a separated bike facility for each Hubway station. I obtained bicycle network data from City of Boston, Cambridge, and Somerville.

4.2.3.4 Bicycle Activity

I used bicycle crashes as a proxy for bicycle usage, following a study from UCLA that found intersections with bikeways and higher bicycle counts had higher crashes (Ligget, 2016). I compiled crash data from the City of Cambridge, Somerville, and a database created by researchers from Harvard School of Public Health, the Boston Police Department, and BARI for the City of Boston. To standardize the data available, a three year period of 2015-2017, 2014-2016, and 2010-2012 was used for Cambridge, Somerville, and Boston, respectively[6]. Only crashes that involved a cyclist were included. I aggregated the data to the catchment area. Since crashes cannot be normalized by cyclist flow, I expect that crashes will be a proxy for bicycle usage. This is a limitation of the data. While research has shown that at a certain threshold more cyclists mean less crashes due to safety in numbers, I assume that the number of overall cyclists in the study area is not high enough to reduce crashes. As cycling increases, the number of crashes also increases, so I expect crashes will have a positive effect on trip origins.

4.2.3.5 Docks

The number of docks at a station is a variable that can control for the supply of bikes at a station. Literature indicates that as the number of docks that a station has increases, so does the usage. I include total number of docks in the catchment area to capture higher demand areas. I expected docks and total number of docks in catchment area to have a positive effect on trip origins.

4.2.4 Land Use

4.2.4.1 Land Use Mix

Studies have indicated that the more mixes of land use, the more trips will start or end at that location. The more types of land use, the more varied the trip attractors or producers there are. Varied land uses

[6] It may be problematic using three different time periods because more recent dates have higher bicycle usage. However, this was the only complete dataset available for each city for crashes of any sort. Somerville had incomplete data for 2017, and Boston only had data from 2010-2012 because a research group studied that time period specifically. I compared the total counts for all three cities and they were on similar scales. This does not, however, indicate that the numbers are a good and consistent measure for bicycle activity between the three cities.

tend to be a proxy for more cycling friendly places. As such, I expect station catchment areas with a higher land use mix will have more trip origins. This measure does not measure magnitude of mixture of land uses, which should be captured in population or jobs.

Frank et al (2006) propose a land use mix measure, using 6 different land use types:

$$\text{Land Use Mix}=-A/(\ln(N));$$

where area =

$A=(b1/a)*\ln(b1/a)+ (b2/a)*\ln(b2/a)+ (b3/a)*\ln(b3/a)+ (b4/a)*\ln(b4/a))+ (b5/a)*\ln(b5/a))+ (b6/a)*\ln(b6/a)$

a=total square feet of land for all six land uses present in buffer

and:

b1= low density residential, single family

b2= medium density residential, high density residential, multi family

b3=retail

b4=office

b5=education

b6=entertainment

N=number of six land uses with area > 0

For the land use mix measure, a higher value indicates more mixture of land uses. The land use mix measure can range from 0 to 1; 0 indicates homogenous land use and a 1 indicates equal mixture of land use types, or higher mix.

The land use data available from MassGIS only included four land use types, however, thus I modified the above formula as:

$$\text{Land Use Mix}=-A/(\ln(N));$$

where area =

$A=(b1/a)*\ln(b1/a)+ (b2/a)*\ln(b2/a)+ (b3/a)*\ln(b3/a)+ (b4/a)*\ln(b4/a)$

a=total square feet of land for all four land uses present in buffer

and:

b1= low density residential, single family

b2= medium density residential, high density residential, multi family

b3=commercial

b4=institution

N=number of four land uses with area > 0

4.2.4.2 Distance to Central Business District

The distance to central business district (CBD) measures how relatively far out a station is from the CBD. All else equal, in a monocentric city, moving further away from the CBD would make likely trip distances longer, and reduce demand for cycling. I use City Hall as the center point due to its central location and identity as a central city point. I expect distance to CBD to negatively impact trip origins, as the farther away a station is from the CBD the lower the demand for cycling. The study area is not a mono-centric city, and has multiple smaller business districts, so the relationship may not be linear.

4.2.4.3 Major Universities

Students have been identified in the literature as a typical user profile for bike share usage. Given their lower income and younger age and the fact that many universities partner with Hubway to offer discounted memberships, I expect the presence of a major university to have a positive impact on trip origins. Using existing point data, Google Maps and campus maps, I manually calculated a categorical variable for presence of a major university in the catchment area, including all campus buildings identifiable on a campus map. The point data was obtained from MassGIS, and included undergraduate and graduate enrollment. I counted as major universities those with over 2,000 total student enrollment. The schools included: Berklee School of Music, Bunker Hill Community College, Boston University, Emerson College, Harvard College, Lesley University, Massachusetts Institute of Technology, Northeastern University, Roxbury Community College, Suffolk University, Tufts University, University of Massachusetts Boston, and Wentworth Institute of Technology. Secondary locations (such as Harvard or Tufts Medical School) were not included.

4.2.5 Transit

4.2.5.1 T Stations

Bike share can be used as a first- or last-mile connection, often in conjunction with transit. MBTA T stations represent potential supply of users. A categorical variable captures this, with a 1 representing at least one T station in the catchment area and a 0 representing no T stations in the catchment area. I expect that stations with a T station in the catchment area will have higher usage than stations without a T Station in the catchment area. I obtained from MassGIS that was provided by MBTA.

4.2.5.2 Bus Frequency

To assess the bus frequency of the catchment area, I calculated the number of buses that arrive or depart during a given time period in the catchment area. The measure is the total frequency of bus service. This can indicate how well an area is served by the bus system, which is related to cycling in multiple ways. First, it can supply demand for trip origins and people using bikeshare for a first or last mile connection. Additionally, other studies indicated that many bikeshare trips are substitutes for public transportation, so areas with higher bus frequency could increase bikeshare usage because users are substituting bikeshare trips for bus trips. Alternatively, areas with high bus frequency could be have good accessibility so there may be less demand for bikeshare.

Using the Better Bus ArcMap tool, which utilizes the MBTA general transit feed specification (GTFS), I calculated the frequency of bus departures and arrivals. I expect that the higher the bus frequency is, the higher the trip origins because more frequency produces more potential trips, and more potential substitute trips. I expect that these two positive effects are larger than the decrease of demand caused by having good accessibility.

4.3 Modelling Approach

For this analysis, I used multiple linear regression analysis to examine the relationship between the number of trips that originate from each station, grouped by time and gender and the various explanatory variables.

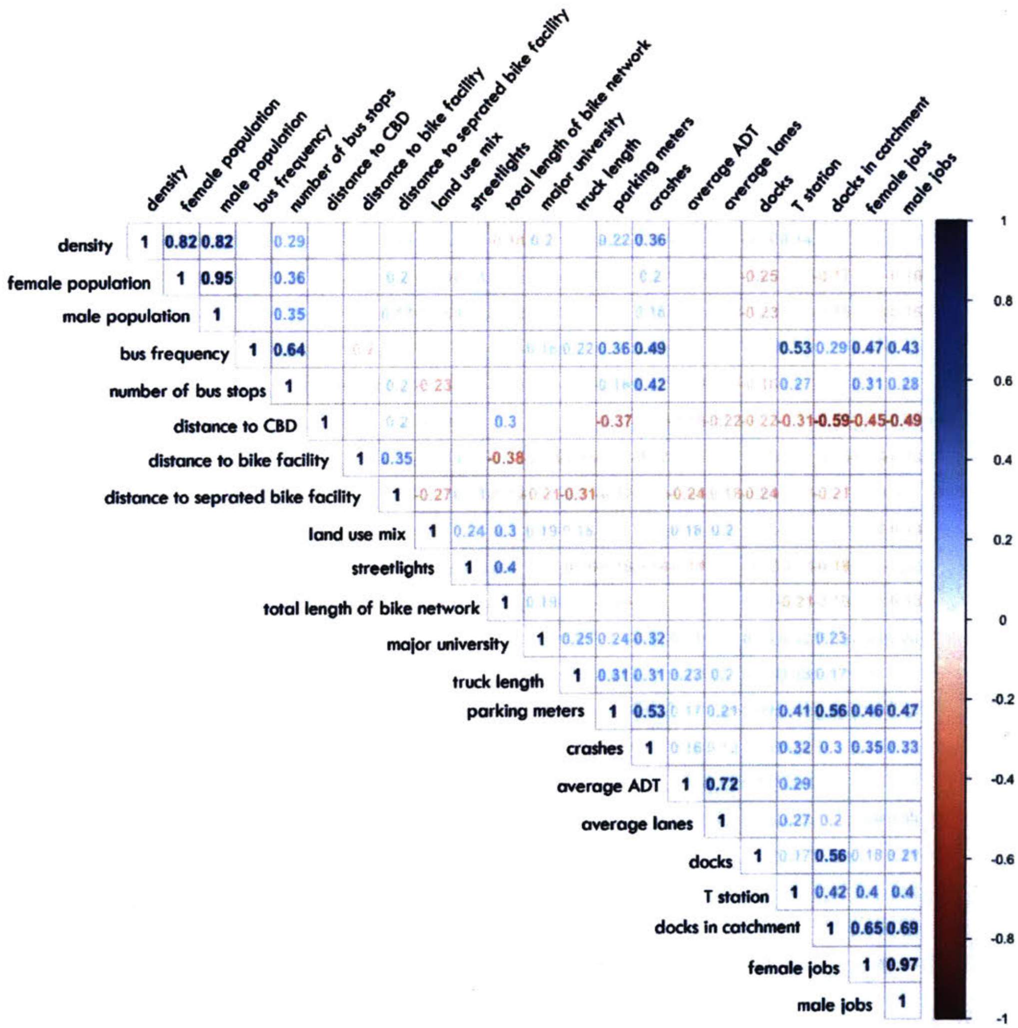
A correlation matrix showed four variables that were highly correlated. Variables with above 0.7 correlation were not included together in the regression models. Then, an ordinary least squares regression was run. The Chow Test, which tests if coefficients on the grouped data are equal, was used to check if the data could be grouped by gender. Next, spatial error and spatial lag models were run for all trip origins, male origins and female origins to determine the variables for the best fit model. Then a Chow Test was run for each time period, and I subsequently ran OLS, spatial lag and spatial error regressions for each time period and gender.

4.3.1 Correlation

Four variables were removed that were highly correlated. Total number of docks in the catchment area are correlated with jobs (0.65 and 0.69 for female and male respectively). Total number of docks in the walkshed was removed because docks at the station directly captures supply variation in stations[7]. Bus frequency (bustrips) and bus stops (NumStops) were highly correlated (0.64). Given that transit accessibility is also captured with T categorical variable, bus frequency was removed. Density was highly correlated with population (0.82 for both female and male population), and was removed. Average daily traffic and average number of lanes were highly correlated (0.72). Average daily traffic was removed because the data were relatively dated, from 2009-2012, and many newer areas, such as the Seaport would likely have underestimated traffic levels. Figure 4-16 illustrates highly correlated variables in darker blue, with numeric values showing the correlation.

[7] The number of docks directly impacts the number of trips a station can produce, as larger stations can produce more trips. This introduces endogeneity into the model, in this case as an issue of simultaneity, where the model is estimating demand based on a variable that is also determined by demand. Simultaneity occurs when an explanatory variable causes the dependent variable, but the dependent variable also causes the explanatory variable. In this instance, the trip origins at a station is likely how Hubway decides how many docks to put at a station, and therefore the number of docks at a station is also determining the demand. I do not account for simultaneity in the models, and this is discussed in my limitations.

Figure 4-16 Correlogram for Explanatory Variables



4.3.2 Base OLS Regression

I ran an ordinary least square (OLS) regression on total trip origins. An OLS regression minimizes the sum of the squared deviations from observations (SSR), and is represented as:

$$y = \propto + \beta_1 x_{i1} + \beta_2 x_{i2} \ldots \beta_p x_{p1} + \epsilon_{i,}$$

where:

$\propto =$ average ridership with no explanatory variables present

$\beta =$ is a coefficient representing the estimated relationship between variable x and the independent variable

$\in =$ residual error

OLS models estimate coefficients by minimizing the sum of square prediction errors. I ran the OLS model for total origin trips, male origin trips, and female origin trips. I use this base model to test if the data can be separated into groups.

4.3.3 Chow Test

I used the Chow Test to determine whether the data can be pooled for OLS modeling or separated into groups for different models based on, in this case, gender and/or time. The test compares the sum of squares error from the pooled regression to the sum of square errors of the regression on the two separate groups. For the pooled regression, the explanatory variable is total usage, and for the two groups the explanatory variables are male usage and female usage. The Chow Test assesses the null hypothesis of the coefficients of the two groups being equal:

$$Chow = \frac{RSS_{total} - (RSS_{female} + RSS_{male}))/k}{(RSS_{female} + RSS_{male})/(N_1 + N_2 - 2k)}$$

where,

$RSS_{total} = regression\ on\ total\ usage$

$RSS_{female} = regression\ on\ female\ usage$

$RSS_{male} = regression\ on\ male\ usage$

$k = number\ of\ explanatory\ variables + constant$

$N = number\ of\ observations$

4.3.4 Spatial Autocorrelation

One issue with using an OLS model for spatial data is that the spatial relationships of the underlying data may violate basic OLS assumptions: the dependent variables and/or the error terms may be related in space. Spatial autocorrelation exists if observations that are closer to each other in space have related values. Spatial error and spatial lag are the primary types of spatial dependence. Spatial error is when the error terms of different spatial units are correlated, and treats spatial autocorrelation as an estimation problem. Spatial lag assumes that dependencies exist among the levels of the dependent variable, for example, the usage at one bike share station is impacted by the usage as nearby stations. I checked the base model for spatial autocorrelation and then add and remove explanatory variables to find the best fit model. I removed four variables: land use mix, number of bus stops length of bicycle network, and distance to bike facility. The final list of variables was: male population, female population, male jobs, female jobs, average number of lanes, parking meters, truck routes, number of bus stops, streetlights, distance to separated bike facility, bicycle traffic, distance to separated bike facility, docks, distance to CBD, major universities and T stations.

4.3.4.1 Moran's I Test

The Moran's I Test is a standard way of testing for spatial autocorrelation. The test is an inferential statistic and evaluates if the attributes and location of features exhibit a pattern of clustering, dispersion or randomness. The null hypothesis is that the data is randomly distributed. For this analysis, the spatial weights were calculated using the five nearest neighbors.

Moran's I statistic is defined as:

$$I = \frac{n}{S_o} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} (x_i - \bar{x})^2}$$

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j}$$

Spatial weights are defined as: $w_{i,j}$ is the weight between observation i and j, and S_o is the sum of all the $w_{i,j}$.

If Moran's index is significantly larger than the expected value, then the null hypothesis is rejected and the data is spatially autocorrelated. For this analysis, the Moran's I statistic was greater than the observed value of I and positive, at a high level of statistical significance. Therefore, the null hypothesis was rejected implying that the data was spatially correlated. See Appendix F for Moran's I calculation and output.

4.3.4.2 Spatial Error and Spatial Lag

I ran both spatial lag and spatial error models and compared for best fit in each model. For the eight time period models, seven of them exhibited spatial autocorrelation, with the AM time period not exhibiting spatial autocorrelation.

5 RESULTS

This chapter presents the results from the models, using the methods as described in the previous chapter. They are run for different time periods, AM peak, midday, PM peak and late night, for a total of eight models. Results are discussed within each time period and then compared across time periods.

5.1 Base Models

I first ran a base model to assess which explanatory variables should be included in the model generally and to test if separate models could be run according to gender and time period. The base models were for total trip origins, female origin trips, and male origin trips. The resulting base models are shown in **Error! Reference source not found.**. I ran a Chow test for the pooled data (total trip origins) and compared that to the grouped data (female origin trips and male origin trips). The Chow Test showed that male and female usage were statistically different. With Chow statistic of 8.27 and F critical of 1.29, the null hypothesis of data being the same pooled as it is grouped was rejected.

The data was highly skewed left, so a square root transformation was applied to reduce skewness. The distribution was then more symmetric, with a skewness of 0.33. Histograms of the trip origins before and after the transformation are shown in Appendix A and Appendix B. After this, I ran a spatial error and spatial lag model for the data to determine which variables made up the best fit model by comparing the AIC of the spatial model. I removed three variables: length of bicycle facilities in the catchment area, distance to bicycle facility, and land use mix. Spatial lag and spatial error results are shown in Table 5-1.

Five variables were statistically significant in all three models: distance to CBD, number of docks, bicycle activity and parking meters.

Table 5-1 Spatial Lag and Spatial Error for Base Models

		All Trip Origins		*Female Trip Origins*		*Male Trip Origins*	
		Spatial Lag	Spatial Error	Spatial Lag	Spatial Error	Spatial Lag	Spatial Error
Demographics	Female Jobs	9.96	14.74	0.84	0.24	-	-
	(per 10,000 jobs)	(13.27)	(13.86)	(2.04)	(2.32)	-	-
	Female Population	18.26*	17.97*	4.41***	4.33***	-	-
	(per 1,000 people)	(7.96)	(7.88)	(1.26)	(1.29)	-	-
	Male Jobs	-9.15	-14.96	-	-	0.811	-0.01
	(per 10,000 jobs)	(13.12)	(13.90)	-	-	(3.55)	(4.10)
Land Use	Male Population	-15.96 *	-15.52*	-	-	0.61	0.85
	(per 1,000 people)	(7.79)	(7.80)	-	-	(2.24)	(2.28)
	Distance to CBD	-13.16***	-14.76***	-3.48**	-4.26***	-11.01***	-12.48***
	(per 10,000 ft)	(2.45)	(2.51)	(1.19)	(1.26)	(2.19)	(2.24)
	Major University	5.82	7.21*	1.60	2.53	4.28	5.38
		(3.27)	(3.50)	(1.69)	(1.82)	(2.93)	(3.15)
	Land Use	3.19	2.77	2.38	0.94	1.74	1.37
		(10.25)	(9.74)	(5.29)	(5.04)	(9.26)	(8.75)
Bicycle Infrastructure	Number of Docks	18.95***	20.2***	7.63***	8.18***	16.32***	17.53***
	(per 10 docks)	(2.94)	(2.87)	(1.53)	(1.49)	(2.65)	(2.56)
	Distance to Bike Facility	-3.15	-2.60	-0.05	0.55	-2.81	-1.75
	(per 1,000 ft)	(3.13)	(2.97)	(1.68)	(1.61)	(2.91)	(2.77)
	Length of Bike Facilities in Catchment Area	-3.11	-0.12	-0.23	-0.12	-0.32	-0.13
	(per 1,000 ft)	(0.60)	(0.61)	(0.30)	(0.31)	(0.53)	(0.54)
	Dist. to Sep. Bike Facility	6.56	-8.45*	-6.26**	-7.35**	-2.41	-3.64
	(per 1,000 ft)	(4.40)	(4.35)	(2.27)	(2.26)	(3.91)	(3.89)
Safety	Average Number of Lanes	-1.82	-1.95	-0.67	-0.68	-0.69	-0.75
		(1.91)	(2.05)	(0.96)	(1.03)	(1.67)	(1.79)
	Bike Activity	57.83***	58.68***	33.12***	33.92***	53.45***	55.89***
	(per 100 crashes)	(15.59)	(16.11)	(8.10)	(8.40)	(13.92)	(14.45)
	Parking Meters	5.21**	5.14**	2.45*	2.39*	4.87**	4.90**
	(per 100 parking metres)	(1.82)	(1.92)	(0.92)	(0.98)	(1.60)	(1.69)
	Truck Length	24.06*	21.34*	11.32*	8.43	18.67*	15.36
		(9.69)	(10.33)	(5.09)	(5.44)	(8.83)	(9.43)
	Streetlights	-83.87	-95.78*	-33.52	-38.53	-57.84	-69.58
		(43.68)	(42.28)	(22.67)	(21.93)	(39.11)	(37.63)
Transit	T Station	-3.04	-1.66	-1.19	-0.71	-3.64	-2.74
		(2.89)	(2.92)	(1.48)	(1.48)	(2.55)	(2.55)
	Intercept	30.49**	31.15**	12.90**	14.01**	25.94**	26.83**
		(9.86)	(10.28)	(4.99)	(5.27)	(8.95)	(9.32)
	Num. obs.	188	188	187	187	187	187
	Log Likelihood	-784.13	-780.28	-660.54	-657.07	-763.07	-758.91
	AIC (Linear model)	1605.06	1605.06	1355.97	1355.970	1561.58	1561.58
	AIC (Spatial model)	1606.25	1598.56	1357.08	1350.13	1562.13	1553.82
	LR test: statistic	0.813	8.50	0.89	7.83	1.45	9.75
	LR test: p-value	0.37	0.004	0.34	0.005	0.23	0.002
	rho	0.04		0.05		0.06	
		(0.46)		(0.05)		(0.05)	
	lambda		0.25		0.25***		0.26***
			(0.08)		(0.08)		(0.08)

*p<0.1 **p<0.05 ***p<0.01

5.2 Time Period Models

The Chow test was subsequently run on each time period, comparing the pooled female OLS regression to the time periods. The null hypothesis, that the data at each break point was the same, was rejected. This supported separating the data by time period.

I ran an OLS regression using the same explanatory variables from the base model for each time period, then checked the results from each model for spatial auto correlation using the Moran I test.

In all models except for AM peak, the p-value calculated from the Moran I test was statistically significant and the z-score was positive. Due to this result, the null hypothesis that the spatial distribution of the data is random, is rejected. Since spatial autocorrelation was detected, an OLS model is not the best model for the data, as it does not take into account spatial tendencies of data. Spatial lag and spatial error models were used instead, to account for spatial autocorrelation in the data. The results from the Moran I test are shown in Appendix F. The spatial error model had a lower AIC than the linear model and the spatial lag model. AIC is used to compare models so I used the spatial error model due to the lower AIC. Maps of spatial lag are shown in Appendix G, illustrating how spatial lag is not the best method for accounting for spatial autocorrelation.

5.2.1 Results AM Peak

5.2.1.1 Consistent Variables Across Genders

Statistically significant variables for both men and women included population, number of docks, and bicycle activity. The more docks a station had, the higher trip origins it had at that station. This variable was positive and statistically significant. As mentioned, however, this may introduce endogeneity in the model. Hubway likely decides how many docks to put at a station based on the demand for trips, and the increased number of docks can produce more trips.

As population near a station increases, the more trip origins at the station. A large portion of morning trips are likely for commuting purposes; the positive coefficient for population during AM peak supports the hypothesis of people using Hubway for home based trips such as to get to work or school. Bicycle activity was also positive, so stations with more bike activity in the catchment area had more ridership. This could be due to simultaneity between bike activity and trip origins. Hubway likely places stations near where there is bicycle activity, and bicycle activity may be increasing where there are stations.

5.2.1.2 Differing Variables Between Genders

Distance to separated bike facility was statistically significant for female usage, but was not in the male usage model: the further a station is from a bike facility, fewer number of trips by women start at that station, supporting the hypothesis that women prefer separate bike facilities. For men, distance to CBD was statistically significant and negative, indicating that as a station is further from the CBD, it experiences less male ridership. This could be due men tending to work in traditional professions that are more likely to locate in downtowns (finance, real estate, engineering) because these professions rely more on clusters. The further a station is from downtown, the less likely it is to attract men's commuting trips. For women, the CBD distance is not significant, possibly because traditionally female jobs such as health care, education, child care, are less likely to to locate downtown. For example, K-12 schools and many health care related jobs are more likely to locate near residential areas.

Table 5-2 AM Models

		OLS		Spatial Lag		Spatial Error	
		Female AM	Male AM	Female AM	Male AM	Female AM	Male AM
Demographics	Female Jobs	-0.82	-	-0.86	-	-1.27	-
	(per 10,000 jobs)	(1.44)	-	(1.39)	-	(1.65)	-
	Female Pop.	5.05***	-	5.19***	-	5.04***	-
	(per 1,000 people)	(0.92)	-	(0.9)	-	(0.93)	-
	Male Jobs	-	-0.15	-	-0.33	-	-0.16
	(per 10,000 jobs)	-	(2.34)	-	(2.25)	-	(0.27)
Land Use	Male Pop.	-	5.22***	-	5.66***	-	4.94**
	(per 1,000 people)	-	(1.55)	-	(1.51)	-	(1.55)
	Dist. to CBD	-1.37	-4.28***	-1.21	-3.72*	-1.73	-5.26***
	(per 10,000 ft)	(0.86)	(1.45)	(0.85)	(1.46)	(0.91)	(1.54)
	Major Univ.	-0.68	-2.31	-0.87	-2.72	-0.12	-1.63
		(1.24)	(2.06)	(1.22)	(2)	(1.32)	(2.19)
Bicycle	Num. of Docks	4.44***	11.78***	4.39***	11.53***	4.64***	11.93***
Infrastructure	(per 10 docks)	(1.16)	(1.92)	(1.12)	(1.85)	(1.08)	(1.77)
	Dist. to Sep. Bike Facility	-2.78*	-1.12	-2.99	-1.51	-3.84*	-2.05
	(per 1,000 ft)	(1.6)	(2.65)	(1.55)	(2.54)	(1.54)	(2.51)
Safety	Avg. Num. Lanes	0.51	2.00*	0.48	1.91	0.14	1.44
		(0.71)	(1.19)	(0.69)	(1.14)	(0.75)	(1.26)
	Bike Activity	1.73***	2.64***	16.82**	25.75**	16.27**	28.01**
	(per 100 crashes)	(0.61)	(1.01)	(5.9)	(9.66)	(6.09)	(9.97)
	Parking Meters	0.89	2.28**	0.75	1.9	0.71	2.11
		(0.65)	(1.08)	(0.65)	(1.08)	(0.71)	(1.17)
	Truck Length	1.95	-2.80	1.61	-3.16	0.68	-4.32
		(3.83)	(6.36)	(3.71)	(6.13)	(4.01)	(6.62)
	Streetlights	-27.6*	-36.98	-25.56	-31.35	-29.81	-40.49
		(15.84)	(26.15)	(15.59)	(25.64)	(15.31)	(25.06)
Transit	T Station	-0.8	-1.96	-0.95	-2.45	-0.4	-1.59
		(1.09)	(1.81)	(1.07)	(1.77)	(1.08)	(1.77)
	Intercept	3.7	0.63	3.4	-0.43	5.62	4.12
		(3.61)	(6.11)	(3.5)	(5.93)	(3.68)	(6.24)
	Num. obs.	188	188	187	187	187	187
	R2	0.41	0.35	0.419	0.355	0.468	0.402
	Adj. R2	0.37	0.31	0.376	0.307	0.428	0.357
	Residual Std. Error (df = 175)	10.45	6.31	-	-	-	-
	F Statistic (df = 12; 175)	10.09***	7.88***	-	-	-	-
	Log Likelihood	-	-	-696.57	-603.06	-691.22	-598.67
	AIC (Linear model)	-	-	1423.95	1235.16	1423.95	1235.16
	AIC (Spatial model)	-	-	1423.15	1236.12	1412.44	1227.33
	LR test: statistic	-	-	2.81	1.04	13.51	9.83
	LR test: p-value	-	-	0.09	0.31	2.37E-04	1.71E-03
	rho	-	-	(0.05)	(0.05)	-	-
		-	-	0.09	0.06	-	-
	lambda	-	-	-	-	0.31***	0.29***
		-	-	-	-	(0.08)	(0.08)

*p<0.1 **p<0.05 ***p<0.01

5.2.2 Midday Models

5.2.2.1 Consistent Variables Across Gender

Statistically significant variables for both men and women were distance to CBD, number of docks at a station, bicycle activity, parking meters, truck route length, and streetlights. The more docks a station had and the more bicycle activity in the catchment area, the higher trip origins were at a station. As discussed in the AM model, this could be due to endogeneity.

Parking meters and length of truck route were both positive, so as parking meters and length of truck routes in the catchment area increase, ridership also increases. Streetlights in the catchment area and distance to CBD were negative, indicating that areas with more streetlights have fewer trip origins and areas closer to the CBD had higher trip origins at a station. Length of truck route could be a proxy for main, non-freeway arterials. These roads coincide with many direct routes throughout the city. For example, Massachusetts Avenue, state Route 2A in Cambridge is a truck route, but is also a key northwest/southeast connector in Cambridge and into Boston. The road is a very direct path to get from many areas in West Cambridge to the Charles River. During the midday time period, when traffic generally is lower, men and women may be more likely to use a direct route that has worse bicycle infrastructure since a decrease in automobile traffic increases perceived safety.

As discussed in Chapter 4, parking meters having a positive relationship with trip origins could be due to parking meters, rather than parking spots, being located in commercial areas. In the early afternoon, common trip types are likely lunch or errands, both of which are more likely to be located in commercial areas. Jobs was not statistically significant, so these trips may not be work-based trips.

Streetlights having a negative relationship with trip origins could be due to the variable measuring more than just how well-lit an area is. Streetlights could be a proxy for underutilized areas, areas that otherwise feel unsafe, or areas where vehicles need lighting, all of which are not appealing for cyclists.

Major universities has a positive statistically significant coefficient, indicating that students are likely starting trips near universities in the afternoon. Given that students have more flexible schedules, this supports students leaving school mid day, either for errands or to go home.

5.2.2.2 Variables Differing Between Genders

Similar to in the first model, distance to a separated bicycle facility was statistically significant for women. As the distance to a separated bicycle facility decreased, ridership for female origin trips increased. As discussed in the AM model, starting more trips near separated bicycle facilities could indicate that women feel safer using these types of facilities and are more likely to take trips when the route can be closer to a separated bicycle facility. Also, the coefficient is about the same as for the AM model. I expected the coefficient to be smaller (or have a larger negative magnitude) because I would expect that women have more constraints during the AM time period since they likely on their way to work, so may choose the origins station that is closest to their origin rather than the one with specific characteristics. Further identifying what type of trips are occurring during the midday period could give more insight into this.

Table 5-3 Midday Models

		OLS		*Spatial Lag*		*Spatial Error*	
		Female Mid	Male Mid	Female Mid	Male Mid	Female Mid	Male Mid
Demographics	Female Jobs	0.53	-	0.35	-	0.55	-
	(per 10,000 jobs)	(1.02)	-	(0.98)	-	(1.16)	-
	Female Pop.	0.75	-	1.01	-	0.91	-
	(per 1,000 people)	(0.65)	-	(0.64)	-	(0.65)	-
	Male Jobs	-	0.31	-	0.00	-	0.04
	(per 10,000 jobs)	-	(1.74)	-	(0.17)	-	(0.2)
	Male Pop.	-	-2.24*	-	-1.43	-	-1.21
	(per 1,000 people)	-	(1.15)	-	(1.14)	-	(1.15)
Land Use	Dist. to CBD	-2.09***	-5.36***	-1.88**	-4.73***	-2.35***	-5.66***
	(per 10,000 ft)	(0.61)	(1.09)	(0.61)	(1.1)	(0.64)	(1.14)
	Major Univ.	2.78***	5.66***	2.37**	4.72**	3.02**	5.55***
		(0.88)	(1.53)	(0.88)	(1.52)	(0.93)	(1.63)
Bicycle Infrastructure	Num. of Docks	2.55***	5.15***	2.5**	5.08***	2.82***	5.93***
	(per 10 docks)	(0.82)	(1.43)	(0.79)	(1.37)	(0.76)	(1.31)
	Dist. to Sep. Bike Facility	-2.65**	-2.28	-2.81**	-2.57	-3.11**	-2.84
	(per 1,000 ft)	(1.13)	(1.97)	(1.08)	(1.88)	(1.08)	(1.86)
Safety	Avg. Num. Lanes	-0.74	-1.53*	-0.66	-1.26	-0.68	-1.25
		(0.5)	(0.89)	(0.48)	(0.85)	(0.53)	(0.94)
	Bike Activity	1.32***	2.62***	12.65**	24.88***	13.06**	25.77***
	(per 100 crashes)	(0.43)	(0.75)	(4.14)	(7.17)	(4.28)	(7.4)
	Parking Meters	1.23***	2.17***	1.09*	1.85*	1.16*	2.03*
	(per 100 parking meters)	(0.46)	(0.81)	(0.46)	(0.8)	(0.5)	(0.87)
	Truck Length	7.59***	12.59***	6.89**	11.43*	5.53*	10.44*
		(2.7)	(4.75)	(2.62)	(4.57)	(2.82)	(4.92)
	Streetlights	-20.1*	-38.2*	-16.89	-29.81	-23.6*	-40.25*
		(11.18)	(19.51)	(10.97)	(19.08)	(10.75)	(18.58)
Transit	T Station	-0.94	-2.07	-1.11	-2.47	-0.87	-1.96
		(0.77)	(1.35)	(0.75)	(1.3)	(0.76)	(1.31)
	Intercept	9.7***	20.28***	8.84***	17.61***	9.74***	18.38***
				(2.49)	(4.48)	(2.59)	(4.64)
	Num. obs.	188	188	187	187	187	187
	R2	0.52	0.56	0.574	0.529	0.610	0.563
	Adj. R2	0.49	0.53	0.542	0.494	0.581	0.530
	Residual Std. Error (df = 175)	4.45	7.8				
	F Statistic (df = 12; 175)	15.79***	18.61***				
	Log Likelihood			0.574	0.529	0.610	0.563
	AIC (Linear model)			0.542	0.494	0.581	0.530
	AIC (Spatial model)			-640.6	-536.83	-635.37	-532.48
	LR test: statistic			1313.34	1104.36	1313.34	1104.36
	LR test: p-value			1311.21	1103.65	1300.73	1094.96
	rho			4.14	2.71	14.61	11.4
				0.04	0.1	1.32E-04	7.36E-04
	lambda			0.11*	0.09	-	-
				(0.05)	(0.05)	-	-

*p<0.1 **p<0.05 ***p<0.01

5.2.3 PM Peak Models

5.2.3.1 Consistent Variables Between Gender

This period had the highest adjusted R2 of all time periods, and also has the highest number of trips for both men and women.

Distance to CBD, number of docks, bicycle activity and parking meters were statistically significant for both male and female models. As in previous models, number of docks, bicycle activity and parking meters were positive, and distance to CBD was negative.

Number of docks and bicycle activity, as discussed in earlier models, could be an indication of endogeneity. Given that many PM peak trips are likely commuting trips, the negative sign of distance to CBD likely supports a mono-centric city model, that people are leaving the city center in the evening. However, jobs were not statistically significant in this model. This could indicate that men and women are engaging in another trip after work, for example running an errand and then using bikeshare. This would support jobs not being statistically significant but distance to CBD being negative and statistically significant.

Additionally, the positive relationship with parking meters could indicate that these trips are starting in commercial areas, especially since jobs was not statistically significant. This would support trips starting from another activity, such as running an errand or going to dinner or a bar.

5.2.3.2 Differing Variables Between Gender

Similar to the first two models, distance to separated bike facility was statistically significant and negative for women, but not statistically significant in the male model. As discussed in the previous models, this could indicate that women feel safer using these types of facilities and are more likely to take trips when the route can be closer to a separated bicycle facility. The coefficient is smaller during PM (-5.02), than for AM (-3.11) and midday (-3.84) time periods, meaning that women's trips are more sensitive to being far from a separated facility in the PM peak. This could indicate that women have less constraints during their PM trips.

Major university and length of truck route in the catchment area were statistically significant in the male model but not in the female model. For men, the existence of a major university in the catchment area leads to higher trip origins, and the higher amount of truck routes in the catchment area also leads to higher trip origins. It is unclear why universities is statistically significant for men but not women. One hypothesis is that women tend to have more household responsibilities, so may take classes during the day or late hours, so they can tend to those responsibilities during the evening. Without having a better understanding of the gender breakdown of enrollment within each university, and what profile of students each university tends to have it is hard to analyze why this temporal difference occurs.

The length of truck route, as mentioned in the previous model, could be a proxy for main, non-freeway arterials. These roads coincide with many direct routes throughout the city. Therefore, during the PM time period, male cyclists could be more likely to decide to start a trip near a road that bisects the city. This follows literature that men may prefer a direct route more than women, especially since women value safety characteristics higher than men.

Table 5-4 PM Models

		OLS		*Spatial Lag*		*Spatial Error*	
		Female PM	Male PM	Female PM	Male PM	Female PM	Male PM
Demographics	Female Jobs	1.58	-	1.17	-	1.1	-
	(per 10,000 jobs)	(1.33)	-	(1.28)	-	(1.49)	-
	Female Pop.	0.68	-	1.09	-	0.81	-
	(per 1,000 people)	(0.85)	-	(0.84)	-	(0.86)	-
	Male Jobs	-	0.31	-	0.22	-	0.23
	(per 10,000 jobs)	-	(0.23)	-	(0.22)	-	(0.27)
	Male Pop.	-	-3.66**	-	-2.42	-	-2.48
	(per 1,000 people)	-	(1.5)	-	(1.48)	-	(1.49)
Land Use	Dist. to CBD	-3.13***	-9.11***	-2.78***	-7.98***	-3.48***	-9.19***
	(per 10,000 ft)	(0.8)	(1.41)	(0.8)	(1.44)	(0.84)	(1.48)
	Major Univ.	1.85	5.21***	1.35	3.96*	2.03	4.96*
		(1.15)	(1.99)	(1.13)	(1.94)	(1.21)	(2.11)
Bicycle Infrastructure	Num. of Docks	4.57***	8.55***	4.54***	8.46***	5.18***	10.05***
	(per 10 docks)	(1.07)	(1.86)	(1.03)	(1.77)	(1)	(1.69)
	Dist. to Sep. Bike Facility	-4.71***	-3.33	-4.91***	-3.85	-5.02***	-4.33
	(per 1,000 ft)	(1.48)	(2.56)	(1.41)	(2.43)	(1.42)	(2.4)
Safety	Avg. Num. Lanes	-0.54	-1.70	-0.43	-1.32	-0.32	-1.21
		(0.66)	(1.15)	(0.63)	(1.09)	(0.69)	(1.21)
	Bike Activity	2.11***	3.24***	20.5***	30.98***	22.28***	33.85***
	(per 100 crashes)	(0.56)	(0.97)	(5.4)	(9.23)	(5.61)	(9.55)
	Parking Meters	1.99***	3.6***	1.71**	3.12**	1.93**	3.61**
		(0.6)	(1.04)	(0.6)	(1.04)	(0.65)	(1.13)
	Truck Length	8.94**	19.32***	7.81*	17.27**	6.06	14.48*
		(3.53)	(6.16)	(3.41)	(5.9)	(3.67)	(6.36)
	Streetlights	-10.38	-34.95	-6.15	-22.24	-12.76	-36.98
		(14.61)	(25.3)	(14.28)	(24.58)	(14.15)	(23.94)
Transit	T Station	-0.4	-1.28	-0.66	-1.95	-0.33	-1.07
		(1.01)	(1.75)	(0.98)	(1.68)	(1)	(1.7)
	Intercept	10.26***	25.67***	8.82**	21.38***	9.3**	21.77***
		(3.33)	(5.91)	(3.23)	(5.78)	(3.38)	(6)
	Num. obs.			187	187	187	187
	R2			0.604	0.672	0.623	0.700
	Adj. R2	188	188	0.574	0.647	0.594	0.678
	Residual Std. Error (df = 175)	0.6	0.66				
	F Statistic (df = 12; 175)	0.58	0.63				
	Log Likelihood	2.48	10.11	-586.39	-688.13	-583.79	-682.86
	AIC (Linear model)	22.31***	27.95***	1204.65	1410	1204.65	1410
	AIC (Spatial model)			1202.77	1406.25	1197.57	1395.71
	LR test: statistic			3.88	5.75	9.07	16.29
	LR test: p-value			0.05	0.02	2.59E-03	5.45E-05
	rho			0.1*	0.12*	-	-
				(0.05)	(0.05)	-	-
	lambda			-	-	0.26***	0.33***
				-	-	(0.08)	(0.07)

$^{*}p<0.1^{**}p<0.05^{***}p<0.01$

5.2.4 Late Night Models

5.2.4.1 Consistent Variables between Gender

For late night trips distance to CBD, number of docks, major university, bike activity and parking meters were statistically significant for both male and female trips. As was in the previous models docks, major university, bike activity and parking meters were positive and distance to CBD was negative.

Number of docks and bicycle activity, as discussed in earlier models, could be an indication of endogeneity. Distance to CBD is negative but much smaller than in other models. Looking at the spatial distribution of trips, Figure 4-12 and Figure 4-13, this concentration of trips around the CBD is evident. Combined with the statistical significance of parking meters, this could be due to trip origins happening around commercial areas. This could be due to users using bikeshare after a social or entertainment trip as well as service industry workers using bikeshare after work, since shifts end during this late night period. Looking into Friday and Saturday late night trips would be interesting to see if there is a more pronounced pattern for nights when more people are engaging in social trips in this time period.

5.2.4.2 Differing Variables between Gender

Female population, distance to separated bike facility and streetlights were statistically significant for women but not men. Population had a positive sign, so areas with more population had higher ridership. Distance to separated bike facility, as in previous models, was negative. As discussed in the previous models, starting more trips near separated bicycle facilities could indicate that women feel safer using these types of facilities and are more likely to take trips when the route can be closer to a separated bicycle facility. The coefficient has the lowest negative magnitude of all female models. This could be explained by women feeling more constrained in the late night time period because of perceived safety (fewer people on the street, darkness), and therefore choose the station closest to their origin rather than with their preferred characteristics.

The spatial distribution of trips shown in Figure 4-12 and Figure 4-13, distance to CBD being statistically significant and negative, and parking meters being statistically significant and positive support trips not starting near residential areas, and occurring in entertainment areas (which also are near the CBD). The statistical significance of population for women could indicate that women are more likely to start trips where there are more eyes on the street or street activity. This is often a factor in perceived safety for women, and would make sense that it is showing up only during late night and for women.

Streetlights was also negative, indicating that areas with fewer streetlights had more trip origins. As discussed in previous model results, streetlights could be a proxy for less safe areas. This would support women being concerned with a different type of safety during the night. For example more concerned with being assaulted than getting hit by a car, so they are more likely to start a trip form an area that has eyes on the street (population) and is not perceived as unsafe (streetlights) than being closer to a separated bike facility.

Jobs was statistically significant for the male model but not the female model. Male jobs had a negative sign, so areas with more jobs had fewer trip origins. This supports the characterization of trips during late night being around entertainment areas, where there are less jobs. Jobs being statistically significant for men but not women could be due to male and female jobs having different spatial distributions, and male jobs being located in more concentrated areas where there is less mixture of land uses.

Table 5-5 Late Night Models

		OLS		Spatial Lag		Spatial Error	
		Female Late	Male Late	Female Late	Male Late	Female Late	Male Late
Demographics	Female Jobs	-1.07*	-	-1.05	-	-1.2	-
	(per 10,000 jobs)	(0.57)	-	(0.54)	-	(0.65)	-
	Female Pop.	1.22***	-	1.34***	-	1.29***	-
	(per 1,000 people)	(0.36)	-	(0.35)	-	(0.36)	-
	Male Jobs	-	-2.62**	-	-2.61**	-	-2.85*
	(per 10,000 jobs)	-	(1.05)	-	(1.01)	-	(1.16)
	Male Pop.	-	1.04	-	1.25	-	1.23
	(per 1,000 people)	-	(0.69)	-	(0.67)	-	(0.69)
Land Use	Dist. to CBD	-0.62*	-2.45***	-0.5	-2.28***	-0.76*	-2.6***
	(per 10,000 ft)	(0.34)	(0.65)	(0.33)	(0.65)	(0.36)	(0.68)
	Major Univ.	0.97**	2.61***	0.76	2.21*	1.28*	2.67**
		(0.49)	(0.92)	(0.48)	(0.92)	(0.52)	(0.96)
Bicycle Infrastructure	Num. of Docks	1.47***	2.37***	1.44***	2.32**	1.62***	2.58**
	(per 10 docks)	(0.46)	(0.86)	(0.43)	(0.82)	(0.42)	(0.81)
	Dist. to Sep. Bike Facility	-1.51**	-2.04*	-1.65**	-2.19	-1.74**	-2.24
	(per 1,000 ft)	(0.63)	(1.19)	(0.6)	(1.14)	(0.6)	(1.14)
Safety	Avg. Num. Lanes	-0.21	-0.23	-0.17	-0.15	-0.21	-0.14
		(0.28)	(0.53)	(0.27)	(0.51)	(0.3)	(0.56)
	Bike Activity	1.39***	2.72***	13.07***	26.29***	13.01***	27.28***
	(per 100 crashes)	(0.24)	(0.45)	(2.31)	(4.36)	(2.38)	(4.49)
	Parking Meters	1.12***	2.12***	0.91***	1.95***	1.05***	2.08***
	(per 100 parking meters)	(0.25)	(0.48)	(0.26)	(0.5)	(0.28)	(0.51)
	Truck Length	3.54**	5.99**	2.92*	5.54*	2.59	5.01
		(1.5)	(2.85)	(1.45)	(2.76)	(1.57)	(2.93)
	Streetlights	-11.81*	-17.59	-10.87	-13.75	-14.4*	-17.58
		(6.22)	(11.71)	(6.04)	(11.46)	(5.96)	(11.41)
Transit	T Station	0.02	-0.93	-0.04	-1.11	0.26	-0.75
		(0.43)	(0.81)	(0.41)	(0.78)	(0.42)	(0.8)
	Intercept	1.8	6.91**	1.45	6.21*	1.94	6.55*
		(1.42)	(2.74)	(1.35)	(2.66)	(1.44)	(2.77)
	Num. obs.	188	188	187	187	187	187
	R2	0.6	0.6	0.617	0.604	0.643	0.618
	Adj. R2	0.58	0.57	0.588	0.570	0.616	0.589
	Residual Std. Error (df = 175)	2.48	4.68				
	F Statistic (df = 12; 175)	22.31***	21.51***				
	Log Likelihood			-426.05	-546.01	-422.24	-543.96
	AIC (Linear model)			885.65	1122.27	885.65	1122.27
	AIC (Spatial model)			882.1	1122.02	874.47	1117.92
	LR test: statistic			5.56	2.25	13.18	6.34
	LR test: p-value			0.02	0.13	2.83E-04	1.18E-02
	rho			0.12*	0.08	-	-
				(0.05)	(0.05)	-	-
	lambda				-	0.31***	0.21**
					-	(0.08)	(0.08)

*p<0.1 **p<0.05 ***p<0.01

5.3 Discussion

Table 5-6 Model Summaries

	Explanatory Variable	*Statistically Significant in Models* M AM	M Mid	M PM	M Late	F AM	F Mid	F PM	F Late	*Expected Sign*
Demographics	Jobs				-					+
	Population	+				+			+	+
Land Use	Distance to CBD	-	-	-	-		-	-	-	-
	Major University		+	+	+		+		+	+
	Commercial Area	+	+	+	+		+	+	+	+
Bicycle	Docks	+	+	+	+	+	+	+	+	+
	Distance to Separated Bike Facility					-	-	-	-	-
Safety	Average Number of Lanes	+								+
	Bike Activity	+	+	+	+	+	+	+	+	+
	Length of Truck Route		+	+			+			-
	Streetlights		-			-	-		-	+
Transit	T Station									+

The results across all time periods show differences in statistically significant variables, indicating that cyclists use bikeshare differently throughout the day, as shown in Table 5-6. However, two variables were statistically significant in both the male and female users in all of the models. These variables included docks and biking activity. Distance to CBD and parking meters were in all models except one. Docks, distance to CBD, parking meters and biking activity had signs in the expected direction. As noted when discussing the model results, number of docks and biking activity may be endogenously related to trip origins, so this could explain the statistical significance for both genders in all models.

The coefficient estimates for streetlights and length of truck route showed unclear results. I expected streetlights to be positive, and length of truck route to be negative but both signs were flipped. Streetlights, as noted earlier, may be a proxy for unsafe areas, or unsafe intersections. This would explain why streetlights had a negative coefficient. Overlaying streetlights with other safety data, including vehicle crashes, pedestrian crashes and crime would be a good place to start in assessing if streetlights was actually measuring how unsafe an area is, rather than how safe it is. Length of truck route could be instead indicating main, non-freeway arterials. These roads coincide with many direct routes throughout the city. For example, Massachusetts Avenue from Harvard University to MIT is a designated truck route but is also a main arterial, with a bike lane, that many cyclists use since it is the most direct route between those two points.

One other unexpected explanatory variable was T stations, which was not statistically significant in any of the models. Given the literature, and that the spatial distribution of bike share trips seemed to support a positive relationship with T stations, this result was surprising. Additionally, the literature discussed bikeshare as a first-last mile connection, which would have supported T stations being statistically significant. This first-last mile connection may have been better captured if trip destinations were analyzed instead of origins. For example, during the AM time period users take bikeshare to a T station, so trip destinations would capture the first-mile connection. This may be less evident for trip origins during the PM time period because users are less constrained leaving work than they are going to work, also seen with a wider spread of trips during the PM time period.

Distance to separated bike facility was negative in female models, indicating that stations closer to separated bike facilities had more trip origins for female users. This negative sign was the expected direction from the literature review. This variable was only statistically significant in female models. The literature supports this result, with studies identifying that females have a strong preference for facilities separated from traffic and that separated facilities have more perceived safety, which is a factor for which women have a stronger preference.

5.3.1 Time Period Comparisons

For AM peak, docks, population and bike activity were significant for both genders. During AM peak users may be more constrained for their trip, if the trip purpose, for example, is commuting. This would support the results of statistically significant factors having to do with location rather than characteristics of the surrounding physical environment such as safety features or bicycle infrastructure.

Results for midday models had more statistically significant variables than the AM models. This could be due to these trips being less constrained, so users have more freedom to choose a station that has their preferred characteristics. Additional variables include major universities, length of truck route, and streetlights. The positive sign of major universities supports that students are starting trips in the afternoon from around campuses. It would be interesting to analyze trip destinations as well to see if students (or trips starting and ending close to universities) exhibit different temporal patterns than other users such as off peak trips. I hypothesize that streetlights is a proxy for less safe areas, and truck routes are a proxy for main arterials. This suggests that people are likely avoiding less safe areas and preferring stations that are closer to main roads.

During PM peak, the time period with the highest number of trips, more bike infrastructure and safety factors show up for both men and women. Similarly, in late night, more bicycle infrastructure and safety variables show up for both men and women. Late night similarities between men and women illustrate both genders exhibit similar behavior. For example, men and women who choose to ride at night have similar preferences or constraints, since they are willing to ride at night, which is perceived to be less safe because visibility and other safety concerns may exist.

Looking at variables that were in the model consistently for women, distance to separated bicycle facility was statistically significant only for women during all time periods. This variable was not statistically significant for men in any model. This indicates that women have more trips origins at stations that are closer to separated bike facilities, regardless of the time of day. Given that literature has shown that women prefer to be separated from traffic often due to an increase in perceived safety, this correlation is likely due to women desiring more perceived safety in bicycle infrastructure. It is surprising that other safety variables were not consistently statistically significant in the models for women since the literature notes that this is a key difference between men and women's bicycle preferences. As mentioned later in my limitations in Section 6.2, this could be due to the safety variables capturing different than expected aspects.

These results show many similarities in factors effecting bikeshare usage between men and women. Many of these variables have shown up in previous literature as well, such as population, jobs, station capacity, and distance to CBD. But, a noticeable difference in factors related to trip origins is that women apparently prefer stations closer to separated bike facilities, at all time periods, all else equal.

6 CONCLUSIONS

This analysis found many similarities in the factors that impact where male and female Hubway users start their trips. Five takeaways from the regression analysis and trip data analysis are listed below:

- Trip origins by men and women do have similarities
    - The rank of stations by trip origin is almost the same for men and women, when aggregated for a full 24 hour period
    - Men and women take almost the same percentage of trips during each time period
- Men take significantly more trips than women
- There are differences in which factors are related to ridership for men and women
- Factors that were statistically significant in a majority of the models for both male and female trip origins include station capacity, distance to CBD, and parking meters
- The only variable that was different for men and women across all models was distance to separated bike facility, which was statistically significant for all female models and none of the male models.
    - This is supported by previous research that women prefer separated bicycle facilities

6.1 Policy Implications

In order to decrease the gender gap in cycling, planners, advocates and policy makers need to better understand the role of different land use, bicycle infrastructure, safety, transit and demographic factors. I suggest three policies to help planners and city officials decrease this gap.

6.1.1 'No One Size Fits All' Strategies for Bicycle Planning

The large difference in ridership for men and women indicates that more strategies for increasing ridership need to be focused on women. The difference in spatial distribution of trips, difference in frequency, and differing variables across models supports that there should be different tactics for increasing ridership for men and women. When planning bicycle facilities, the differences in gender of users should be better understood locally for the specific environment to pick interventions that can decrease the gender gap in cycling.

The varied preferences throughout the day also should be a part of bicycle infrastructure and network planning. Even though late night users are a small portion of overall trips, incorporating additional safety aspects into bicycle infrastructure so that some safety concerns are addressed could increase female ridership. For example, adding more separated bicycle facilities on all streets, not only the ones that are most unsafe, or most used, such as Beacon/Hampshire Street that runs through Somerville and Cambridge.

6.1.2 Improved Hubway Station Placement for Gender Equity

The results give detailed information for factors affecting usage at different times of day. This analysis gives Hubway a baseline for how these factors differ by gender. As Hubway becomes Blue Bikes and starts a massive expansion, new stations can be placed at locations that have more factors that are related to increased usage by women. Additionally, the amount of overlap in factors affecting both men and women could be used to create a base typology for factors that can lead to Hubway usage to help cities and Hubway locate stations around factors that will lead to usage.

Finally, the varied preferences throughout the day indicate that planning facilities only for the morning and evening peak may not benefit all cyclists. In particular, thinking about perceived safety for women during the late night period needs to be addressed differently than safety in other time periods. These results indicate that at night, female trip origins are higher where there are more people, something that station placement can directly impact. This could be due to certain types of places generating late night trips (for example, a cluster of bars or restaurants). But this relationship should be explored more.

6.1.3 Increase Use of Separated Bike Facilities in Cities

The results show that the main difference between where men and women start their bikeshare trips is that female trip origins are correlated with being closer to separated bicycle facilities, while male trip origins are not. This relationship should not be interpreted as increasing separated bike facilities will lead to more women ridership, but the correlation is still important. Where possible, cities should advocate for separated bike lanes. This can lead to increased perceived safety, which previous research has shown is preferred for female riders. Additionally, Hubway should look to place stations closer to separated bicycle facilities since that is shown to increase female ridership.

6.2 Limitations

One limitation in using regressions as a method is that the models are only as good as the data. Data limitations include data consistency across three municipalities, and measurement error for manually calculated variables such as streetlights, and major universities.

Data limitations also extend to availability of factors that I initially wanted to include. For example, I chose parking meters to measure safety, but the analysis suggests that parking meters may be a proxy for something like commercial corridors or areas with activity. Similarly, I intended for bicycle crashes to be a measure of general safety, but literature revealed it might also be a proxy for activity. I had initially used bike crashes instead of vehicle crashes because I was not able to find data for all three municipalities on overall vehicle crashes. One limitation with bicycle crashes is that the data was from different years for Boston, Cambridge and Somerville. This could be problematic since bicycle activity has increased over the years, so this variable may be representing different realities as entered in the models.

Some variables that were removed in the base model were shown in other research to be statistically significant, including land use mix and total length of bike facilities. This may be due to measurement error or data quality, since I was combining data from three different municipalities.

Specifically, my safety variables, which research indicates are important factors that women consider when riding, may not have directly accounted for safety. Length of truck route, and streetlights had the opposite signs than expected, and as mentioned above, may have been accounting for other factors not related to safety. A better measure of safety would be to include the bike level of stress calculation which factors in speed, average annual daily traffic, and number of lanes into one score. Additionally, with additional time or resources, more precise data could have been collected, such as perceived safety. Women think about safety in many ways that are more complicated to measure (for example deciding not to pick up a bike at night because there is no street activity or because there are a lot of men close by). Identifying these specific safety variables that impact women could have also been useful.

Endogeneity between docks at a station and trip origins, as well as between bike activity and trip origins was identified in the model but not accounted for. Docks was both a measure for demand but also contributes to demand. Bike activity is also likely both a measure and a contributor. Discussing with Hubway what factors influence where they place stations could help clearly identify what factors are accounting for where they place stations. To circumvent the problem, the model would ideally be able to include the amount of demand at a station, if there was an unlimited supply of bikeshare bikes. Bicycle redistribution may exacerbate this since Hubway move bikes away from low ridership stations to higher ridership stations throughout the day. A better measure may be an average number of available bikes per station per hour. This could capture a more precise measure of bikeshare demand at a station.

Finally, it is important to keep in mind that I model trips, not the individuals making the trips, nor the details about trip types or purposes. The literature notes that preferences vary by experience level, trip type and purpose so such analysis could shed light on who chooses to use Hubway, as well as when, where and why they do.

6.3 Future Research

Future studies should continue to explore what factors impact women's ridership. One approach that I could have benefited from is combining qualitative methods with quantitative data. Interviewing Hubway users about what factors impact where they start or end their trip could better inform what quantitative data should be used or collected.

Understanding the experience levels of Hubway users would be an area for future research, and allow for more substantial policy implications. For example, the literature notes that cycling preferences vary by experience level. My analysis could not account for experience level of each user, or overall how experienced Hubway users are. If all women were very experienced riders but men had a lower experience level, there could be more similarities than otherwise would occur if the experience level was consistent. I would expect that since fewer women are biking generally, so the women who ride Hubway might have a higher experience level than men. A survey of Hubway users' experience could help identify what type of cyclists are using Hubway. This would clearly indicate which types of cyclists are being captured with Hubway subscribers. For example, if Hubway users are all 'strong and fearless' type of cyclists results such as bicycle infrastructure not having an impact on usage would not be surprising.

Analyzing the same dataset with the same methods but further dividing the data into age groups could also produce useful results. There might not enough observations for women's trips to allow such a detailed age analysis, but this analysis could further refine preferences for different demographics of the population. Especially when many cities use the phrase "8 to 80" in their bicycle policy to express planning facilities that can be used safely by someone from age 8 to 80. An analysis on factors that impact usage by age group could yield useful information on how to actually plan for '8 to 80'.

To gain more granular insights into gender differences in biking, route level data should be analyzed for bike share users. Cities may now have more availability of this data with dockless bikesharing systems expanding in the greater Boston region. These systems collect route level data for cyclists, so analysis on where users are riding and how this differs for men and women would produce more insightful information.

Bibliography

Akar, G., Fischer, N., & Namgung, M. (2013). Bicycling Choice and Gender Case Study: The Ohio State University. *International Journal of Sustainable Transportation*, *7*(5), 347–365. https://doi.org/10.1080/15568318.2012.673694

Aldred, R. (2013). Incompetent or Too Competent? Negotiating Everyday Cycling Identities in a Motor Dominated Society. *Mobilities*, *8*(2), 252–271. https://doi.org/10.1080/17450101.2012.696342

Anzilotti, E. (2017, July 5). What it Will Take to (Finally) Make a Bike-Share System That'll Benefit Everyone. *Fast Company*. Retrieved from https://www.fastcompany.com/40435917/creating-a-more-equitable-bike-share-system-is-possible-but-itll-take-some-work

Annear, S. (2018, March 3). Hubway is Changing its Name to Blue Bikes. *Boston Globe*. Retrieved from https://www.bostonglobe.com/metro/2018/03/07/hubway-changing-its-name-blue-bikes/ixOzaTK6y4jrNkMnRpz06J/story.html

Bauman, A., Rissell, C., Garrard, J., Kerr, I., Speidel, R., Fishman, E. (2008). Cycling: Getting Australia moving- barriers, facilitators and interventions to get more Australians physically active through cycling. 31st Australasian Transport Research Forum

Bachand-Marleau, J., Lee, B., El-Geneidy, A. (2012). *Better Understanding of Factors Influencing Likelihood of Using Shared Bicycle Systems and Frequency of Use* (Vol. 2314).

Broach, J., Dill, J., & Gliebe, J. (2012). Where do cyclists ride? A route choice model developed with revealed preference GPS data. *Transportation Research Part A: Policy and Practice*, *46*(10), 1730–1740. https://doi.org/10.1016/j.tra.2012.07.005

Broach, J., Dill, J., & Gliebe, J (2009). Development of a multi-class bicyclist route choice model using revealed preference data. Presented at the 12th International Conference on Travel Behavior Research, Jaipur, India. pdxscholar.library.pdx.edu/cgi/viewcontent.cgi?article=1020&context=usp_fac

Buck, D., & Buehler, R. (2011). Bike lanes and other determinants of capital ikeshare trips. Paper presented at the Transportation Research Board Annual Meeting 2012, Washington, DC. Conference paper. Retrieved from http://ralphbu.files.wordpress.com/2012/02/buck-buehler-poster-cabi-trb-2012.pdf

Campbell, A. A., Cherry, C. R., Ryerson, M. S., & Yang, X. (2016). Factors influencing the choice of shared bicycles and shared electric bikes in Beijing. *Transportation Research Part C: Emerging Technologies*, *67*, 399–414. https://doi.org/10.1016/j.trc.2016.03.004

Cervero, R., & Duncan, M. (2003). Walking, Bicycling, and Urban Landscapes: Evidence From the San Francisco Bay Area. *American Journal of Public Health, 93*(9), 1478–1483. https://doi.org/10.2105/AJPH.93.9.1478

Cervero, R., & Ewing, R.,(2001). Travel and the Built Environment: A Synthesis. *Transportation Research Record: Journal of the Transportation Research Board, 1780*, 87–114. https://doi.org/10.3141/1780-10

Cichocki, M. (1980). Women's Travel Patterns in a Suburban Development. In *New Space for Women* (pp. 151–163). Boulder, Colorado: Westview Press.

Coleman, C. (2000). Women, Transport and Cities: An Overview and an Agenda for Research. In *Women and the City: Visibility and Voice in Urban Space* (pp. 83–97). Palgrave.

Collins, D., & Tisdell, C. (2002). Gender and Differences in Travel Life Cycles. *Journal of Travel Research, 41*(2), 133–143. https://doi.org/10.1177/004728702237413

Crane, R. (2000). The Influence of Urban Form on Travel: An Interpretive Review. *Journal of Planning Literature, 15*(1), 3–23. https://doi.org/10.1177/08854120022092890

Daddio, D.W. Maximizing Bicycle Sharing: An Empirical Analysis of Capital Bikeshare Usage. (2012). University of North Carolina at Chapel Hill, Department of City and Regional 11 Planning.

Davis, L. S. (2014). Rolling along the last mile: Bike-sharing programs blossom nationwide. Planning, 80(5), 10–16

DeMaio, P. (2009). Bike-sharing: History, impacts, models of provision, & future. Journal of Public Transportation, 12(4), 41–56.

Dill, J., & Carr, T. (2003). Bicycle commuting and facilities in major U.S. cities: If you build them, commuters will use them. Transportation Research Record: Journal of the Transportation Research Board, 1828, 116–123

Dill, J., & Voros, K. (2007). Factors Affecting Bicycling Demand: Initial Survey Findings from the Portland, Oregon, Region. Transportation Research Record: Journal of the Transportation Research Board 2031:pp 9-17.

Dill, J. (2009). Bicycling for transportation and health: the role of infrastructure. *Journal of Public Health Policy, 30 Suppl 1*, S95-110. https://doi.org/10.1057/jphp.2008.56

Dill, J., & McNeil, N. (2012). *Four types of cyclists? Examination of typology for better understanding of bicycling behavior and potential.*

Ehrgott, M., Wang, J. Y. T., Raith, A., & van Houtte, C. (2012). A bi-objective cyclist route choice model. *Transportation Research Part A: Policy and Practice*, *46*(4), 652–663. https://doi.org/10.1016/j.tra.2011.11.015

Emond, C., Tang, W., & Handy, S. (2009). Explaining gender difference in bicycling behavior. *Transp Res Rec*, (2125), 16–25. https://doi.org/https://doi.org/10.3141/2125-03

Ferenchak, N.N., & Marshall, W.E., (2016). Relative (In)Effectiveness of Bicycle Sharrows on Ridership and Safety Outcomes, in: Transportation Research Board 95th Annual Meeting. Washington, D.C.

Fishman, E, Washington, S & Haworth, N (2012). Barriers and Facilitators to Public Bicycle Scheme Use: A Qualitative Approach. Transportation Research Part F-Traffic Psychology and Behaviour 15, 686-698

Fuller, D., Gauvin, L., Kestens, Y., Daniel, M., Fournier, M., Morency, P., & Drouin, L. (2011a). Use of a new public bicycle share program in Montreal, Canada. American Journal of Preventive Medicine, 41(1), 80–83. doi: 10.1016/j.amepre.2011.03.002

Garrard, J., Rose, G., & Lo, S. K. (2008). Promoting transportation cycling for women: The role of bicycle infrastructure. *Preventive Medicine*, *46*(1), 55–59. https://doi.org/10.1016/j.ypmed.2007.07.010

Gatersleben, B., & Appleton, KM (2007) Contemplating cycling to work: Attitudes and perceptions in different stages of change. *Transportation Research Part a-Policy and Practice*, 41 (4). pp. 302-312.

Geller, R. (2006). Four types of cyclists. Portland, OR: Retrieved from http://www.portlandoregon.gov/transportation/article/264746.

Gordon, P., & Richardson, H. W. (1998). Bicycling in the United States: A fringe mode? *Transportation Quarterly*, *52*(1), 9–11.

Grieco, M., & McQuaid, R. W. (2012). Gender and transport: An editorial introduction. *Gender and Transport: Transaction Costs, Competing Claims and Transport Policy Gaps*, *34*(1), 1–2. https://doi.org/10.1016/j.retrec.2011.12.009

Haans, A., & de Kort, Y. A. W. (2012). Light distribution in dynamic street lighting: Two experimental studies on its effects on perceived safety, prospect, concealment, and escape. *Journal of Environmental Psychology*, *32*(4), 342–352. https://doi.org/10.1016/j.jenvp.2012.05.006

Hamilton, K., & Jenkins, L. (n.d.). Women and Transport. In *Travel Sickness, the Need for a Sustainable Transport Policy for Britain* (p. 57). London: Lawrence and Wishart.

Heinen, E., van Wee, B., Maat, K. (2010). Commuting by Bicycle: An overview of the literature. Transport Reviews, 30(1), pp 56-96.

Heinen, E., & Handy, S. (2012). Similarities in Attitudes and Norms and the Effect on Bicycle Commuting: Evidence from the Bicycle Cities Davis and Delft. *International Journal of Sustainable Transportation*, *6*(5), 257–281. https://doi.org/10.1080/15568318.2011.593695

Hood, J., Sall, E., & Charlton, B. (2011). *A GPS-based bicycle route choice model for San Francisco, California* (Vol. 3). https://doi.org/10.3328/TL.2011.03.01.63-75

Jacobsen, P. L. (2003). Safety in numbers: more walkers and bicyclists, safer walking and bicycling. *Injury Prevention*, *9*(3), 205. https://doi.org/10.1136/ip.9.3.205

Keijer, M. J. N., & Rietveld, P. (2000). How do people get to the railway station? The dutch experience. *Transportation Planning and Technology*, *23*(3), 215–235. https://doi.org/10.1080/03081060008717650

Krizek, K. J., Johnson, P. J., & Tilahun, N. (2005). Gender differences in bicycling behavior and facility preferences. *Research on Women's Issues in Transportation*, *2*, 31–40.

Krizek, K. J., Handy, S. L., & Forsyth, A. (2009). Explaining Changes in Walking and Bicycling Behavior: Challenges for Transportation Research. *Environment and Planning B: Planning and Design*, *36*(4), 725–740. https://doi.org/10.1068/b34023

Krizek, K., & Johnson, P.J. (2006) Proximity to trails and retail: Eff ects on urban cycling and walking. Journal of the American Planning Association, 72(1), pp. 33–42

Krykewycz, G.R., Puchalsky, C.M., Rocks, J., Bonnette, B., & Jaskiewicz, F. (2010). Defining a Primary Market and Estimating Demand for Major Bicycle-Sharing Program in Philadelphia, Pennsylvania. *Transportation Research Record*, 117-124. doi:10.3141/2143-15.

LDA Consulting. (2012). Capital bikeshare 2011 member survey report. Washington, DC: LDA Consulting

Ligett, Robert. (2016). Bicycle Crash Risk: How Does It Vary, and Why?. *CalTrans.* Retrieved from https://www.its.ucla.edu/wp-content/uploads/sites/6/2016/08/Final-Report-to-Caltrans-Bicycle-Crash-v3.pdf

Litman, T. (2007). Land use impacts on transport: How land use factors affect travel behavior. Victoria: Victoria Transport Institute

Lutkevich, P., D. McLean, and J. Cheung. 2012. FHWA Lighting Handbook. Report No. FHWA-SA-11-22. Federal Highway Administration, Washington, DC

Ma, T., Liu, C., & Erdoğan, S. (2015). *Bicycle Sharing and Transit: Does Capital Bikeshare Affect Metrorail Ridership in Washington, D.C.* (Vol. 2534).

Mitra, R., & Nash, S. (2017). 1953 - Does the Built Environment Explain Gender Gap in Cycling? a Study of Post-Secondary Students in Toronto, Canada. *Journal of Transport & Health*, *5*(Supplement), S24–S25. https://doi.org/10.1016/j.jth.2017.05.307

Miranda-Moreno, L., Nosal, T., Schneider, R., & Proulx, F. (2013). *Classification of Bicycle Traffic Patterns in Five North American Cities* (Vol. 2339).

Moritz, William E. (1998). Survey of North American Bicycle Commuters: Design and Aggregate Results. Transportation Research Record 1578:91-101

Moudon, A. V., Lee, C., Cheadle, A. D., Collier, C. W., Johnson, D., Schmid, T. L., & Weather, R. D. (2005). Cycling and the built environment, a US perspective. *Transportation Research Part D: Transport and Environment*, *10*(3), 245–261. https://doi.org/10.1016/j.trd.2005.04.001

Murphy, H. (2010). Dublin bikes: An investigation in the context of multimodal transport. Dublin: MSc Sustainable Development, Dublin Institute of Technology

NACTO (2018). Bike Share in the U.S. 2010-2016. Retrieved April 28, 2018, from https://nacto.org/bike-share-statistics-2016/

New Zealand Transport Agency. (2011). Assessment of the type of cycling infrastructure required to attract new cyclists. New Zealand Transport Agency.

Noland, R.B. 1995. Perceived risk and modal choice: Risk compensation in transportation systems. Accident Analysis & Prevention, 27, (4) 503-521

Ogilvie F, Goodman A. (2012). Inequalities in usage of a public bicycle sharing scheme: socio-demographic predictors of uptake and usage of the London (UK) cycle hire scheme. Prev Med. 2012 Jul;55(1):40-5. doi: 10.1016/j.ypmed.2012.05.002.

Parker K.M., Rice J., Gustat J., Ruley J., Spriggs A., Johnson C. (2013) Effect of bike lane infrastructure improvements on ridership in one New Orleans neighborhood. Ann. Behav. Med.45:S101–S107.

Parkes, S.D., Marsden, G., Shaheen, S.A., & Cohen, A.J. (2013). Understanding the diffusion of public bikesharing systems: evidence from Europe and North America.

Pedler, A., & Davies, D.G. (2000). *Cycle track crossings of minor roads.*

Petritsch T. A., Landisb. W., Huang H. F., Challa S. (2006) Sidepath Safety Model: Bicycle Sidepath Design Factors Affecting Crash Rates. Transportation Research Record: Journal of the Transportation Research Board

Pucher, J., & Buehler, R. (2006). Why Canadians cycle more than Americans: A comparative analysis of bicycling trends and policies. Transport Policy, 13, 265–279.

Pucher, J., & Buehler, R. (2008). Making Cycling Irresistible: Lessons from The Netherlands, Denmark and Germany. *Transport Reviews*, *28*(4), 495–528. https://doi.org/10.1080/01441640701806612

Pucher, J., Buehler, R., Merom, D., Bauman, A.: Walking and cycling in the United States, 2001–2009: Evidence from the NHTS. Am J Public Health 101 e1–e8 (2011a). doi:10.2105/AJPH.2010.300067

Rixey, R. (2013). *Station-Level Forecasting of Bikesharing Ridership* (Vol. 2387).

Schmucki, B. (2012). "If I Walked on my Own at Night I Stuck to Well Lit Areas." Gendered spaces and urban transport in 20th century Britain. *Gender and Transport: Transaction Costs, Competing Claims and Transport Policy Gaps*, *34*(1), 74–85. https://doi.org/10.1016/j.retrec.2011.12.002

Shaheen, S., Guzman, S., & Zhang, H. (2010). Bikesharing in Europe, the Americas, and Asia. Transportation Research Record: Journal of the Transportation Research Board, 2143, 159–167. doi: 10.3141/2143-20

Shaheen, S., Martin, E., Cohen, A.P., & Finson, R. (2012). Public bikesharing in North America: Early operator and user understanding. San Jose, CA: Mineta Transportation Institute.

Shaheen, S., Zhang, H., Martin, E., & Guzman, S. (2011). Hangzhou public bicycle: Understanding early adoption and behavioural response to bike sharing in Hangzhou, China. Paper presented at the TRB Annual Meeting, Washington, DC. Retrieved from http://76.12.4.249/artman2/uploads/1/ Hangzhou_Public_Bicycle.pdf

Shankwiler, K. D. (2006) Developing a framework for behavior assessment of bicycling commuters: a cyclist-centric approach. School of Industrial Design, Atlanta: Georgia Institute of Technology. pp. 87.

Stinson, M., & Bhat, C. (2004). *A Comparison of the Route Preferences of Experienced and Inexperienced Bicycle Commuters.*

Stinson MA, Bhat CR (2003) An analysis of commuter bicyclist route choice using a stated preference survey. Transportation Research Record 1828: 107-115

Transport for London. (2010). Travel in London report 3. London: Transport for London, Retrieved from http://www.tfl.gov.uk/assets/downloads/corporate/travel-in-london-report-3.pdf.

Trench, S., Oc, T., & Tiesdell, S. (1992). Safer Cities for Women: Perceived Risks and Planning Measures, *60*(3).

Troiano RP (2005). A timely meeting: objective measurement of physical activity. *Med Sci Sports Exerc.* 37:S487–9.

Van Wee B, Rietveld P, Meurs H. (2006). Is average daily travel time expenditure constant? In search of explanations for an increase in average travel time. Transport Geogr 14:109–122

Wang, X., Lindsey, G., Schoner, J., & Harrison, A. (2015). *Modeling Bike Share Station Activity: Effects of Nearby Businesses and Jobs on Trips to and from Stations* (Vol. 142). https://doi.org/10.1061/(ASCE)UP.1943-5444.0000273

Weber, E. U., Blais, A.-R., & Betz, N. E. (2002). A domain-specific risk-attitude scale: measuring risk perceptions and risk behaviors. *Journal of Behavioral Decision Making*, *15*(4), 263–290. https://doi.org/10.1002/bdm.414

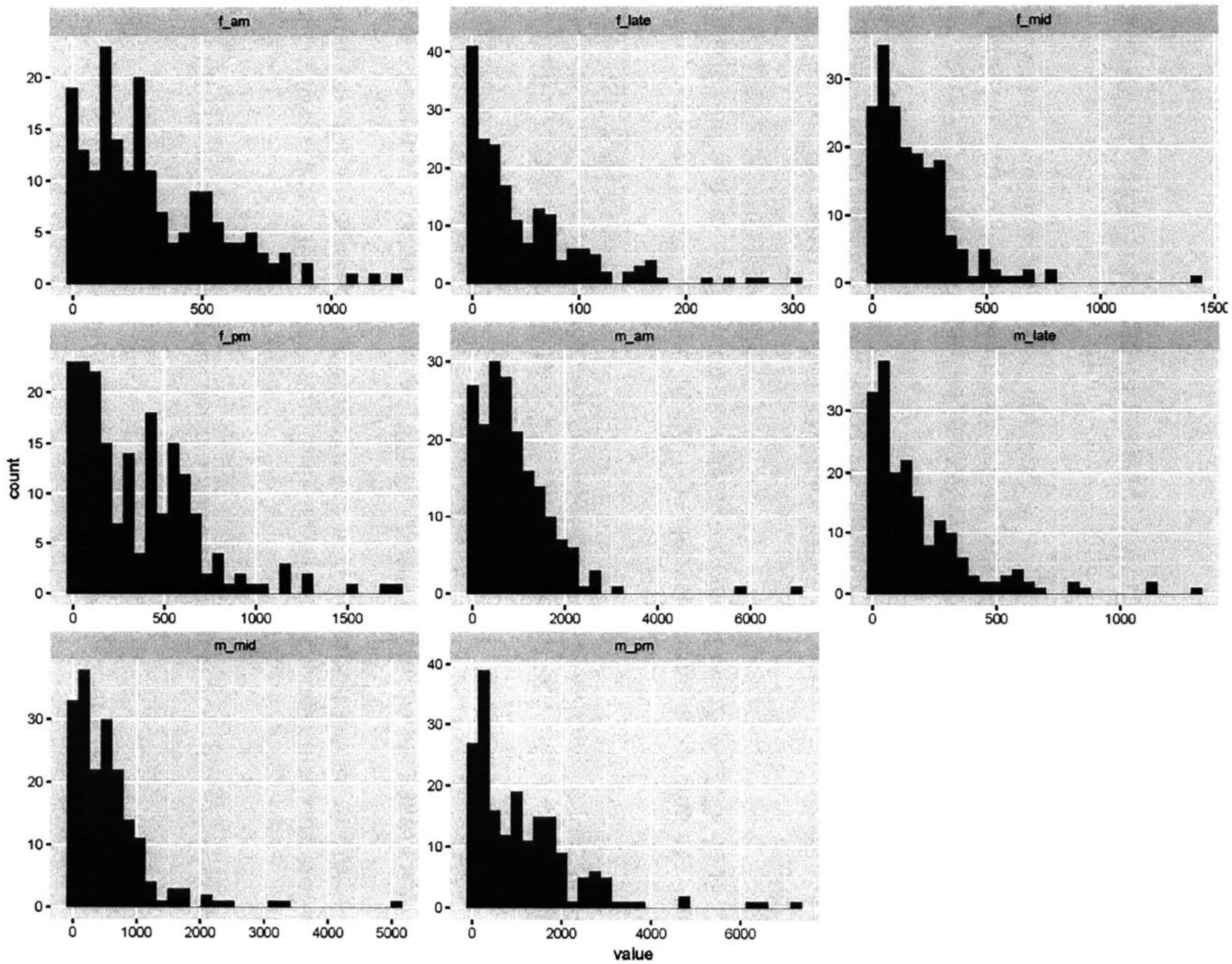
Winters, M., Davidson, G., Kao, D., & Teschke, K. (2011). Motivators and deterrents of bicycling: comparing influences on decisions to ride. *Transportation*, *38*(1), 153–168. https://doi.org/10.1007/s11116-010-9284-y

Witlox, Frank, & Tindemans, H. (2004). Evaluating bicycle-car transport mode competitiveness in an urban environment: an activity-based approach. *World Transport Policy & Practice*, *10*(4), 32–42

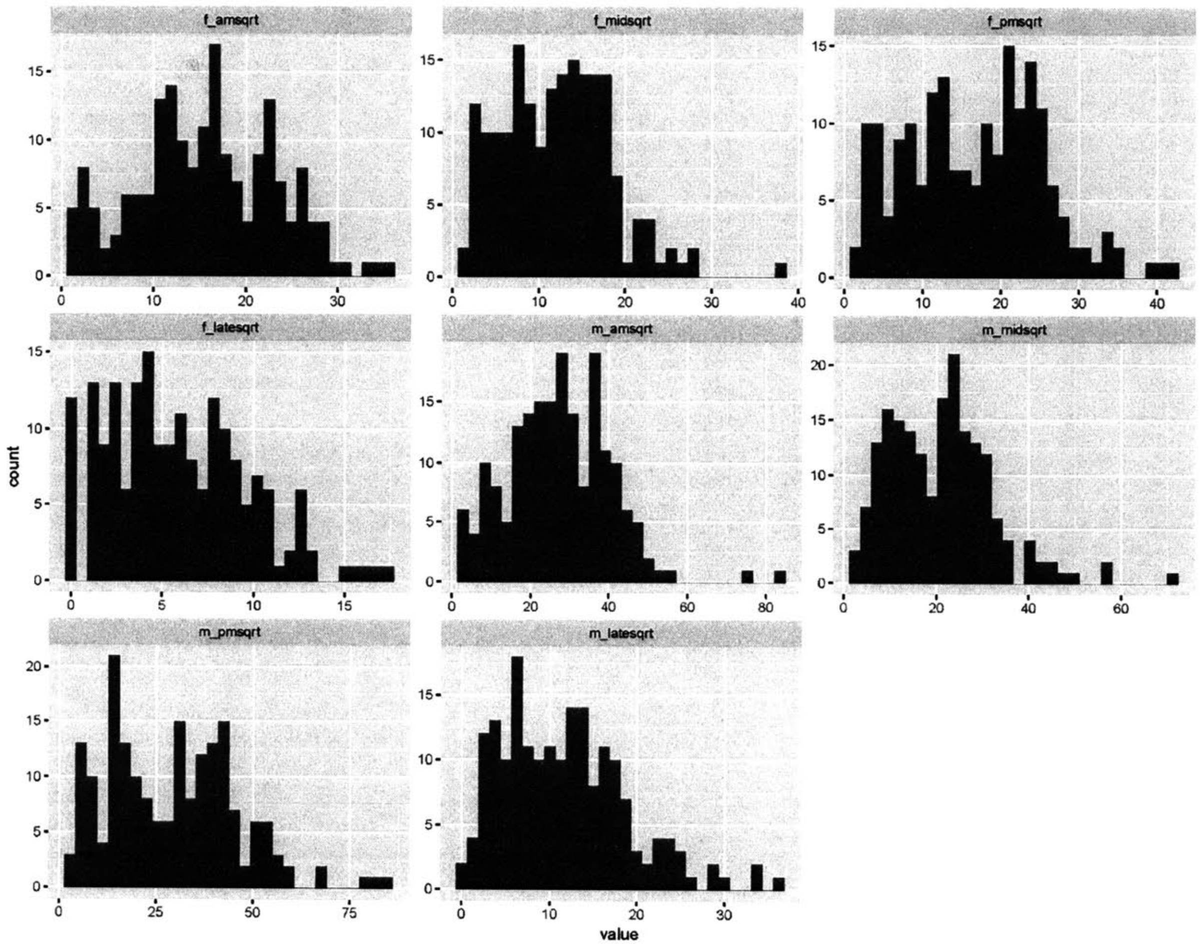
Yang, T., Haixiao, P., & Qing, S. (2010). Bike-sharing Systems in Beijing, Shanghai and Hangzhou and their Impact on Travel Behaviour. Paper presented at the Transportation Research Board Annual Meeting 2011, Washington, DC.

Zacharias, J. (2005). Non-motorized transportation in four Shanghai districts. *International Planning Studies*, *10*(3-4), 323–340. https://doi.org/10.1080/13563470500378911

APPENDIX A: DEPENDENT VARIABLE HISTOGRAM



APPENDIX B: DEPENDENT VARIABLE HISTOGRAMS



APPENDIX C: TRIP ORIGINS FOR ALL STATIONS

Station	*Total Trips*	*Femal e AM*	*Male AM*	*Femal e Mid*	*Male Mid*	*Femal e PM*	*Male PM*	*Femal e Late*	*Male Late*
MIT at Mass Ave / Amherst St	19085	688	2093	1421	5078	1509	6572	276	1309
South Station - 700 Atlantic Ave	19016	763	5826	513	2259	1773	7252	98	429
Central Square at Mass Ave / Essex St	13271	731	2316	664	1700	1690	4695	303	1115
MIT Stata Center at Vassar St / Main St	13046	130	607	796	3349	1269	6330	75	465
Kendall T	12760	593	1834	768	3166	1035	4715	102	526
Nashua Street at Red Auerbach Way	11722	1154	6998	222	756	550	1658	40	296
Beacon St at Massachusetts Ave	11197	1254	2137	528	1551	1133	3008	266	1128
MIT Vassar St	10184	667	3176	304	2057	523	2768	96	539
MIT Pacific St at Purrington St	10034	696	2569	489	2032	700	2422	154	878
Charles Circle - Charles St at Cambridge St	9702	1092	2139	471	1088	1130	2997	116	567
Ames St at Main St	9479	260	962	709	2425	807	3655	102	520
One Kendall Square at Hampshire St / Portland St	9417	610	1714	628	1819	773	3106	103	577
Back Bay T Stop - Dartmouth St at Stuart St	9289	701	2766	261	883	901	3257	120	323
Copley Square - Dartmouth St at Boylston St	8927	582	1372	496	1231	1262	3387	153	400
Harvard Square at Mass Ave/ Dunster	8529	294	885	564	1536	1135	3032	244	801
Boston City Hall - 28 State St	8300	529	1873	350	1541	660	2963	53	282
University Park	7686	475	1589	267	1335	552	2455	177	805
Lechmere Station at Cambridge St / First St	7219	676	1499	280	1117	576	2775	35	233
Boylston St at Fairfield St	7029	495	1217	368	1162	615	2717	73	345
Christian Science Plaza - Massachusetts Ave	6985	750	1428	334	811	811	1958	151	595
Central Sq Post Office / Cambridge City Hall	6897	815	1324	442	1046	596	1873	167	573
Cross St at Hanover St	6874	656	2023	300	849	551	1901	121	351
Yawkey Way at Boylston St.	6630	531	1575	379	840	616	1777	155	646
Arch St at Franklin St	6604	134	1255	330	1210	681	2838	31	96
Cambridge St at Joy St	6497	441	1898	276	891	712	1714	69	342
Congress St at Sleeper St	6468	98	954	263	1731	541	2693	31	153
Prudential Center - Belvedere St	6465	594	1242	324	746	553	2496	101	314
Kenmore Square	6431	402	1541	276	991	657	1638	166	657
Boylston St at Massachusetts Ave	6328	583	1328	345	863	668	1620	162	654
Boston Medical Center - E Concord St	6241	244	1641	488	1135	777	1730	59	134
Inman Square at Vellucci Plaza / Hampshire St	6189	889	2192	303	743	458	1089	81	336
Davis Square	5971	446	998	293	538	954	2010	221	500
Washington St at Rutland St	5954	435	2271	203	499	618	1567	62	173
Rowes Wharf at Atlantic Ave	5810	299	1847	77	483	433	2436	29	196
Boylston St at Arlington St	5546	267	745	307	830	595	2495	49	222
Porter Square Station	5514	783	2092	164	416	594	1002	125	269
Post Office Square - Pearl St at Milk St	5485	137	844	217	936	532	2719	9	83
Cambridge St - at Columbia St / Webster Ave	5252	701	1729	294	530	543	1046	59	286
Washington St at Waltham St	5196	481	1937	205	547	414	1260	49	180
Boylston St at Berkeley St	5170	165	749	324	1201	453	2080	31	149
Aquarium T Stop - 200 Atlantic Ave	5168	518	1862	126	496	412	1388	59	275

Longwood Ave at Binney St	5136	273	553	314	987	847	1756	72	295
Tremont St at West St	5107	199	836	224	926	583	1906	80	325
Harvard Square at Brattle St / Eliot St	5008	269	565	527	978	694	1581	105	281
Surface Rd at India St	4978	228	1704	88	657	323	1796	25	152
Commonwealth Ave at Buick St	4967	359	1245	316	781	560	1263	98	311
359 Broadway - Broadway at Fayette Street	4955	923	1664	257	642	327	908	33	154
Lower Cambridgeport at Magazine St	4920	478	1266	272	638	618	1323	61	192
Packard's Corner - Commonwealth Ave	4892	570	1708	195	662	311	918	78	308
Lafayette Square at Mass Ave	4869	280	781	250	886	436	1516	164	514
Chinatown Gate Plaza	4859	274	820	205	772	461	2077	41	189
Warren St at Chelsea St	4842	822	1746	273	451	442	862	36	105
Harvard University Housing - 115 Putnam Ave	4806	648	1533	283	743	377	885	37	228
Landmark Center - Brookline Ave at Park Dr	4783	272	951	298	845	534	1487	74	306
HMS/HSPH - Avenue Louis Pasteur	4778	150	321	343	991	932	1781	77	173
Newbury St at Hereford St	4772	388	900	243	663	611	1392	144	392
Boylston St at Washington St	4717	265	797	227	661	508	1797	66	366
Cambridge Main Library	4711	519	1101	378	689	698	963	76	258
Beacon St at Arlington St	4694	341	1042	208	556	591	1639	67	218
B.U. Central - 725 Comm. Ave.	4659	244	501	414	942	711	1377	111	304
Tremont St at E Berkeley St	4640	490	1556	200	577	307	930	99	349
CambridgeSide Galleria - CambridgeSide PL	4637	128	437	311	1040	636	1952	32	99
One Broadway / Kendall Sq at Main St / 3rd St	4628	254	334	257	970	507	2140	21	139
Harvard University / SEAS Cruft-Pierce Halls	4486	113	439	203	983	519	1935	59	227
Lewis Wharf at Atlantic Ave	4418	491	1526	145	536	291	1086	21	143
Binney St / Sixth St	4418	167	894	217	629	494	1757	34	173
Brigham Circle - Francis St at Huntington Ave	4343	307	778	171	736	470	1514	52	253
South End Library - Tremont St at W Newton St	4328	519	1529	239	516	406	810	42	151
Northeastern University - North Parking Lot	4324	495	775	248	618	422	1296	84	365
Harvard University Gund Hall	4311	318	628	377	850	521	1229	89	269
Ink Block - Harrison Ave at Herald St	4291	545	1234	242	440	527	964	80	235
Ruggles T Stop - Columbus Ave	4261	259	1401	183	485	558	1079	62	214
Purchase St at Pearl St	4162	166	803	222	615	525	1753	14	61
Park Dr at Buswell St	4064	308	1413	172	493	410	933	42	272
Congress St at North St	3958	342	1068	122	524	319	1379	57	143
Stuart St at Charles St	3936	255	845	117	561	344	1334	59	393
Harvard University River Houses at DeWolfe St	3811	561	932	240	507	392	825	73	262
Beacon St at Washington / Kirkland	3773	714	1359	139	356	204	728	59	151
Harvard Kennedy School at Bennett St	3754	119	277	248	862	649	1323	73	196
Sidney Research Campus/ Erie Street	3730	231	1261	218	785	244	888	19	75
Third at Binney	3723	269	481	195	516	460	1564	32	172
Seaport Square - Seaport Blvd at Northern Ave	3652	142	471	170	521	452	1724	29	130
Dana Park	3638	557	1358	142	449	219	692	36	136
Charles St and Beacon St	3545	303	946	166	435	430	949	74	185
Coolidge Corner - Beacon St @ Centre St	3540	394	1446	165	386	285	537	40	139
Watermark Seaport - Boston Wharf Rd	3540	111	364	147	692	333	1704	32	151
Kendall Street	3533	67	409	184	541	455	1691	17	151
EF - North Point Park	3453	187	695	148	521	516	1204	35	135

Columbus Ave at Massachusetts Ave	3433	424	1038	204	335	409	672	77	207
TD Garden - West End Park	3401	497	2631	19	77	20	149	2	5
175 N Harvard St	3400	356	1053	116	466	227	925	40	174
State Street at Channel Center	3391	150	936	74	583	326	1238	16	50
Harvard Law School at Mass Ave / Jarvis St	3346	232	550	189	575	406	990	112	275
Allston Green District - Griggs St	3315	667	1282	154	433	166	356	111	98
Boylston St at Dartmouth St	3310	187	430	179	520	357	1442	38	130
W Broadway at D St	3261	472	1631	62	262	156	499	19	76
Silber Way	3232	177	440	254	617	426	1079	60	165
Roxbury Crossing T Stop - Columbus Ave	3228	300	1181	114	431	247	712	34	153
Spaulding Rehabilitation Hospital	3212	122	587	278	459	634	1021	18	69
W Broadway at Dorchester St	3048	468	1276	101	293	126	470	19	87
Union Square - Somerville	3044	509	1121	120	367	160	511	41	188
Seaport Hotel - Congress St at Seaport Ln	2986	61	358	131	528	282	1518	9	93
Harvard University Radcliffe Quadrangle	2920	500	665	278	301	230	640	108	152
Soldiers Field Park - 111 Western Ave	2919	324	771	184	410	289	744	25	137
Conway Park - Somerville Avenue	2888	436	1003	136	293	203	464	92	253
Linear Park - Mass. Ave. at Cameron Ave.	2811	821	1011	122	221	220	331	17	40
ID Building West	2797	21	98	169	566	311	1575	7	49
Fan Pier	2679	55	111	76	640	163	1501	13	119
Main St at Austin St	2666	286	1231	152	324	200	391	9	43
ID Building East	2620	6	72	138	644	400	1310	4	45
Colleges of the Fenway - Fenway	2599	181	306	189	327	450	970	63	110
Congress St at Northern Ave	2570	81	383	118	467	172	1194	31	111
South Boston Library - 646 E Broadway	2559	382	1233	81	226	137	328	21	79
Union Square - Brighton Ave at Cambridge St	2397	329	948	123	294	120	396	21	120
Jackson Square T Stop	2319	507	566	98	394	152	424	33	94
Wentworth Institute of Technology	2121	143	288	105	277	334	728	52	184
Edwards Playground - Main St at Eden St	2116	276	1309	63	92	99	212	5	12
Andrew T Stop - Dorchester Ave at Dexter St	2095	200	1040	59	126	121	437	20	55
Burlington Ave at Brookline Ave	2019	100	653	85	314	143	501	46	164
The Lawn on D	2008	108	438	148	243	237	707	20	96
Green Street T Stop - Green St at Amory St	1929	584	597	88	173	92	290	12	66
Dorchester Ave at Gillette Park	1914	232	677	75	194	188	401	15	77
Washington St at Lenox St	1862	181	628	113	273	154	420	2	57
Wilson Square	1853	312	790	56	152	114	323	23	76
Innovation Lab - 125 Western Ave	1824	87	277	155	355	208	662	21	54
Lesley University	1760	262	694	93	194	116	226	38	92
Brookline Village - Station Street @ MBTA	1747	159	737	80	239	132	314	17	44
Commonwealth Ave At Babcock St	1684	213	707	51	182	121	274	20	102
Bunker Hill Community College	1658	235	950	66	111	55	204	6	26
Brian P. Murphy Staircase at Child Street	1653	152	774	30	73	121	423	8	54
Hyde Square - Barbara St at Centre St	1627	281	686	63	188	78	251	14	40
Washington Square at Washington St.	1622	267	722	90	183	71	166	12	41
Teele Square at 239 Holland St	1584	349	734	32	86	145	164	5	52
JFK Crossing at Harvard St. / Thorndike St.	1530	363	716	40	100	59	141	14	76
Verizon Innovation Hub 10 Ware Street	1483	60	372	59	216	145	382	54	182

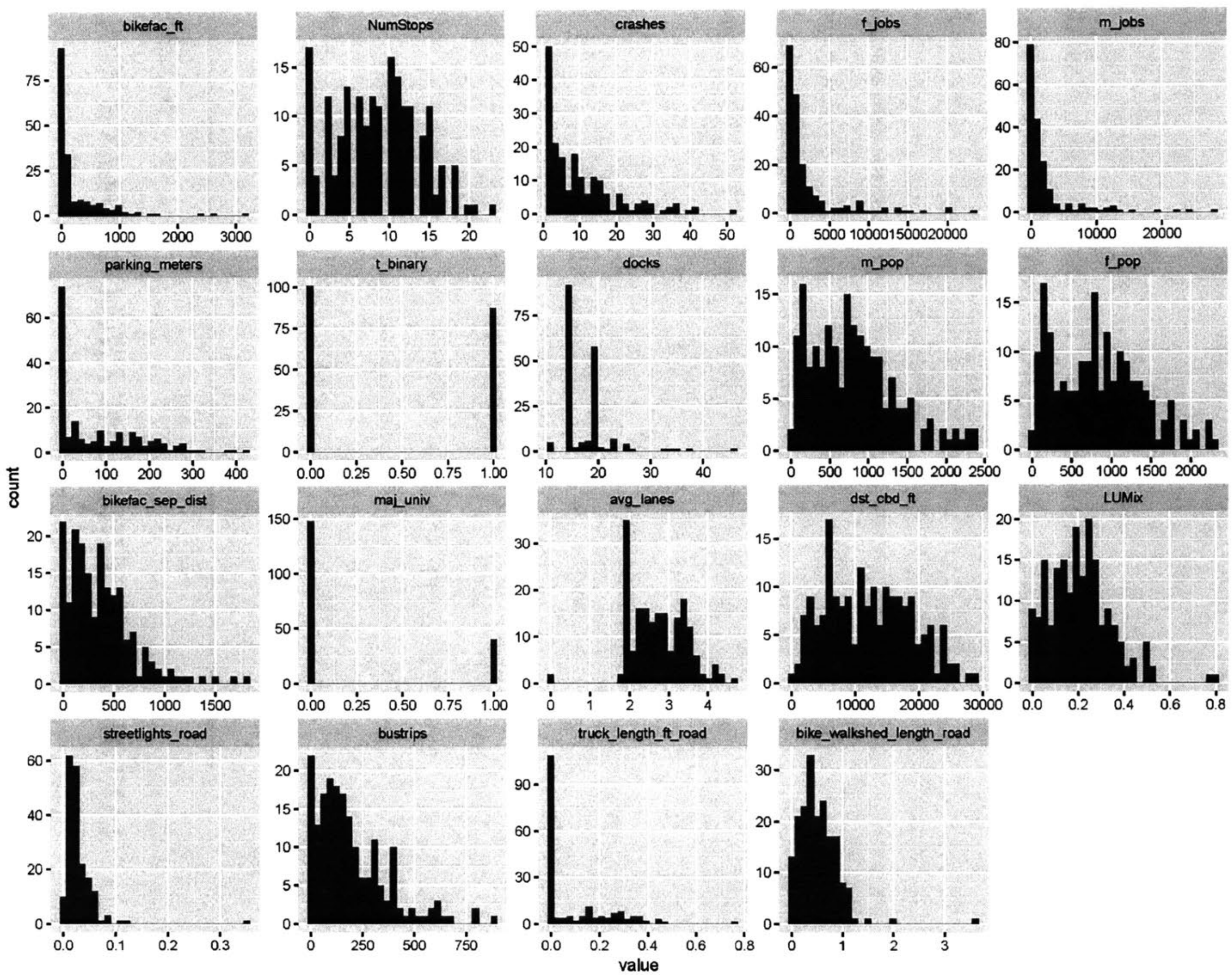
Danehy Park	1481	208	380	96	126	279	325	22	44
Brighton Center - Washington St	1364	132	466	69	296	100	225	17	47
Mt Auburn	1330	146	393	94	187	182	271	10	41
Somerville City Hall	1329	199	613	54	156	63	163	18	44
Magoun Square at Trum Field	1316	212	626	36	129	67	182	7	40
Brighton Mills - 370 Western Ave	1280	175	488	64	176	58	254	13	49
Museum of Science	1276	62	329	60	122	169	479	12	39
Powder House Circle - Nathan Tufts Park	1230	244	483	59	87	69	173	14	35
Hayes Square - Vine St at Moulton St	1177	265	457	34	115	100	166	6	21
S Huntington Ave at Heath St	1164	121	381	50	218	77	248	4	29
Dudley Square - Dudley St at Warren St	1113	109	270	52	297	68	252	5	45
Rindge Avenue - O'Neill Library	1093	253	450	83	70	76	87	15	17
New Balance - 20 Guest St	1082	113	198	43	170	140	346	7	60
Murphy Skating Rink - 1880 Day Blvd	1048	110	430	47	178	50	197	2	25
Curtis Hall - South St at Centre St	1015	136	405	56	139	77	169	5	23
Boston Convention and Exhibition Center	1009	42	94	31	185	121	473	18	40
Packard Ave / Powderhouse Blvd	1007	161	317	65	117	84	207	12	43
Broadway St at Mt Pleasant St	919	83	382	28	148	32	207	5	32
Ryan Playground - Dorchester Ave	887	107	496	34	54	43	78	3	38
Alewife Station at Russell Field	856	52	250	42	105	134	227	13	25
Alewife MBTA at Steel Place	842	45	205	24	88	182	271	7	16
Washington St at Melnea Cass Blvd	836	71	189	111	120	158	167	3	17
E Cottage St at Columbia Rd	799	146	275	30	129	17	92	2	12
JFK/UMass T Stop	764	126	237	18	95	42	224	3	15
Egleston Square - Atherton St at Washington St	631	186	275	9	59	7	54	4	31
Clarendon Hill at Broadway	621	120	293	41	80	30	43	5	9
Newmarket Square T Stop	609	44	103	44	126	40	205	4	28
Washington St at Brock St	581	127	217	12	81	19	101	3	19
Maverick Square - Lewis Mall	521	7	61	25	49	152	201	19	7
Roxbury YMCA - Warren St at MLK Blvd	491	95	162	16	116	17	67		14
University of Mass Boston - Integrated Sciences	409	1	11	18	69	96	206		8
NCAAA - Walnut Ave at Crawford St	404	65	246	6	28	6	27	1	20
Airport T Stop - Bremen St at Brooks St	403	39	37	34	45	59	155	9	24
Piers Park	392	153	70	19	44	37	63		6
Upham's Corner	391	7	114	9	74	18	97		18
East Boston Neighborhood Health Center	369	1	8	2	63	40	198	5	50
Savin Hill T Stop - S Sydney St at Bay St	328	56	157	9	56	10	25	2	12
Bowdoin St at Quincy St	277	9	76	26	37	10	25	3	15
Central Square - East Boston	271	11	120	1	73	9	48	1	4
Fresh Pond Reservation	260	25	95	19	28	23	62	2	3
MLK Blvd at Washington St	250	54	67	19	47	5	50	1	6
Oak Square - 615 Washington St	232	12	103	15	44	3	40		14
Upham's Corner T Stop - Magnolia St	190	12	49	4	49	2	54	1	5
Glendon St at Condor St	190	30	106	20	6	6	22		
Grove Hall Library - 41 Geneva Ave	179	2	26	8	45	80	17		1
Orient Heights T Stop - Bennington St	163	8	13	28	43	19	48	2	2
Walnut Ave at Warren St	139	6	59	7	24	7	29		6

Bennington St at Byron St	119	14	17	8	7	36	28	1	8
Franklin Park Zoo - Franklin Park Rd	116	7	9	4	35	13	42		5
Chelsea St at Saratoga St	108	4	67	11	7	6	11		2
Franklin Park - Seaver St at Humbolt Ave	106	3	47	8	14	17	14		
Columbia Rd at Ceylon St	93	5	9	7	13	7	41		10
The Eddy - New St at Sumner St	92	1	21	9	14	18	23	2	4

APPENDIX D: EXPLANATORY VARIABLE DESCRIPTIVE STATISTICS

Statistic	*N*	*Mean*	*St. Dev.*	*Min*	*Max*
Male Population	188	808.48	547.49	1.95	2,373.63
Female Population	188	842.78	550.67	0.14	2,310.25
Male Jobs	188	2,338.93	4,337.49	6.03	27,999.01
Female Jobs	188	2,352.61	4,099.22	14.13	23,378.51
Average ADT	188	15,648.47	8,903.81	0.00	49815.21
Average Lanes	188	2.74	0.70	0.00	4.67
Parking Meters	188	82.28	97.58	0.00	423
Truck Route/Road	188	0.10	0.14	0.00	0.76
Bus Stops	188	8.53	5.23	0.00	23
Streetlights/Road	188	0.03	0.03	0.00	0.35
Length of Bike Network/Road	188	0.52	0.40	0.00	3.61
Distance to Bike Facility	188	266.84	459.30	1.31	3,161.57
Distance to Separated Bike Facility	188	375.29	325.32	0.40	1,809.52
Bicycle Traffic	188	10.24	10.00	1	51
Docks	188	17.53	4.35	11	46
Land Use Mix	188	0.21	0.14	0.00	0.80
Distance to CBD (ft)	188	12,183.14	6,647.01	438.09	29,263.52
Major University	188	0.21	0.41	0	1
T Station	188	0.46	0.50	0	1
Bus Accessibility	188	192.39	173.44	0.00	888.00

APPENDIX E: EXPLANATORY VARIABLE HISTOGRAMS



APPENDIX F: MORAN I TEST

	Moran I Statistic	*Expectation*	*P value*
AM Female	0.136	-0.009	0.086
AM Male	0171	-0.009	0.034
Mid Female	0.270	-0.009	0.003
Mid Male	0.297	-0.009	9.56e-04
PM Female	0.269	-0.009	0.004
PM Male	0.354	-0.009	2.24e-04
Late Female	0.389	-0.009	6.961e-05
Late Male	0.325	-0.009	6.098e-04

APPENDIX G: CHOROPLETH OF SPATIAL LAG

Figure 6-1 Lagged Mean for Trip Origins

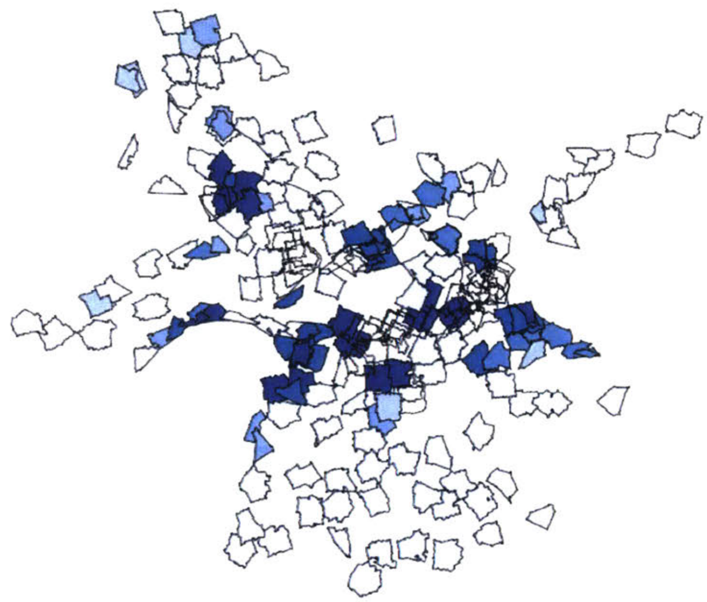


Figure 6-2 Lagged Mean for Male Trip

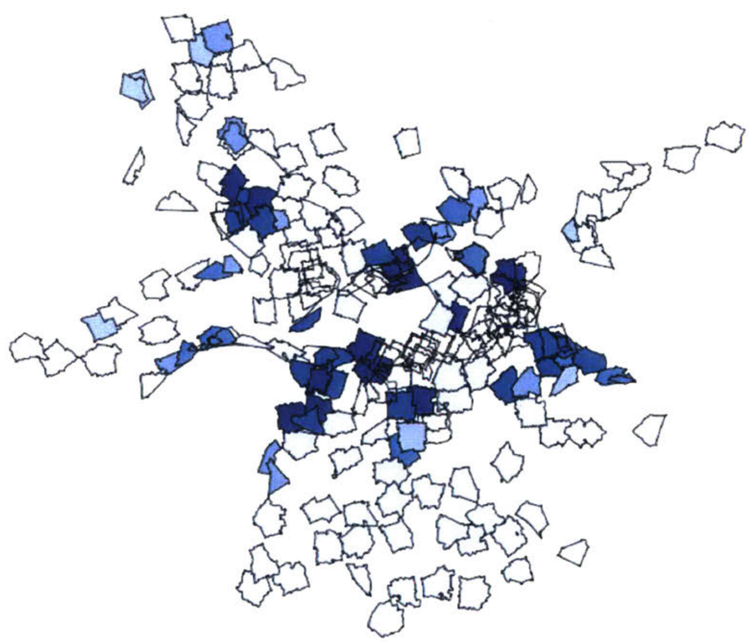


Figure 6-3 Lagged Mean for Female Trip