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EQUITY IN MOTION: Bikeshare in Low-Income Communities

Analyzing barriers & setting targets for Capital Bikeshare ridership in Washington, DC's low-income communities

A comprehensive project submitted in partial satisfaction of the requirements for the degree Master of Urban and Regional Planning (MURP)

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Disclaimer: *This report was prepared in partial fulfillment of the requirements for the Master in Urban and Regional Planning degree in the Department of Urban Planning at the University of California, Los Angeles. It was prepared at the direction of the Department and of [insert client name] as a planning client. The views expressed herein are those of the authors and not necessarily those of the Department, the UCLA Luskin School of Public Affairs, UCLA as a whole, or the client.*

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Abstract

On the promise of bikeshare programs to transform urban transportation, Philadelphia's former Chief of Staff Andrew Stober said, "It's only typically a couple times in any given century that a city gets to introduce a new form of public transportation. It's very important that you do it in a way that creates as much opportunity as possible for as many citizens as possible" (Ferrentino & Monroe 2014). But bikeshare opportunities don't always translate into outcomes. In Washington DC, a 2013 Member Survey of its public bicycle sharing program, Capital Bikeshare, showed that 80 percent of members were white, 80 percent had an income of $50K or more, and 95 percent had at least a 4-year college education. Indeed, Capital Bikeshare, which operates the DC system, reports that in disadvantaged communities, the bicycles are seldom used, the tires of their shared bikes are frequently slashed, and their parking docks are often vandalized. With Capital Bikeshare embarking on an ambitious three-year plan to expand to 454 stations and forging new partnerships with community health clinics, the District Department of Transportation (DDOT) asked me to analyze current and predicted bikeshare ridership in low-income DC communities. To do this I thoroughly reviewed of the literature, conducted a geospatial analysis, estimated multivariate regression models predicting utilization, and conducted field observations. My findings suggest that ridership can increase even in high crime and high poverty areas if four major financial, cultural, and structural barriers are addressed: (1) a lack of convenient, reliable accessibility to bikeshare stations, (2) fear for safety, (3) difficult-to-afford membership costs, and (4) a perceived lack of diversity in the ages and ethnicities of users. To overcome these barriers, I conclude that a variety of intra-agency, inter-agency, and partnerships with local institutions will be needed to support the adoption of Capital Bikeshare in historically disadvantaged, low bikeshare usage communities.

1 ACKNOWLEDGEMENTS

This research was made possible with guidance from UCLA, Foursquare ITP, the District Department of Transportation (DDOT) and Slow Streets. My field study travel was generously supported by the UCLA Lewis Center for Regional Policy Studies. First and foremost, I would like to thank my mother Leyla Cohen and my father Allen Cohen for their patience, love and wisdom. Secondly, I am grateful for my faculty advisor, Dr. Brian Taylor and the UCLA faculty and staff for their insightful feedback, critical lessons and passionate enthusiasm which has kept me on track, on schedule and on target. My project would not be complete without support from afar from the District Department of Transportation (DDOT) and the Foursquare ITP consulting team. I was fortunate to have interned with DDOT over the summer of 2015 and am honored to continue the social equity and bikeshare research I started there through this capstone project at UCLA. Lastly, I would like to thank my UCLA classmates for all the laughs, tears, tips and fun times throughout my Masters of Urban Planning (MURP) degree program. I am so happy to have met you all and hope we will continue to learn and work with each other in the future ahead!

2 Introduction and Overview

Approximately 965 public bicycle sharing systems, commonly known as bikeshare, exist throughout the world, with nearly 2 million bicycles available for use (DeMaio & Meddin 2015). Bikeshare systems allow users to use a transit pass or a key fob to unlock a bicycle from one unmanned, often solar-powered, bikeshare station and return the bicycle to another station in the network within an allotted period of time, usually thirty to sixty minutes (ITDP 2014). Stations are typically spaced within 1,000 feet of one another to encourage riders to make several trips throughout the day, with convenient connections to public transit, rideshare, and carshare services for longer commutes (ITDP 2015). In 2008, Washington, DC opened the first bikeshare system in North America, expanding across three jurisdictions in Virginia, Maryland, and the District of Columbia to grow from just 10 stations to 355 with 2,494 bicycles today (DDOT 2015).

On the promise of bikeshare programs to transform urban transportation, Philadelphia's former Chief of Staff Andrew Stober said, "It's only typically a couple times in any given century that a city gets to introduce a new form of public transportation. It's very important that you do it in a way that creates as much opportunity as possible for as many citizens as possible" (Ferrentino & Monroe 2014). But bikeshare opportunities don't always translate into outcomes. In Washington DC, a 2013 Member Survey of its public bicycle sharing program, Capital Bikeshare, showed that 80 percent of members were white, 80 percent had an income of $50K or more, and 95 percent had at least a 4-year college education. Indeed, Capital Bikeshare, which operates the DC system, reports that in disadvantaged communities, the bicycles are seldom used, the tires of their shared bikes are frequently slashed, and their parking docks are often vandalized.

Capital Bikeshare does, however, represent one of first large-scale public bicycle programs in the United States, which found itself nearly operationally profitable in 2012, reporting a remarkable 97 percent return on investment (ITDP 2014). In comparison, the Washington Metropolitan Area Transit Authority (WMATA) public transit system only recovers 31 percent of its operational costs to run its buses and trains. After Capital Bikeshare was introduced in 2010, bicycling mode share rose at over twice national rate from 2010 to 2012 (a 32% increase versus 15%) (Buck 2014). Additionally, the number of car-free households in DC has grown by 14.3 percent, from 35 to 37.9 percent, some by choice and others by economic circumstance (Chung 2014). By contrast, the District only added 1,662 car-owning households since 2010, an increase of just 1.0 percent (Chung 2014).

In 2015, Capital Bikeshare received a $25,000 in funding from the JPB Foundation's "Better Bikeshare Partnership", a collaboration between The City of Philadelphia, Bicycle Coalition of Greater Philadelphia, the National Association of City Transportation Officials (NACTO), and PeopleForBikes that aims to build equitable and replicable bike share systems (BBP 2015). This grant will be used to, "strengthen and expand [Capital Bikeshare's] network of local community service organizations as ambassadors" and to "create resources including a training curriculum and manual, multi-lingual demonstration video on how to use bike share, new member kits, and an ambassador network that links and supports community partners" (BBP 2015).

Capital Bikeshare recently announced an ambitious plan to add 99 stations over the next three years, for a total of 454 stations (DDOT 2015). By 2018, the Department of Transportation projects that 90 percent of jobs, 65 percent of residents, and 97 percent of all public transit boardings will be within a quarter-mile walk of a bikeshare station (DDOT 2015). These 99 new stations would be concentrated in (1) minority and low-income neighborhoods, (2) high bikeshare demand neighborhoods, and (3) around popular tourist destinations (DDOT 2015).

The District Department of Transportation is also developing new partnerships with community health clinics to enable doctors to "Prescribe-a-Bike" to patients experiencing cardiovascular diseases, obesity, and asthma (K. Lucas, personal communication, June 17, 2015). DDOT's transportation planners are also currently considering allowing Capital Bikeshare membership to be associated with welfare recipients' Electronic Benefit Transfer (EBT) cards to accommodate the "unbanked," the term used to describe those with no formal access to bank accounts or credit cards (K. Lucas, personal communication, June 17, 2015).

It is in this context that the District Department of Transportation (DDOT) asked me to analyze current and predicted bikeshare ridership in traditionally underserved low-income communities. Specifically, I have been asked to use a combination of geospatial and statistical analyses to identify barriers to ridership around a "walkshed, or a ¼ mile "buffer," at each bikeshare station in low-income communities in the District. Given the barriers identified at each station location, I have also been asked to recommend achievable targets for bikeshare use in low-income neighborhoods. This report is to be used in community planning meetings by the District Department of Transportation (DDOT) and their consultants as they expand their 355 station system by an additional 99 stations (D. Buck, personal communication, October 15, 2015).

3 Overcoming Barriers to Bikeshare Use in Low-Income Communities

Capital Bikeshare has great potential to bring benefits to low-income people, from reducing bicycle and motor vehicle ownership costs, to expanding transport options and flexibility. However, a variety of structural, financial, and cultural barriers have combined to discourage people in low-income communities from fully embracing and using these systems.

As illustrated in Table 1, studies suggest that bikeshare programs which address three or more barriers have the potential to increase ridership in low-income areas (Kodransky, M., & Lewenstein, G., 2014):

Table 1: ***POLICIES ADDRESSING BARRIERS TO BIKESHARE USE IN LOW-INCOME COMMUNITIES***

The most promising systems address at least three barriers.

Case Studies		Barriers Addressed				
Program	Location	Siting	Logistical Access	Cost of Service	Unbanked	Outreach
Hubway (*Bike-share*)	Boston, MA	X	X	X		X
Citibike (*Bike-share*)	New York City, NY		X	X	X	
Capital Bikeshare	Washington D.C.	X		X	X	X
Buffalo Carshare	Buffalo, NYC	X		X	X	X
eGo Carshare	Denver, CO	X	X	X		
City Carshare	San Francisco, CA	X	X	X		X
Heritage Community Transport Microbus (*Ride-share*)	Pittsburgh, PA	X	X	X	X	X
King County Vanpool (*Ride-share*)	King County, WA	X	X	X	x	
LA Metro Vanpool (*Ride-share*)	LA County, CA	X		X		X

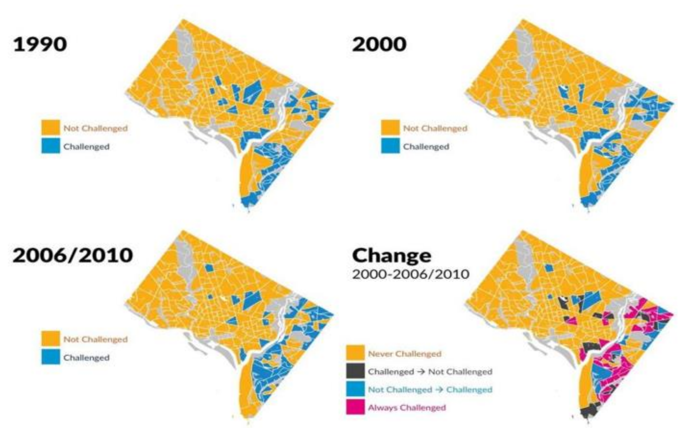
BARRIER 1: CONVENIENT & RELIABLE ACCESS

Capital Bikeshare currently fails to adequately address the transportation needs of the poorest areas of Washington, DC. Poverty has dramatically concentrated east of the Anacostia River into Wards 7 and 8 over the last two decades (Fig. 1, Schwabish & Acs, 2015). Since Capital Bikeshare launched in 2010, these wards have garnered only 38 bikeshare members who have made only 946 trips total from the area's 7 bikeshare stations (Kodransky & Lewenstein, 2014). This is in stark contrast to the 1,317 members in wealthier zip codes of the city who have made 24,271 trips from one station alone, DuPont Circle, as of April 11, 2011 (Kodransky & Lewenstein, 2014). This disparity of use is at least in part due to the fact that, in these low-income areas, Capital Bikeshare stations are clustered around Metro stations but not yet available in the rest of the community to service origin-to-station and station-to-destination first- and last mile trips (Figure 2, Kodransky & Lewenstein 2014).

This paucity of bikeshare stations low-income districts is exacerbated by the fact that, especially during peak hours, some stations are full and can accept no more bike returns, and others are empty with no bikes to rent. Correcting these imbalances requires a sometimes expensive act of "rebalancing" (Fishman 2015). Reliability – knowing that one can pick-up and drop-off a bike -- is key for all commuters, including those with low-incomes (Surface Transportation Policy Project, 2000). Studies have found that fair weather and the presence of nearby restaurants are positively correlation of bike station activity (Faghih-Imani et al., 2014)(Rudloff & Lackner, 2013). Some studies have found that inclement weather has been shown to have a larger impact on casual users than on bikeshare members who regularly use bikes to commute. In contrast, Buehler et al. (2012) and Cervero et al. (2003) did not find a significant relationship between bike commuting and precipitation. Hilly topography, however, has been shown to affect station reliability (Frade & Ribeiro, 2014; Jurdak, 2013). Lastly, bikeshare stations integrated with the surrounding bicycle infrastructure network have been shown to have higher ridership (Faghih-Imani et al., 2014).

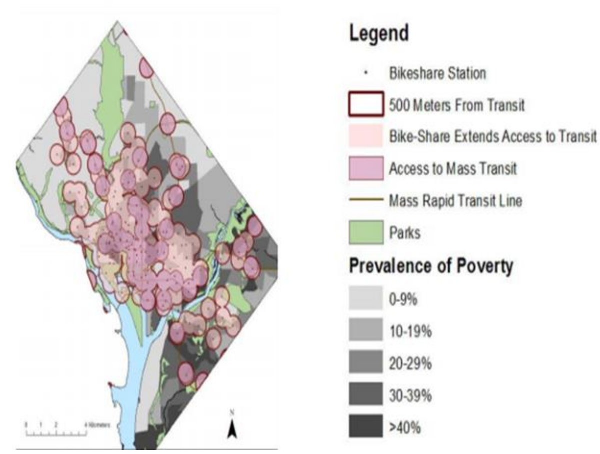
The disparity between wards can be explained in part by the "spatial mismatch" between where low-income people live and where jobs are located at their skill level within a 90-minute commute (Brookings, 2011). This echoes a trend of the decentralization of employment, with over 70 percent of regional jobs located over 3 miles away from central business districts (Glaeser, 2001). Increasingly, many low-income people work during off-peak hours, such as nights and weekends, when transit routes are poorly served (King, 2014). Yet both research and federal transportation funding is largely focused on ensuring access to 9-5 jobs only (Kodransky & Lewenstein, 2014).

Fig. 1: **POVERTY CONCENTRATES OVER TIME**



Schwabish & Acs, Urban Institute, 2015

Fig. 2: **BIKESHARE & TRANSIT ACCESS FOR THE POOR**



Gabriel Lewenstein, ITDP, 2014

Complicating this gap between the rich and poor wards is a political battle. In a recent board report, the Washington Area Metropolitan Transit Authority (WMATA) cited bicycling and Capital Bikeshare's increasing popularity, especially for trips under seven miles, as one of the top five causes of what one former general manager described as a "death-spiral" of financial woes as customer dissatisfaction reaches at an all-time high (WMATA 2015, 2016)(Layton 2004). These reports belie the fact that 54 percent of Capital Bikeshare users reported Metrorail and 21 percent reported Metrobus as being their origin or destination (LDA Consulting, 2013).

Survey results in Washington, DC and elsewhere consistently confirm that convenient and reliable access to bikeshare is a major factor in users' decision to ride. In 2013, approximately half of Capital Bikeshare's 11,100 members were emailed a survey about their bikeshare ridership, with a response rate 34 percent (LDA Consulting 2013). Sixty-nine percent of those respondents said that "getting around more easily, faster and shorter" as "very important" in their motivation for bikeshare use (LDA Consulting 2013). Similarly, Montreal respondents living within 500 meters of a bikeshare station were 3.2 times more likely to have used bikeshare (Bachand-Marleau, Lee, and El-Geneidy, 2012). These findings are consistent with earlier studies of the Capital Bikeshare program, similar surveys of bikeshare users in London, multiple cities in North America, Melbourne and Brisbane (Transport for London,2014) (Shaheen et al., 2013)(Fishman, Washington, Haworth, & Mazzei, 2014).

Surveys of those who choose not to use bikeshare are not commonly done, however one was completed with a small sample size (n = 60) in Brisbane regarding their CityCycle bikeshare program. In focus groups, those surveyed with no known connections to bikeshare said their major barrier was mainly that driving was too convenient and also that docking stations were considered to be too far from respondents' homes (Fishman 2015). This finding is consistent with previous studies that suggest bikeshare members are more likely to live in close proximity to a bikeshare station (Bachand-Marleau et al.,2012)(Goodman & Cheshire, 2014)(Fishman et al.,2014,2015).

RESPONSE 1: BIKESHARE EXPANDS & CHANGES TRAVEL BEHAVIOR

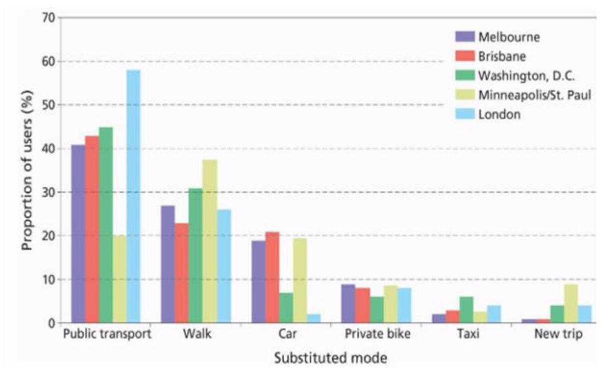
As noted above, Capital Bikeshare recently announced an ambitious expansion plan to add 99 stations over the next three years to increase the total to 454 stations (DDOT 2015). By 2018, the Department of Transportation projects that 90 percent of jobs, 65 percent of residents, and 97 percent of all transit boardings will be within a quarter-mile walk of a bikeshare station (DDOT 2015). These 99 new stations are to be concentrated in (1) minority and low-income neighborhoods, (2) high bikeshare demand neighborhoods, and (3) around popular tourist destinations (DDOT 2015). These stations were sited considering population density, the proximity of bicycle infrastructure, retail job density, and the share of non-single-occupant vehicle commuters, which have all been positively associated with ridership across multiple cities (Rixey 2013)(Buck et al, 2013)(Fishman 2015).

Capital Bikeshare has recently been shown to have a causal effect in reducing traffic congestion by 2 to 3 percent on streets where bikeshare stations are present (Hamilton & Wichman, 2015). Although researchers note that traffic diverts to neighboring roads without bikeshare stations, the results suggest that bikeshare has a traffic calming impact on city streets, which may enhance road safety (Hamilton & Wichman, 2015). Additionally, a multi-city analysis of bikeshare's overall impact on changes to vehicle miles travelled (VMT), shows that bikeshare reduces car use, even after factoring in the distance covered by redistribution and maintenance trucks (Figure 3, Fishman et al., 2014a). Montreal bikeshare users possessing a driver's license had 1.5 times greater odds of using bikeshare (Bachand-Marleau et al., 2012).

A modest mode shift toward active transportation, like biking, was found in a before/after study of the Montreal bikeshare system after it was implemented using a cross-sectional telephone survey of 2,500 individuals by Fuller, Gauvin, Morency, Kestens, and Drouin (2013). On average, 60 percent of bikeshare trips were found to have replaced sedentary modes (Fishman, Washington, and Haworth, 2014b). Similarly, bikeshare members were estimated to gain an additional 74 million minutes of physical activity in London, and 1.4 million minutes of physical activity in Minneapolis/St. Paul, for 2012 (Fishman et al., 2014b).

Despite WMATA operators' aforementioned fear of losing transit ridership to Capital Bikeshare, studies show that bikeshare actually complements rather than competes with the historically under-resourced U.S. public transit systems (Kodransky & Lewenstein, 2014). Six out of seven Capital Bikeshare stations with more than 500 daily trips were found to be close to WMATA Metrorail stations (Erdoğan & Liu, 2015). Furthermore, multivariate statistical analyses suggest that a 10 percent increase of Capital Bikeshare ridership will lead to a 2.8 percent increase in WMATA Metrorail ridership (Erdoğan & Liu, 2015). This suggests that the co-location of shared mobility with conventional transit service may help both systems expand. Shared mobility can help fill in the gaps as well as extend the reach of existing public transit networks (Figure 1, Kodransky & Lewenstein, 2014). A study surveying 10,000 riders in multiple North American cities found bikeshare to open up additional capacity on congested bus and rail lines in the urban core (Shaheen & Martin 2015).

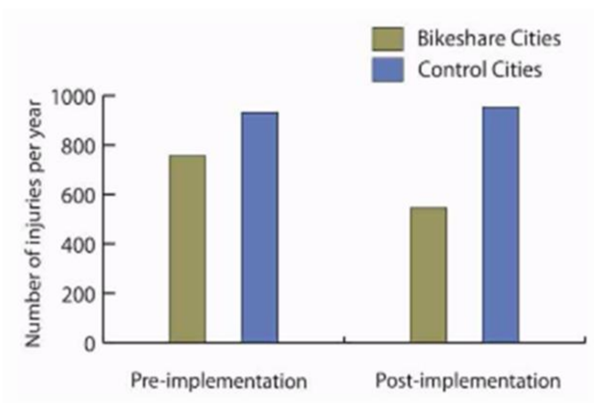
Fig. 3: **BIKESHARE DECREASES CAR USE**



Fishman et al., 2014a

BARRIER 2: PERCEPTIONS OF SAFETY

Fig. 4: **BIKESHARE SAFER THAN BICYCLING**



Fishman 2015

The perception of safety or lack thereof is a major determinant of cycling in studies across the United States, Australia, and the United Kingdom (Gardner,2002)(Horton, Rosen, & Cox, 2007)(Fishman, Washington, & Haworth,2012b). Concerns about riding in traffic also ranked high on a survey of non-bikeshare users in Brisbane, which corroborated previous qualitative research in Brisbane (Fishman et al., 2012a). In a series of focus groups exploring barriers to bicycling in Portland, 100 percent of the African-American participants expressed a fear that drivers would be hostile to them while they were cycling; no Hispanic or African immigrant participants expressed that fear (Community Cycling Center, 2012).

Washington, DC's bikeshare membership is lowest in Wards 7 and 8 which are home to nearly half of the most dangerous intersections in the city, have the highest concentrations of poverty, and are 96 percent and 94 percent African-American, respectively (DC Trust, 2011)(Kodransky & Lewenstein, 2014)(Hughes 2015). Additionally, 2015 saw a 20 percent uptick in the homicide rate, with a sharp increase in Ward 8 which doubled its homicide rate from 2013 to 2015 (Azar 2015). Multivariate statistical models estimated in the following sections explore how these increases in crime and traffic crash rates correlate to bikeshare ridership in low-income areas.

RESPONSE 2: BIKESHARE AMONG THE SAFEST FORMS OF CYCLING

Studies show that, in order to feel safe, those who have not used bikeshare are considerably more sensitive to a lack of bike street infrastructure than those who are bikeshare members. Specifically, 60 percent of non-BSP members said they felt "very unsafe," compared to about 40 percent for bikeshare members (Fishman et al., 2015). Additionally, despite early concerns regarding the safety of bikeshare users, no one has died to date due to a bikeshare ride, with over 23 million bikeshare rides tallied since the first system launched in the United States in 2007 (Goldberg, 2014). Bikeshare has had a better safety record than bicycling generally, and bikeshare members fell they received more considerate treatment from motorists than when on their private bicycles (Fishman & Schepers, 2014)(Figure 4, Fishman 2015). One study found a dramatic reduction in the total number of hospital-recorded injuries in the bikeshare cities, post implementation, compared to a slight increase in control cities (Graves et al., 2014).

This auspicious safety record is in part due to the weight of the bikes, their low center of gravity, wide tires, drum brakes that keep the braking system dry even in inclement weather, the visibility of the bikeshare bike and cyclist, and the generally slow speeds of the bicycles (Tucker et al., 2014) (Walker, Garrard, & Jowitt, 2014). After Capital Bikeshare was introduced in 2010, bicycle use, as a mode share, rose at over twice national rate from 2010 to 2012 (up 32% versus 15%) (Buck 2014). As Capital Bikeshare expanded, the number of car-free households in Washington, DC grew by 14.3 percent, from 35 percent to 37.9 percent, some by choice and others by economic circumstance (Chung 2014). By contrast, the District added only 1,662 car-owning households between 2010 and 2014, an increase of just 1.0 percent (Chung 2014). The safety in numbers phenomenon, in which a rise in the amount of cycling does not lead to a proportional rise in the number of injuries, may explain the increased traffic safety for Washington, DC's growing alternative commuter population (Elvik, 2009).

4 Addressing Financial Barriers in Low-Income Communities

BARRIER 3: LIMITED FINANCIAL MEANS

As a whole, bikeshare members tend to have higher average incomes than the general population (Fishman et al., 2015; Lewis, 2011; Woodcock, Tainio, Cheshire, O'Brien, &Goodman, 2014). They also have been shown to be highly educated (e.g. Fishman et al., 2014; LDA Consulting, 2013; Shaheen et al., 2013). Lastly, bikeshare members tend to be employed with full-time or part-time work (Woodcocket al.,2014). In keeping with these trends, a 2013 Member Survey of Capital Bikeshare in Washington, DC showed that 80 percent of members were white, 80 percent had an income of $50K or more, and 95 percent had at least a 4-year college education (DDOT 2015).

Capital Bikeshare users are more likely to have lower mean household incomes than regular cyclists ($81,920 compared to $93,180) (Buck et al, 2013). This places both bikeshare users and general bicyclists in income brackets above the general population in the Washington, D.C. ($64 267) (United States Census Bureau, 2013). It is, however, possible that a response bias (where higher income bikeshare members are more likely to respond to surveys) contributes to this difference (Buck et al, 2013).

Despite their relatively high average incomes, bikeshare members tend to be price adverse. For example, an increase in usage fees in January 2013 resulted in a reduction in casual ridership in low-income areas of London. For low-income members of Capital Bikeshare in Washington, DC, over 70 percent of respondents note that saving money on transport is an important motivation to become a bikeshare member (LDA Consulting, 2013).

Cities who have offered low-income residents subsidized bikeshare memberships with no other inducements have generally been ineffective at closing the bikeshare usage income gap. Out of 400,000 residents in the New York City Housing Authority (NYCHA), including over 15,000 residents that live within the Bikeshare system's catchment area in the Lower East Side, only 285 NYCHA housing residents became system subscribers (Kodransky, M., & Lewenstein, G., 2014). Denver Housing Authority residents were offered a discounted $15 membership for B-Cycle bike-share. Still, community members claimed that membership costs remained too expensive (Kodransky, M., & Lewenstein, G., 2014). When a local organization donated 100 B-Cycle memberships to Denver Housing Authority residents, only 32 people signed up and only 23 of those used the bikes more than once (Kodransky, M., & Lewenstein, G., 2014).

RESPONSE 3: EXPANDING FINANCIAL ACCESS

Outside of the U.S., some cities have seen a rise in low-income bikeshare membership. London, for example, began with disproportionately wealthy members in 2010 (Goodman and Cheshire, 2014). Once the program expanded, however, the proportion of low-income users increased from 6 to 12 percent between 2010 and 2013 (Goodman and Cheshire, 2014). Another study of London showed that bikeshare members who were residents of poorer areas had higher trip rates than members of more affluent suburbs (Ogilvie & Goodman, 2012). These results suggest that the Capital Bikeshare expansion plan of 99 new stations could see a corresponding rise in low-income users.

Since 2012, the District Department of Transportation (DDOT) has partnered with the nonprofit "Back on my Feet" to extend reduced fares to the unemployed and homeless who are enrolled with at least 90 percent attendance in job training seminars, educational sessions and weekly group runs (Corbin, 2016). DDOT is also developing new partnerships with community health clinics, to enable doctors to "Prescribe-a-Bike" to patients experiencing cardiovascular diseases, obesity, and asthma following Boston Medical Center's successful program (K. Lucas, personal communication, June 17, 2015). DDOT's transportation planners are also currently considering allowing Capital Bikeshare membership to be associated with welfare recipients' Electronic Benefit Transfer (EBT) cards to accommodate the unbanked (K. Lucas, personal communication, June 17, 2015). This would complement current programs, which allow Arlington residents to pay in cash at Metro Commuter Stores, verified by government rosters as low-income. It would also bolster the DDOT's current "Bank on DC" program to offer individuals without a bank account discounted bikeshare memberships to those who open a free Credit Union account and also to low-income individuals who attend a "National Night Out" crime prevention event with the Metropolitan Police Department (MPD)(K. Lucas, personal communication, June 17, 2015).

Boulder and Denver, Colorado have worked with their local housing authority to offer reduced-rate or free memberships when new tenants sign a lease on an apartment near a bike sharing station (Kodransky, M., & Lewenstein, G., 2014).

5 Examining Cultural Barriers in Low-Income Communities

BARRIER 4: INCLUDING A DIVERSITY OF AGE GROUPS AND ETHNICITIES

Research shows Capital Bikeshare members are more likely to be female, younger, and own fewer cars and bicycles (Buck 2013). Research shows that if Capital Bikeshare captured a diversity of age groups, it would improve public health. In a London study, for example, the greatest health benefits were projected to be from an increase in middle-aged and older people using bikeshare (Woodcock et al., 2014). More benefit would be gained if users were older, Woodcock's study argued, as older people have fewer healthy life years to lose (2014). Conversely, when a young person crashes, they have many more healthy life years at risk (Woodcock et al., 2014).

A complex subscription process was highlighted by 54 percent of short-term local subscribers as the main area requiring improvement, many of whom noted they would not return as CityCycle users (Roy Morgan Research, 2013). Users and would-be users value bikeshare's spontaneity and policies should seek to minimize hurdles associated with becoming bikeshare users (Fishman et al., 2012a). These informational hurdles must be addressed in order to expand bikeshare access to older age groups, people of lower-incomes and limited language skills.

Actual usage of bike-share, car-share, and ride-share systems alike by low-income individuals has been minimal (Berman, 2013; DDOT, 2007; Golub, 2007; Fuller et al., 2011). The for-profit operators do not have stated goals of high usage by low-income individuals per se. For example, in the first seven months of London bikeshare's operation (July 2010 to February 2011), bikeshare use was even more male-dominated than cycling in London in general, with 82 percent of trips made by men (Ogilvie and Goodman, 2012). Bikeshare compounded the general tendency for London's cyclists to be drawn from more affluent households or neighborhoods (Goodman, 2013 and Steinbach et al., 2011).

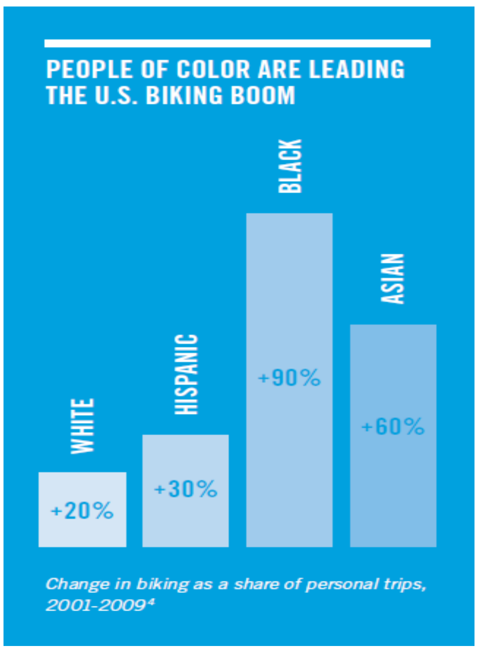
Only 3 percent of Capital Bikeshare members are African-American, compared to 8 percent for general bicycle riders in the D.C. area (Buck et al., 2013), despite African-Americans making up some 50 percent of the Washington, D.C. population (United States Census Bureau, 2013). Eighty-eight percent of respondents to a Transport for London identified as being white (Transport for London, 2014), compared to 55 percent for the general London population (Office of National Statistics, 2014).

RESPONSE 4: INCLUDING THE NEXT GENERATION

Bikeshare users may indirectly encourage cycling as a normal, everyday activity because they are much less likely than personal bicycle users to wear helmets or cycling clothes (Fischer et al., 2012, Fishman et al., 2013 and Goodman et al., 2014). A survey of casual bikeshare users in Washington, D.C. found that 75 percent were traveling in groups of two or more, and that 60 percent did not identify themselves as "cyclists" (Buehler et al., 2012).

Bikeshare has been shown to increase public health. In London, men's major benefit was estimated to come from reductions in ischemic heart disease, whereas women have been found to be more likely to benefit from reductions in depression (Woodcock et al., 2014). Woodcock et al. proved these benefits using trip data to model the health impacts of the bikeshare via comparison to a scenario in which bikeshare did not exist.

Figure 5: "The New Majority"



Source: National Household Travel Survey, 2009.

Bicycling as a whole, however, is becoming more diverse. Between 2001 and 2009, cycling rates rose fastest among African Americans (by 100%), Hispanics (by 50%), and Asian Americans (by 80%). Those three groups also account for a growing share of all bike trips, rising from 16 percent in 2001 to 21 percent in 2009 (Pucher 2011)(League of American Bicyclists 2013). Data from the U.S. Census Bureau indicate that these growth trends have continued, particularly among those with low household incomes and those who self-identify as Hispanic, Some Other Race, or Two or More Races (McKenzie 2014). This increasing diversity in bicycling demographics has been referred to by some as the "New Majority" (League of American Bicyclists 2013; Taylor 2013; Lugo et al. 2014). This is bolstered by the growing trend in the United States that values access over ownership (Earley, 2014). Owning a car may be no longer viewed as a critic al need by many city dwellers who prefer paying for and using vehicles only when needed (Earley, 2014). Combined, these trends suggest that there is potential to attract a great diversity of ethnic groups to bikeshare.

Similarly, children from low-income and minority households, particularly African-Americans and Hispanics, are more likely to bike or walk to school than whites or higher-income students (McDonald 2008). Velib, the bikeshare operator in Paris, has piloted a special bikeshare for children in France with success called P'tit Vélib. The P'tit Vélib program was in response to a study indicating half of Parisian children learn to cycle outside of the city and also to a January 2012 City Hall survey which found that 86 percent of Parisian families were interested in a children's cycle hire service (Coldwell 2014).

In countries with low levels of general cycling, such as the UK, the USA and Australia, between 65 percent and 90 percent of cycling trips are by men (Pucher & Buehler, 2012). Less than 20 percent of trips by registered users of the London bikeshare are by women (Goodman & Cheshire, 2014), though this proportion rises slightly when looking at casual users. With strong levels of general cycling such as the Netherlands, however, women cycle more than men (Harms, Bertolini, & Brommelstroet, 2013). Female participation rises substantially for trips that start or finish in a park (Goodman & Cheshire, 2014). Women have a stronger preference for traffic free bicycle riding in general (Johnson, Charlton, & Oxley, 2010). Women account for 23 to 40 percent of annual members in Melbourne and Brisbane, respectively, but it is not clear what accounts for the discrepancy between the two (Fishman et al., 2014).

Proportion of female CityCycle members is greater than for private bike riding in Australia (Pucher, Greaves, & Garrard, 2010). Similarly, Dublin's bike-share gender split is 22 percent female (Murphy & Usher, 2015). In intercept surveys of short-term Capital Bikeshare users, the gender split was even (Buck et al., 2013). In annual member survey of the same program, 55 percent of respondents were male, which is broadly in line with the intercept survey results (Buck et al., 2013).

6 Next Steps Forward

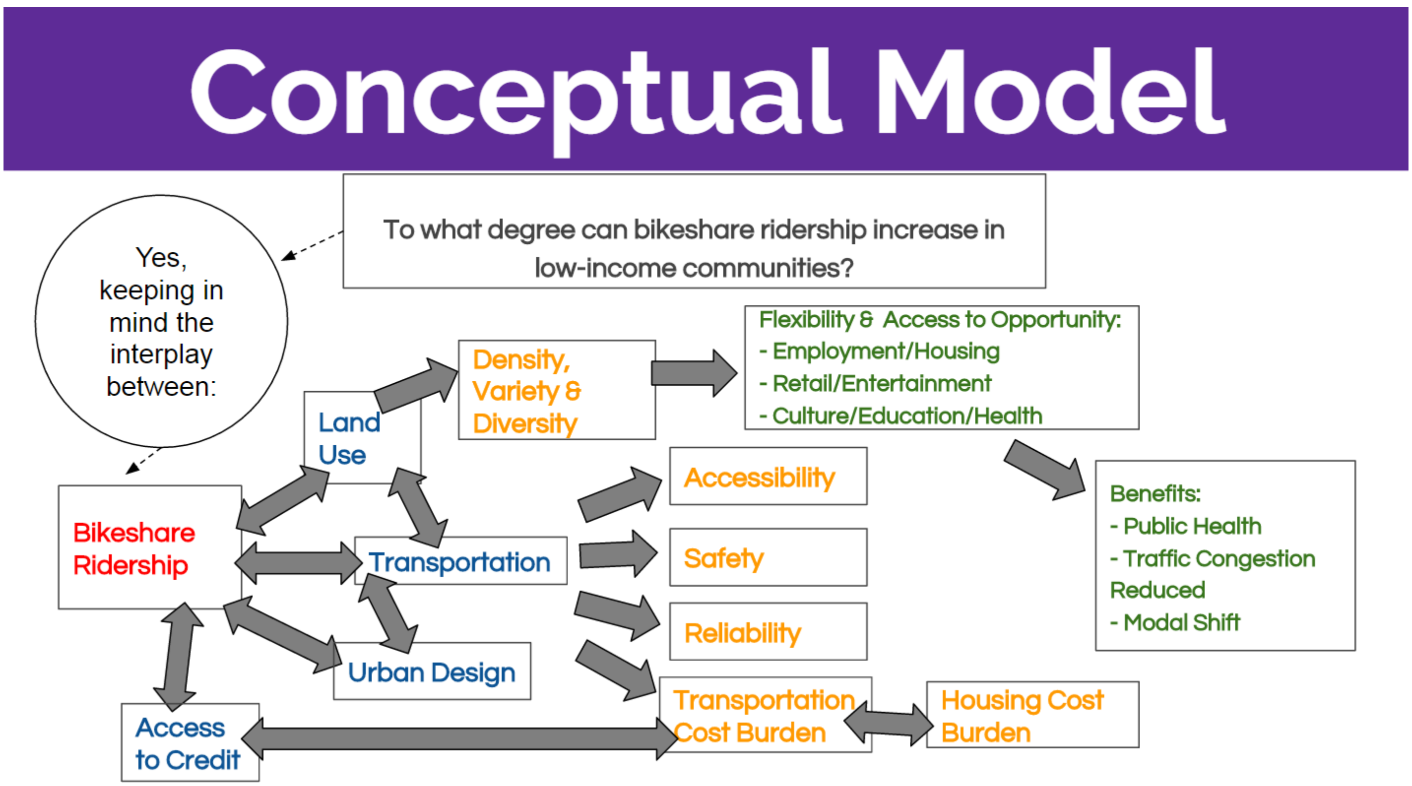
This review has examined bikeshare research from around the world to explore how bikeshare ridership varies depending on the degree of: (1) structural barriers, such as accessibility and safety, (2) financial barriers, and (3) cultural barriers, such as age, ethnicity, gender, and shifting attitudes. While significant progress has been made in addressing these challenges, there remains a paucity of research on the behavior, preferences, challenges, and attitudes of low-income individuals in relation to bikeshare. The data and analysis section below will examine the salient factors to increasing bikeshare ridership in Washington, DC using a combination of statistical and geospatial analyses. The concluding recommendation section will suggest concrete policies and programs the District Department of Transportation (DDOT) can implement to encourage bikeshare use in advance of the upcoming addition of 99 new stations, which will be primarily placed in low-income communities where bikeshare ridership is lowest.

7 Research Design and Data

CONCEPTUAL MODEL

Figure 6 below illustrates the conceptual framework that connects the independent predictor variables with the dependent variable of bikeshare ridership further described in Table 2 below. Each step in the model is based on my literature review of issues related to convenient and reliable access, perceptions of safety, financial burdens and socioeconomic diversity in low-income communities where bikeshare operates.

Figure 6: Conceptual Framework



UNIT OF ANALYSIS

The units of analysis are the bikeshare stations in the Washington, DC area (202 stations out of a total of 355 stations in the region). Each station is treated as an individual observation by analyzing the respective trips that flow into and out of selected bikeshare stations over the course of a year. The dependent variable is the number of trips at each Capital Bikeshare stations. Ridership data were limited to stations with at least 30 trips annually to satisfy the Central Limit Theorem. In this way, the error for the estimated mean of the data for each bikeshare station will approach a normal distribution and the results will be generalizable to other bikeshare stations within the system.

Most of the independent variables, detailed below in Table 2, were collected at the smallest unit of analysis they are readily available, which is the census block group. In total, I analyzed and ranked 84 independent variables from a variety of sources to determine their correlation to bikeshare ridership for the year 2014.

DATA DEFINITIONS, SOURCES AND THRESHOLDS

The following 84 independent variables and one dependent variable were aggregated and assembled from a variety of federal, state and local sources enumerated below in Table 2. Each variable was then categorized by type and by what barrier to bikeshare ridership it addressed, following my literature review from Chapters 3 through 5. Each data set was aggregated first at the census block group or neighborhood cluster level. When possible, I ascertained the methodology, collection year and creator of the datasets I collected by reading the metadata catalogues provided with each file. I also spoke with the curators of large datasets, including Foursquare's Capital Bikeshare Ridership data and the EPA's Smart Location Database, in order to determine the best way to export and assemble this data for analysis, as detailed the following chapters.

Table 2: Data Definitions and Sources

CATEGORY	DESCRIPTION	SOURCE	CODE NAME	BARRIER ADDRESSED
Land Use	Gross residential density (housing units/acre)	EPA Smart Location Database	Avg_D1A	Barrier #1: Convenience and Reliability
Land Use	Gross population density (people/acre)	EPA Smart Location Database	Avg_D1B	Barrier #1: Convenience and Reliability
Land Use	Gross employment density (jobs/acre)	EPA Smart Location Database	Avg_D1C	Barrier #1: Convenience and Reliability
Land Use	Gross retail employment density (jobs/acre)	EPA Smart Location Database	Avg_D1C5_R	Barrier #1: Convenience and Reliability
Land Use	Gross office employment density (jobs/acre)	EPA Smart Location Database	Avg_D1C5_O	Barrier #1: Convenience and Reliability
Land Use	Gross industrial employment density (jobs/acre)	EPA Smart Location Database	Avg_D1C5_I	Barrier #1: Convenience and Reliability
Land Use	Gross service employment density (jobs/acre)	EPA Smart Location Database	Avg_D1C5_S	Barrier #1: Convenience and Reliability
Land Use	Gross entertainment employment density (jobs/acre)	EPA Smart Location Database	Avg_D1C5_E	Barrier #1: Convenience and Reliability
Land Use	Gross activity density (employment + housing units)	EPA Smart Location Database	Avg_D1D	Barrier #1: Convenience and Reliability

Land Use	Employment entropy* (denominator set to observed employment types in the census block group)	EPA Smart Location Database	Avg_D2B_E5	Barrier #1: Convenience and Reliability
Land Use	Employment and household entropy*	EPA Smart Location Database	Avg_D2A_EP	Barrier #1: Convenience and Reliability
Connectivity	Total road network density	EPA Smart Location Database	Avg_D3a	Barrier #1: Convenience and Reliability
Connectivity	Network density in terms of facility miles of auto-oriented links per square mile	EPA Smart Location Database	Avg_D3aao	Barrier #1: Convenience and Reliability
Connectivity	Network density in terms of facility miles of multi-modal links per square mile	EPA Smart Location Database	Avg_D3amm	Barrier #1: Convenience and Reliability
Connectivity	Network density in terms of facility miles of pedestrian-oriented links per square mile	EPA Smart Location Database	Avg_D3apo	Barrier #1: Convenience and Reliability
Connectivity	Street intersection density (weighted, auto- oriented intersections eliminated)	EPA Smart Location Database	Avg_D3b	Barrier #1: Convenience and Reliability
Connectivity	Intersection density in terms of auto-oriented intersections per square mile	EPA Smart Location Database	Avg_D3bao	Barrier #1: Convenience and Reliability
Connectivity	Intersection density in terms of multi-modal intersections having three legs per square mile	EPA Smart Location Database	Avg_D3bmm 3	Barrier #1: Convenience and Reliability
Connectivity	Intersection density in terms of multi-modal intersections having four or more legs per square mile	EPA Smart Location Database	Avg_D3bmm 4	Barrier #1: Convenience and Reliability
Connectivity	Intersection density in terms of pedestrian- oriented intersections having three legs per square mile	EPA Smart Location Database	Avg_D3bpo3	Barrier #1: Convenience and Reliability
Connectivity	Station Network Effects	EPA Smart	StnNetworkEf	Barrier #1:

	(Low, Medium, High number of stations within 1/4-mile of station)	Location Database	fects	Convenience and Reliability
Connectivity	Intersection density in terms of pedestrian- oriented intersections having four or more legs per square mile	EPA Smart Location Database	Avg_D3bpo4	Barrier #1: Convenience and Reliability
Mode (Transit)	Average Daily Boardings, WMATA Metrobus (80th percentile)	WMATA	ADB_80pcl	Barrier #1: Convenience and Reliability
Mode (Transit)	Distance from population weighted centroid to nearest transit stop (meters)	EPA Smart Location Database	Avg_D4a	Barrier #1: Convenience and Reliability
Mode (Transit)	Proportion of employment within 1/4 mile of fixed-guideway transit stop	EPA Smart Location Database	Avg_D4b025	Barrier #1: Convenience and Reliability
Mode (Transit)	Proportion of employment within 1/2 mile of fixed-guideway transit stop	EPA Smart Location Database	Avg_D4b050	Barrier #1: Convenience and Reliability
Mode (Transit)	Aggregate frequency of transit within 0.25 miles of block group boundary per hour during evening peak period	EPA Smart Location Database	Avg_D4c	Barrier #1: Convenience and Reliability
Mode (Transit)	Aggregate frequency of transit service (D4c) per square mile	EPA Smart Location Database	Avg_D4d	Barrier #1: Convenience and Reliability
Mode (Transit)	WMATA Metrorail Stations	DC GIS (OCTO)	RailStn	Barrier #1: Convenience and Reliability
Mode (Carsharing)	Carsharing Locations	DC GIS (OCTO)	CarSharing	Barrier #1: Convenience and Reliability
Mode (Bicycling)	Bicycle Lanes	EPA Smart Location Database	BikeLanes	Barrier #1: Convenience and Reliability
Mode (Driving)	Zero Car Households (2010 average)	EPA Smart Location Database	Avg_AUTOOW	Barrier #1: Convenience and Reliability
Mode (Driving)	One Car Households (2010 average)	DC GIS (OCTO)	Avg_AUTO_1	Barrier #1: Convenience and

				Reliability
Destinations	Points of Interest - Health (Childcare, Pharmacy, Primary Care, Hospitals, Recreational Facility)	DC GIS (OCTO)	Health_Cou	Barrier #1: Convenience and Reliability
Destinations	Points of Interest - Culture (Public Art, Museums, Arts Nonprofits, Memorials)	DC GIS (OCTO)	Culture_Co	Barrier #1: Convenience and Reliability
Destinations	Points of Interest - Food (Grocery Store, Sidewalk Vendor)	DC GIS (OCTO)	Food	Barrier #1: Convenience and Reliability
Destinations	Points of Interest - Education (College, Vocational School, Human Services)	DC GIS (OCTO)	Edu_Count	Barrier #1: Convenience and Reliability
Destinations	Points of Interest - Total of Health, Culture, Food and Education related Points of Interest)	DC GIS (OCTO)	Fac_Count	Barrier #1: Convenience and Reliability
Tree Canopy Cover	Street Trees	DC GIS (OCTO)	Trees	Barrier #1: Convenience and Reliability
Traffic	Average Annual Daily Traffic Volume (AADT) (2010 estimate, in thousands)**	DC GIS (OCTO)	Traffic_Vol10	Barrier #2: Perception of Safety
Topography	Elevation Change	Foursquare ITP	Avg_Elev_C	Barrier #2: Perception of Safety
Crime	Violent Crime total for 2014	DC GIS (OCTO)	V_Crime_To	Barrier #2: Perception of Safety
Crime	Homicides in 2014	DC GIS (OCTO)	Homicides	Barrier #2: Perception of Safety
Crime	Assault in 2014	DC GIS (OCTO)	Assault	Barrier #2: Perception of Safety
Crime	Robbery in 2014	DC GIS (OCTO)	Robbery	Barrier #2: Perception of Safety
Crime	Sexual Abuse in 2014	DC GIS (OCTO)	SexualAbuse	Barrier #2: Perception of Safety
Crashes	Collision Rate for Pedestrians (2014)	DC GIS (OCTO)	PedCrash	Barrier #2: Perception of Safety
Crashes	Collision Rate for Bicyclists (2014)	DC GIS (OCTO)	BikeCrash	Barrier #2: Perception of Safety

Lighting	Street Lighting (total)	DC GIS (OCTO)	AllStreetLighting	Barrier #2: Perception of Safety
Lighting	Pedestrian Lighting (16' and below in height)	DC GIS (OCTO)	PedLighting	Barrier #2: Perception of Safety
Income	Low-Wage Job Sites (incomes $1250/month or less)	EPA Smart Location Database	Avg_E_LOWW	Barrier #3: Affordability
Income	Medium-Wage Job Sites (incomes $1250/month or more)	EPA Smart Location Database	Avg_E_MEDW	Barrier #3: Affordability
Income	Unemployment rate (%)	ACS 2007-2011 Four-Year Estimate	Avg_PctUne	Barrier #3: Affordability
Income	Poverty rate	ACS 2007-2011 Four-Year Estimate	Avg_PERC_Poverty	Barrier #3: Affordability
Income	Poverty dummy variable	ACS 2007-2011 Four-Year Estimate	Pov_Dummy	Barrier #3: Affordability
Unbanked	Alternative Financial Services	DC GIS (OCTO)	CheckCash	Barrier #3: Affordability
EBT	Persons receiving food stamps, 2014	DC Department of Human Services	Avg_fs_cli	Barrier #3: Affordability
EBT	Persons receiving TANF, 2014	DC Department of Human Services	Avg_tanf_c	Barrier #3: Affordability
Housing	Occupied housing units, 2010	Census (2010)	Avg_NumOcc	Barrier #3: Affordability
Housing	% same house 5 years ago, 2000	Census (2000)	Avg_PctSam	Barrier #3: Affordability
Housing	Rental vacancy rate (%), 2007-11	ACS 2007-2011 Four-Year Estimate	Avg_PctVac	Barrier #3: Affordability
Housing	Homeownership rate (%), 2007-11	ACS 2007-2011 Four-	Avg_PctOwn	Barrier #3: Affordability

		Year Estimate		
Housing	Number of home sales, 2012	DC Office of Tax and Revenue (OTR)	Avg_sales_	Barrier #3: Affordability
Housing	Predatory Lending Rate (% subprime loans, 2006)	Federal Financial Institutions Examination Council, Home Mortgage Disclosure Act (HMDA)	Avg_PctSub	Barrier #3: Affordability
Housing	Median sales price, 2012	DC Office of Tax and Revenue (OTR)	Avg_Med_Sa	Barrier #3: Affordability
Housing	% annual change median home price, 2002-2012	DC Office of Tax and Revenue (OTR)	Avg_PctAnn	Barrier #3: Affordability
Education	Persons without a high school diploma (%)	ACS 2007-2011 Four-Year Estimate	Avg_Pct25a	Barrier #4: Diversity
Race	% African-American	ACS 2007-2011 Four-Year Estimate	Avg_PctBla	Barrier #4: Diversity
Race	% White residents	ACS 2007-2011 Four-Year Estimate	Avg_PctWhi	Barrier #4: Diversity
Race	% Hispanic residents	ACS 2007-2011 Four-Year Estimate	Avg_PctHis	Barrier #4: Diversity
Race	% Asian residents	ACS 2007-2011 Four-Year	Avg_PctAsi	Barrier #4: Diversity

		Estimate		
Gender	% Female-headed households	ACS 2007-2011 Four-Year Estimate	Avg_PctFam	Barrier #4: Diversity
Bikeshare Ridership	Total bikeshare trips made to/from each station (2014)	Foursquare ITP	TotalTrips	Dependent Variable (Ridership)

** Note: Average Annual Daily Traffic Volume (AADT) estimates were not available for all street segments in the study area. Specifically, out of a possible 15,961 records, there were only 979 AADT records for 2014, 1,199 AADT records in 2013, 1,289 AADT records for 2012, 1,206 AADT records for 2011 and 1,722 AADT records for 2010.
* Note: Employment and Household Entropy calculations are based on employment and occupied housing, illustrated in Equation 1 below.

Equation 1: Entropy of Households and Employment

D2a_EP = -**A**/(ln(**N**))

Where:
A = (**HH**/**TotAct**)*ln(**HH**/**TotAct**) + (**E5_Ret10**/ **TotAct**)*ln(**E5_Ret10**/ **TotAct**) + (**E5_Off10**/ **TotAct**)*ln(**E5_Off10**/ **TotAct**) + (**E5_Ind10**/ **TotAct**)*ln(**E5_Ind10**/ **TotAct**) + (**E5_Svc10**/ **TotAct**)*ln(**E5_Svc10**/ **TotAct**) + (**E5_Ent10**/ **TotAct**)*ln(**E5_Ent10**/ **TotAct**)

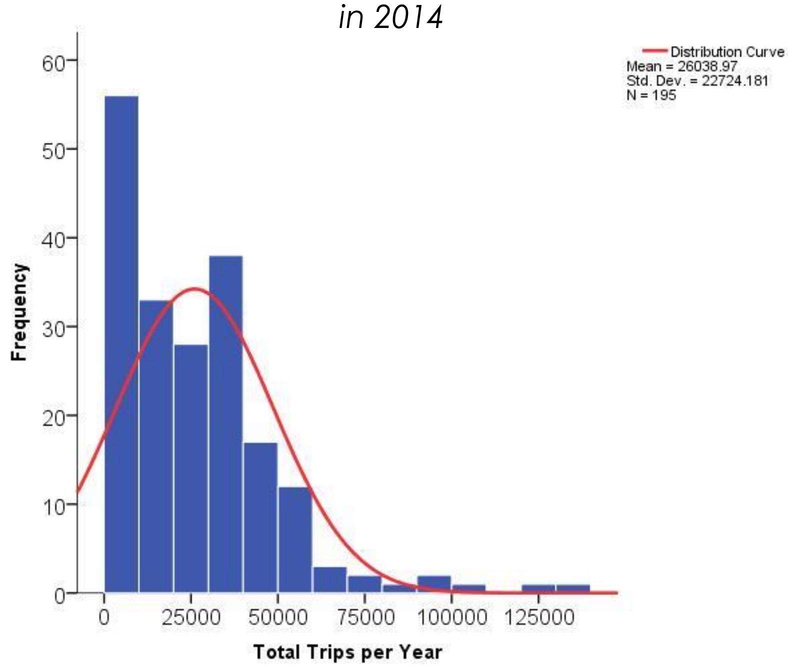
If:
N = number of activity categories (employment or households) with count > 0.
HH = Households (occupied housing units), 2010
TotEmp = Total employment, 2010
TotAct = TotEmp + HH
E5_Ret10 = Retail jobs within a 5-tier employment classification scheme (LEHD: CNS07)
E5_Off10 = Office jobs within a 5-tier employment classification scheme (LEHD: CNS09 + CNS10 + CNS11 + CNS13 + CNS20
E5_Ind10 = Industrial jobs within a 5-tier employment classification scheme (LEHD: CNS01 + CNS02 + CNS03 + CNS04 + CNS05 + CNS06 + CNS08)
E5_Svc10 = Service jobs within a 5-tier employment classification scheme (LEHD: CNS12 + CNS14 + CNS15 + CNS16 + CNS19)
E5_Ent10 = Entertainment jobs within a 5-tier employment classification scheme (LEHD: CNS17 + CNS18)

Source: United States Environmental Protection Agency (EPA), Smart Location Database, 2014

DEPENDENT VARIABLE: BIKESHARE RIDERSHIP

First, I examined a raw bikeshare trip dataset of over 2.8 million trips recorded for the year 2014 in Microsoft Access kindly given to me by the District Department of Transportation (DDOT)'s consultant, Foursquare Integrated Transportation Planning (Foursquare ITP). Then, I compared this raw dataset to a cleansed dataset where outliers in the system trip activity relative to the project scope were removed. The first set of outliers in the raw dataset, removed by Foursquare ITP, were all the trips that started and ended at the same bikeshare station with a trip duration of less than two minutes. These excluded trips likely represented a person who decided against a trip or saw a malfunction in the bicycle, and thus did not complete a full bikeshare trip. The second set of outliers, removed by myself, were trips made outside of the District Department of Transportation (DDOT)'s jurisdiction. The third set of outliers, also removed by myself, were stations with insufficient start or end trip data. In this way, the error of the estimated mean should approach a normal distribution for each station examined. To provide a standard of comparison between Capital Bikeshare stations, the number of trips per bikeshare station was normalized by the number of days the bikeshare station was in operation over the timeframe. Previous studies have shown that at least two weeks are needed to avoid extreme fluctuations in average trip usage per day (Proulx 2014).

Figure 7: Frequency Distribution of Capital Bikeshare Trips in 2014



Lastly, all the trips going from and to each bikeshare station in 2014, also known as O-D, or origin-destination data, were added together in order to produce the total trips per station. Overall, I examined approximately 2.8 million bikeshare trips taken in 2014 across 195 bikeshare stations managed by the District Department of Transportation (DDOT).

Table 3: Descriptive Statistics for Bikeshare Ridership (2014 Total)

Dependent Variable	Mean	Variance	Skewness	Std. Error
Total Ridership (2014)	26,272	516,409,309	1.647	0.175

As illustrated by Figure 7, annual bikeshare trips are positively skewed around the mean. This asymmetric distribution is confirmed by Table 3, which shows the absolute value of the skewness statistic, 1.647, which is greater than twice the value of the Standard Error of .175 (Field 2013). Figure 7 shows that over half the bikeshare stations had fewer than 10,000 annual trips in 2014, while nearly 40% of the distribution had between 30,000 and 40,000 trips that year. However, due to the large sample size of 195 stations, it can be assumed that the lack of normality in the trip distribution will not affect the analysis and therefore no data transformation was perfomed (Field 2013).

DESCRIPTIVE STATISTICS

Table 4, below, illustrates the descriptive statistics of each independent and dependent variable defined in Table 2. Each dependent variable categorizes trip attractors, trip generators and transportation network factors hypothesized to affect bikeshare ridership within each station's quarter-mile catchment area (Figure 8).

Table 4: Descriptive Statistics for Bikeshare Station Catchment Areas

Category	Description	Mean	SD	Min.	Max.
Bikeshare Ridership	Total Ridership (Dependent Variable)(2014)	26,272.20	22,724.64	78	134,006
Connect-ivity	Intersection density in terms of auto-oriented intersections per square mile	5.32	6.74	0.00	31.00
	Intersection density in terms of multi-modal intersections having four or more legs per square mile	27.45	15.61	0.90	75.38
	Intersection density in terms of multi-modal intersections having three legs per square mile	21.99	12.66	3.58	60.48
	Intersection density in terms of pedestrian-oriented intersections having four or more legs per square mile	48.01	20.21	10.34	114.97
	Intersection density in terms of pedestrian-oriented intersections having three legs per square mile	74.02	34.43	16.96	199.50
	Network density in terms of facility miles of auto-oriented links per square mile	2.37	2.98	0.00	13.37
	Network density in terms of facility miles of multi-modal links per square mile	5.80	2.50	1.09	12.60
	Network density in terms of facility miles of pedestrian-oriented links per square mile	19.78	3.30	11.43	27.38
	Station Network Effect	1.81	1.13	0.00	6.00
Connect-ivity	Street intersection density (weighted, auto- oriented intersections eliminated)	139.50	37.03	58.39	251.31
	Total road network density	27.95	5.11	15.13	41.16

Category	Description	Mean	SD	Min.	Max.
Crashes	Collision Rate for Bicyclists (2014)	2.34	2.71	0.00	14.00
	Collision Rate for Pedestrians (2014)	3.10	3.12	0.00	18.00
Crime	Assault (2014)	6.67	6.57	0.00	48.00
	Homicides (2014)	0.27	0.57	0.00	3.00
	Robbery (2014)	12.96	11.79	0.00	54.00
	Sexual Abuse (2014)	0.92	1.25	0.00	5.00
	Violent Crime (total, 2014)	20.81	18.07	0.00	104.00
Destinations	Points of Interest – Culture	6.16	6.27	0.00	29.00
	Points of Interest – Education	0.16	0.40	0.00	2.00
	Points of Interest – Food	3.97	7.06	0.00	34.00
	Points of Interest – Health	2.66	3.27	0.00	33.00
	Points of Interest – Total	22.11	22.32	0.00	96.00
EBT	Persons receiving food stamps, 2014	3,151.50	2,890.10	0.00	19,127
	Persons receiving TANF, 2014	898.40	921.76	0.00	7,691.00
Education	Persons without a high school diploma (%)(2012 ACS five-year estimate)	11.24	6.40	0.00	24.50
Gender	% Female-headed households (2012 ACS five-year estimate)	39.12	23.39	0.00	84.00
Housing	% annual change median price, 2002-2012	4.36	1.79	1.10	11.00
	% same house 5 years ago, 2000	44.06	12.79	0.00	72.00
	% subprime loans, 2006	6.38	6.46	0.00	24.00
	Homeownership rate (%), 2007-11	40.05	12.80	0.00	78.00
	Median sales price, 2012	685,155	265,533	187,000	1,210,000
	Number of home sales, 2012	90.31	92.83	0.00	337.00
	Occupied housing units, 2010	8,660.33	3,513.25	0.00	19,514.00
	Rental vacancy rate (%), 2007-11	6.10	2.91	0.00	15.00
Income	Dummy Poverty Variable	0.32	0.47	0.00	1.00
	Low-Wage Job Sites (incomes $1250/month or less)	851.34	1,169.70	6.83	6,940.50
Income	Medium-Wage Job Sites (incomes $1250/month or more)	1,655.49	2,264.27	9.33	9,753.00
	Poverty Rate	0.18	0.06	0.00	0.39
	Unemployment rate (%)(2012 ACS five-year estimate)	8.71	5.33	0.00	25.00

Category	Description	Mean	SD	Min.	Max.
Land Use	Employment and household entropy	0.49	0.13	0.14	0.85
	Employment entropy (denominator set to observed employment types in the census block group)	0.49	0.14	0.10	0.82
	Gross activity density (employment + housing units)	90.78	93.62	6.16	416.69
	Gross employment density (jobs/acre)	74.17	93.79	0.20	407.85
	Gross entertainment employment density (jobs/acre)	7.68	10.29	0.00	54.04
	Gross industrial employment density (jobs/acre)	2.14	3.29	0.00	19.95
	Gross office employment density (jobs/acre)	27.75	41.22	0.02	153.22
	Gross population density (people/acre)	30.23	19.66	0.09	86.94
	Gross residential density (housing units/acre)	16.61	12.83	0.02	61.42
	Gross retail employment density (jobs/acre)	1.60	2.20	0.00	11.26
	Gross service employment density (jobs/acre)	27.50	42.61	0.05	237.99
Lighting	Pedestrian Lighting (16' and below in height)	53.74	47.82	0.00	207.00
	Street Lighting (total)	198.13	83.77	0.00	414.00
Mode (Bicycling)	Bicycle Lanes	8.91	8.97	0.00	39.00
	Bike to Work (2010 ACS, five-year estimate)	36.74	32.24	0.00	133.80
Mode (Car)	Drive Alone to Work (2010 ACS, five-year estimate)	219.19	94.88	0.00	478.50
	Motorcycle to Work (2010 ACS, five-year estimate)	1.87	2.54	0.00	14.13
	One Car Households (2010 average)	330.65	137.26	0.00	766.00
	Zero Car Households (2010 average)	299.79	157.25	0.00	759.00
Mode (Carpool)	Carpool to Work (2010 ACS, five-year estimate)	35.16	23.53	0.00	108.80
Mode (Carsharing)	Carsharing Locations	1.87	1.89	0.00	8.00

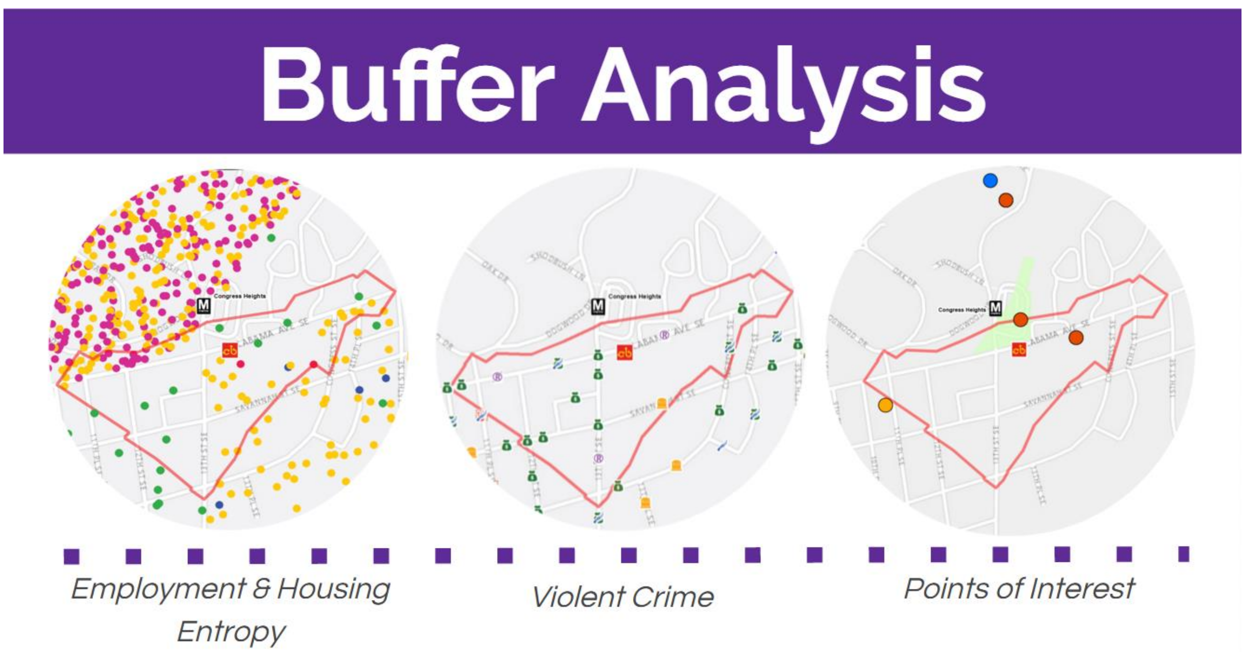
Category	Description	Mean	SD	Min.	Max.
Mode (Taxi)	Taxi to Work (2010 ACS, five-year estimate)	4.88	5.82	0.00	37.00
Mode (Tele-commute)	Work from Home (2010 ACS, five-year estimate)	40.94	23.93	0.00	114.50
Mode (Transit)	Aggregate frequency of transit service (D4c) per square mile	3,766.85	2,278.86	697.31	11,838.33
	Aggregate frequency of transit service within 0.25 miles of block group boundary per hour during evening peak period	520.97	467.58	103.13	2,298.33
Mode (Transit)	Average Daily Boardings, WMATA Metrobus (80th percentile)	9.88	8.56	0.00	45.00
	Bus to Work (2010 ACS, five-year estimate)	98.00	77.87	0.00	386.89
	Distance from population weighted centroid to nearest transit stop (meters)	540.42	92.90	300.53	765.99
	Proportion of employment within 1/2 mile of fixed-guideway transit stop	0.71	0.33	0.00	1.00
	Proportion of employment within 1/4 mile of fixed-guideway transit stop	0.32	0.24	0.00	0.98
	Subway to Work (2010 ACS, five-year estimate)	207.43	127.49	0.00	713.40
	Train to Work (2010 ACS, five-year estimate)	2.50	3.10	0.00	14.60
	Transit to Work (2010 ACS, five-year estimate)	310.37	154.80	0.00	817.40
	WMATA Metrorail Stations	0.34	0.52	0.00	2.00
Mode (Walking)	Walk to Work (2010 ACS, five-year estimate)	177.13	146.08	0.00	662.50
Race	% African-American (2012 ACS five-year estimate)	52.33	31.88	0.00	98.00
	% Asian residents (2012 ACS five-year estimate)	6.35	4.40	0.00	14.00
	% Hispanic residents (2012 ACS five-year estimate)	7.88	5.78	0.00	27.00
	% White residents (2012 ACS five-year estimate)	43.74	24.78	0.00	81.00
Topography	Elevation Change (average)	21.53	17.01	0.67	90.00
Traffic	Average Annual Daily Traffic Volume,	12.83	14.51	1.75	175.42

Category	Description	Mean	SD	Min.	Max.
	2010 (estimate, in thousands)				
Tree Canopy	Street Trees	419.05	200.57	0.00	833.00
Unbanked	Alternative Financial Services	0.44	0.74	0.00	5.00

GEOSPATIAL ANALYSIS

Using a network dataset provided by Foursquare ITP, which included streets, bicycle lanes, and bicycle paths, I rendered a ¼-of-a-mile "walkshed", or catchment area, around each bikeshare station. The catchment areas were created with ArcGIS Network Analyst to approximate the five minute walk to and from every bikeshare station in Washington, DC. The resulting street network buffers, defining a five minute walk to a station, are irregular in shape due to the non-uniform street network pattern. Therefore, the urban form surrounding each bikeshare station is not only defined by the independent variables of roadway connectivity, lighting, topography and tree canopy cover, analyzed later in Table 8 and Table 12, but also by this spatial unit of analysis of a street network buffer. Studies suggest that five minutes is the average distance a person is willing to walk to access public transportation (TRB, 2003).

Figure 8: Geospatial Analysis of Independent and Dependent Variables



Next, the ArcGIS Spatial Analyst "join by field or spatial location" feature was used to create an attribute table computing the average and sum of all 84 independent variables that fell within the service area buffers around each bikeshare station (Table 3). I used the "Table to Excel" feature of ArcGIS to export this geocoded attribute data into a workable spreadsheet. Microsoft Queries helped me merge datasets bound by the service area buffers, such as those in Figure 8, with bikeshare origin and destination data, derived from Microsoft Access. This produced a comprehensive spreadsheet containing (1) annual bikeshare ridership, or the sum of the origins and destinations, at each station, plus (2) the average amounts of each independent variable found in each station's walkshed buffer.

BIVARIATE ANALYSIS

First, I imported into SPSS the aforementioned spreadsheet which contained both the total ridership figures from Microsoft Access and the ArcGIS outputs from the Network Analyst and Spatial Analyst tool. Using SPSS, statistical analysis software developed by IBM, I measured the direction and magnitude of the linear relationship between total bikeshare ridership per station and my independent variables using Pearson's Correlation. Positively statistically significant (±0.05) Pearson Correlation coefficients indicate a direct relationship, or correlation, with the volume of trips. Negatively statistically significant (±0.05) Pearson Correlation coefficients indicate an inverse relationship with higher volumes of trips. The closer the Pearson Correlation Coefficient is to ±1, the stronger the linear correlation (which does not demonstrate causation). Tables 7 through 13 below compare and rank the correlation coefficients of my 84 independent variables with total bikeshare ridership per station using Pearson's Correlation by category. Overall, however, the top ten factors most strongly correlated with bikeshare ridership were:

Table 5: Pearson's Correlations with Bikeshare Usage, Uncontrolled for Poverty

RANK	CATEGORY	VARIABLE NAME	CORRELATION	STRENGTH
#1	Connectivity	Total road network density	.499**	Moderate
#2	Mode (Walking)	Walk to Work (2010 ACS, five-year estimate)	.471**	Moderate
#3	Mode (Transit)	Aggregate frequency of transit service (D4c) per square mile	.438**	Moderate
#4	Connectivity	Street intersection density (weighted, auto-oriented intersections eliminated)	.433**	Moderate
#5	Topography	Elevation Change (average)	-.426**	Moderate
#6	Income	Unemployment rate (%)(2012 ACS five-year estimate)	-.418**	Moderate
#7	Crashes	Collision Rate for Bicyclists (2014)	.400**	Moderate
#8	Mode (Bicycling)	Bicycle Lanes	.396**	Weak
#9	Mode (Transit)	Proportion of employment within 1/2 mile of fixed-guideway transit stop	.395**	Weak
#10	Land Use	Gross activity density (employment + housing units)	.392**	Weak

However, if poverty were controlled for, the most strongly correlated factors shifted. I used a partial correlation and created a dummy variable for poverty, at the 20% threshold level, to reveal the top ten factors correlated with bikeshare ridership. Specifically, I first used ArcGIS to divide concentrations of poverty around a quarter-mile of bikeshare stations into quintiles, as illustrated in Figure 9. In SPSS, I created a dummy variable where values over 20 percent were assigned a 1 and all of the values were assigned a 0. The Department of Housing and Urban Development (HUD) uses this 20 percent threshold as an indicator of neighborhood outcomes including crime rates, educational achievement, physical health, and mental wellbeing (HUD 2011). In other words, the factors listed below show what is highly likely to determine bikeshare ridership, regardless of the poverty level of the area:

Table 6: Partial Correlations with Bikeshare Usage, Controlling for Poverty

OLD RANK	NEW RANK	CATEGORY	VARIABLE NAME	CORRELATION Controlled for Poverty	STRENGTH
#1	#1	Connectivity	Total road network density	.484	Moderate
#2	#2	Mode (Walking)	Walk to Work (2010 ACS, five-year estimate)	.477	Moderate
#9	#3	Mode (Transit)	Proportion of employment within 1/2 mile of fixed-guideway transit stop	.420	Moderate
#5	#4	Topography	Elevation Change (average)	-.413	Moderate
#4	#5	Connectivity	Street intersection density (weighted, auto-oriented intersections eliminated)	.409	Moderate
#6	#6	Income	Unemployment rate (%)(2012 ACS five-year estimate)	-.408	Moderate
#3	#7	Mode (Transit)	Aggregate frequency of transit service (D4c) per square mile	.402	Moderate
#10	#8	Land Use	Gross activity density (employment + housing units)	.388	Weak
#8	#9	Mode (Bicycling)	Bicycle Lanes	.388	Weak
#7	#10	Crashes	Collision Rate for Bicyclists (2014)	.383	Weak

The most encouraging result of this study was that poverty was weakly correlated (-.031) with bikeshare ridership, and only .011 for the Poverty Dummy Variables. Violent crime came in near last with both bivariate regression models, explaining -.024 of the variation before poverty was controlled for and -.068 of the variation in bikeshare ridership afterwards. Therefore, we can conclude that poverty, and especially crime rate, is not destiny when it comes to bikeshare's future in disadvantaged communities. The results explained in Tables 5 and 6 suggest that factors within the local government's purview, such as land use, transit frequency, and traffic calming, may have a greater impact on bikeshare use than was previously thought (Fishman 2014).

In both poverty controlled and poverty uncontrolled models (Table 7), the density of destinations such as retail, employment, housing, entertainment, office and cultural facilities, featured prominently in bivariate regressions. This result suggests that densely populated and mixed land uses are likely both final destinations and origin locations for bikeshare riders. Similarly, road network density was highly correlated to bikeshare ridership in both regression results, indicating that 0having a multiplicity of routes to cycle on encourages bikeshare use. After road network density, when controlling for poverty, the frequency of transit was the second highest correlating factor with bikeshare ridership. This suggests that bikeshare plays a role in the first and last mile of frequent transit routes, as measured by GTFS data of transit stops and schedules. Elevation change was negatively correlated with bikeshare ridership when controlling for poverty, indicating that flat terrain is preferable for bikesharing trips. Zero car households correlated with bikeshare ridership when poverty was controlled for, indicating that bikeshare provides car-free families with a flexible alternative to car travel. Peculiarly, the percentage of Asian residents was correlated, although weakly (.393), with bikeshare ridership. Lastly, medium and even low-wage work sites were moderately correlated (by .535 and .517) to bikeshare ridership before poverty was controlled for. This result suggests that bikeshare could attract more low-income riders by targeting employee transportation coordinators to provide discounted, subsidized or corporate bikeshare memberships to their employees.

Figure 9:
Concentrated Poverty around Bikeshare Stations

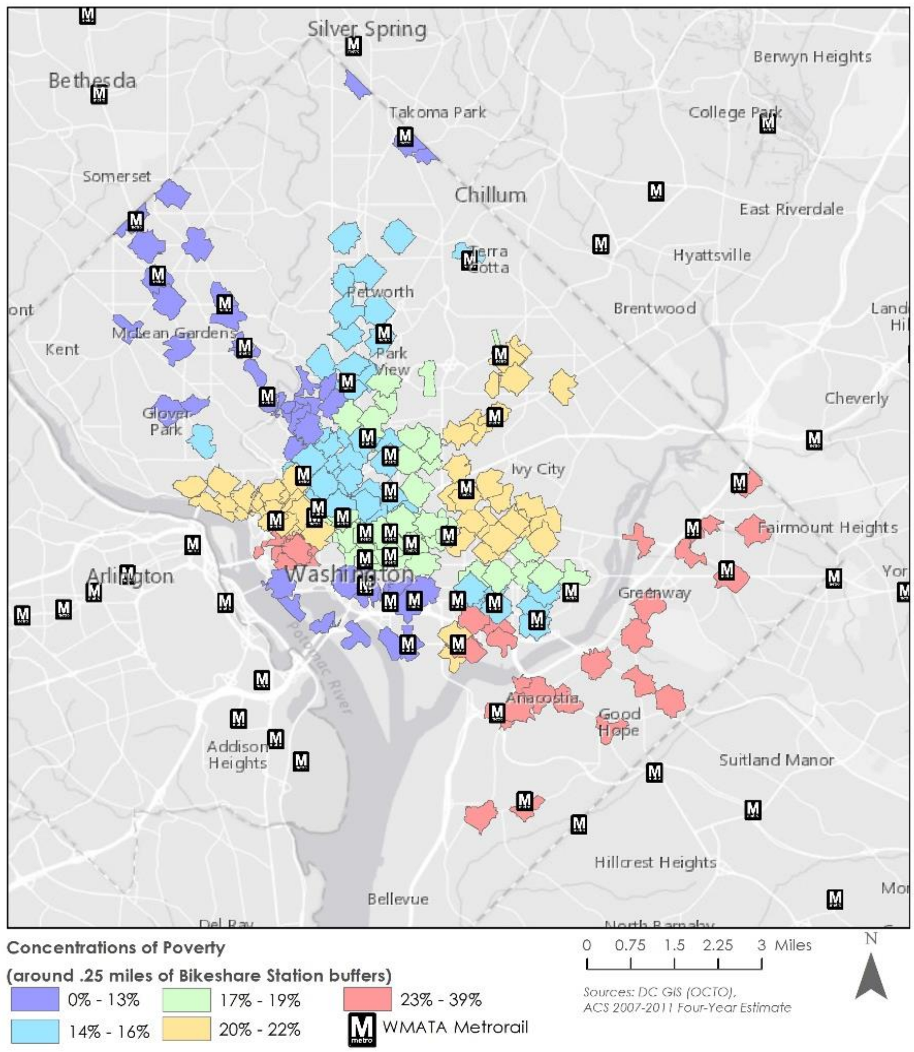
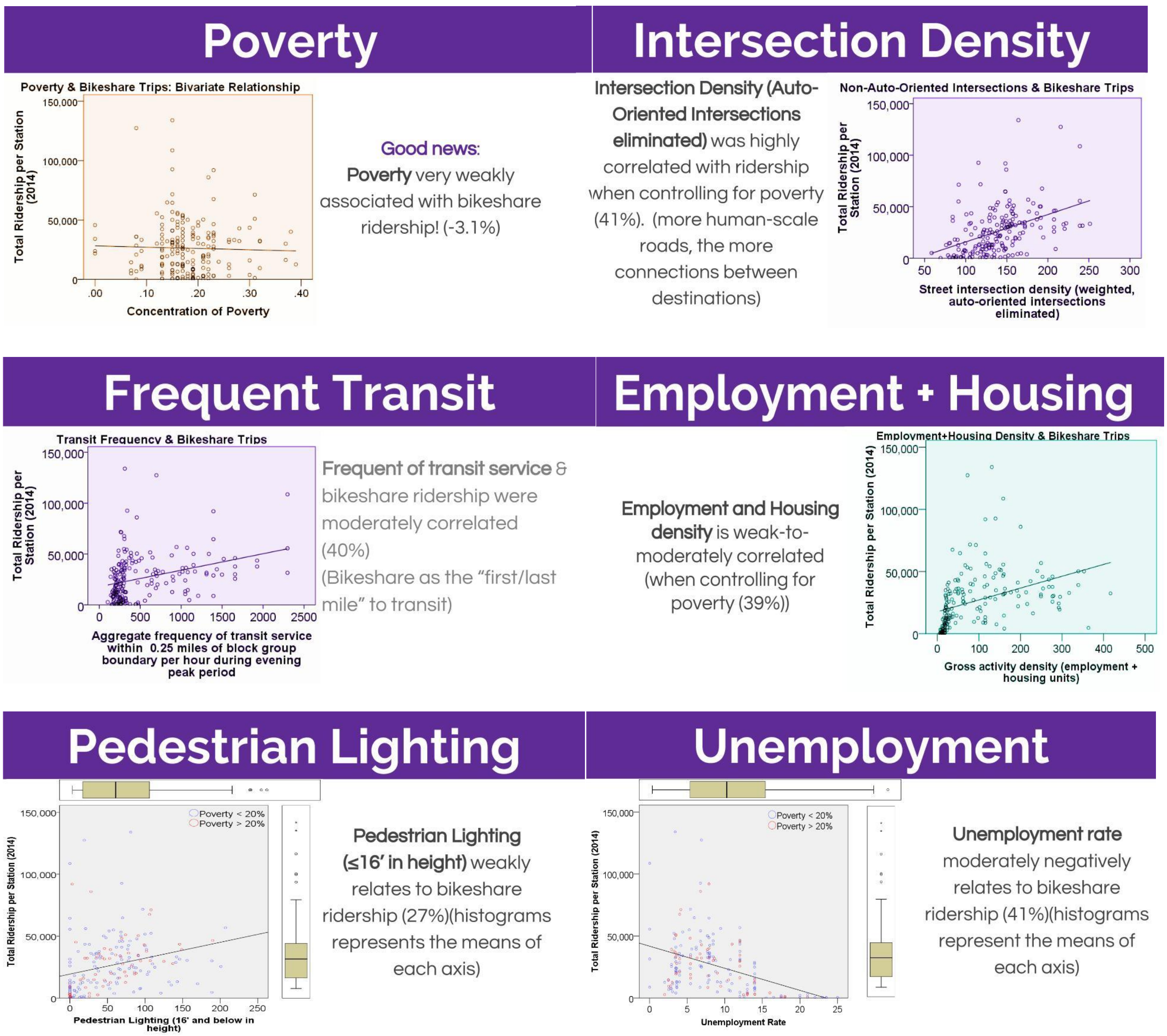


Figure 10 below represents some of the most highly and weakly correlated independent variables from various categories. The graphs of pedestrian lighting and unemployment rates have colored dots representing quintiles ranging from red (concentrated poverty at a rate of 20% or over) to blue (poverty not concentrated). In both cases, these red concentrated poverty dots tend to cluster closer to the trend line:

Figure 10: Sample Scatterplots of Bivariate Analysis



CORRELATION MATRICIES

Table 7 below lists summarize the result of all correlation matrices, organized by strength, category and magnitude, for the 84 independent variables tested against bikeshare ridership (with and without controls for poverty):

Table 7: Correlation Matrix Summary: Income

CATEGORY	VARIABLE TESTED Against Total Bikeshare Trips	CORRELATION BEFORE Controlled for Poverty	CORRELATION AFTER Controlled for Poverty	STRENGTH of Relationship to Total Trips
Unbanked (1 variable)	Alternative Financial Services	-.052	-.107	Very Weak
EBT (2 variables)	Persons receiving food stamps, 2014	-.234**	-.236	Weak
	Persons receiving TANF, 2014	-.305**	-.310	Weak
Housing (8 variables)	Median sales price, 2012	.311**	.299	Weak
	Occupied housing units, 2010	.198**	.162	Very Weak
	Rental vacancy rate (%), 2007-11	-.035	-.046	Very Weak
	% annual change median price, 2002-2012	-.088	-.071	Very Weak
	Number of home sales, 2012	-.117	-.135	Very Weak
	Homeownership rate (%), 2007-11	-.145*	-.162	Very Weak
	% same house 5 years ago, 2000	-.214**	-.211	Weak
	% subprime loans, 2006	-.258**	-.249	Weak
Income (5 variables)	Medium-Wage Job Sites (incomes $1250/month or	.319**	.311	Weak

CATEGORY	VARIABLE TESTED Against Total Bikeshare Trips	CORRELATION BEFORE Controlled for Poverty	CORRELATION AFTER Controlled for Poverty	STRENGTH of Relationship to Total Trips
	more)			
	Low-Wage Job Sites (incomes $1250/month or less)	.272**	.265	Weak
	Poverty Dummy Variable (20% threshold)	.011	.051	Very Weak
	Unemployment rate (%)(2012 ACS five-year estimate)	-.418**	-.408	Moderate
	Poverty Rate	-.031		Very Weak

***. Correlation is significant at the 0.01 level (2-tailed).*
**. Correlation is significant at the 0.05 level (2-tailed).*

Table 8: Correlation Matrix Summary: Connectivity

CATEGORY	***VARIABLE TESTED*** *Against Total Bikeshare Trips*	***CORRELATION BEFORE*** *Controlled for Poverty*	***CORRELATION AFTER*** *Controlled for Poverty*	***STRENGTH*** *of Relationship to Total Trips*
Connectivity *(11 variables)*	Total road network density	.499**	.484	Moderate
	Street intersection density (weighted, auto-oriented intersections eliminated)	.433**	.409	Moderate
	Intersection density in terms of pedestrian-oriented intersections having three legs per square mile	.362**	.345	Weak
	Network density in terms of facility miles of pedestrian-oriented links per square mile	.351**	.316	Weak
	Intersection density in terms of auto-oriented intersections per square mile	.266**	.272	Weak
	Network density in terms of facility miles of auto-oriented links per square mile	.241**	.251	Weak
	Intersection density in terms of pedestrian-oriented intersections having four or more legs per square mile	.231**	.223	Weak
	Network density in terms of facility miles of multi-modal links per square mile	.270**	.220	Weak
	Intersection density in terms of multi-modal intersections having four or more legs per square mile	.121	.114	Very Weak
	Station Network Effect	.141	.106	Very Weak
	Intersection density in terms of multi-modal intersections having three legs per square mile	.139	.084	Very Weak

***. Correlation is significant at the 0.01 level (2-tailed).*
**. Correlation is significant at the 0.05 level (2-tailed).*

Table 9: Correlation Matrix Summary: Safety (Crashes & Crime)

CATEGORY	***VARIABLE TESTED*** *Against Total Bikeshare Trips*	***CORRELATION BEFORE*** *Controlled for Poverty*	***CORRELATION AFTER*** *Controlled for Poverty*	***STRENGTH*** *of Relationship to Total Bikeshare Trips*
Crashes *(2 variables)*	Collision Rate for Bicyclists (2014)	.400**	.383	Moderate
	Collision Rate for Pedestrians (2014)	.199**	.172	Very Weak
Crime *(5 variables)*	Sexual Abuse (2014)	.066	.066	Very Weak
	Robbery (2014)	.006	-.037	Very Weak
	Violent Crime (total, 2014)	-.024	-.068	Very Weak
	Assault (2014)	-.079	-.122	Very Weak
	Homicides (2014)	-.103	-.134	Very Weak

***. Correlation is significant at the 0.01 level (2-tailed).*
**. Correlation is significant at the 0.05 level (2-tailed).*

Table 10: Correlation Matrix Summary: Demographics

CATEGORY	***VARIABLE TESTED*** *Against Total Bikeshare Trips*	***CORRELATION BEFORE*** *Controlled for Poverty*	***CORRELATION AFTER*** *Controlled for Poverty*	***STRENGTH*** *of Relationship to Total Trips*
Race *(4 variables)*	% Asian residents	.377**	.359	Weak
	% White residents	.303**	.265	Weak
	% African-American	-.305**	-.283	Weak
	% Hispanic residents	.061	.040	Very Weak
Education *(1 variable)*	Persons without a high school diploma (%)	-.280**	-.269	Weak
Gender *(1 variable)*	% Female-headed households	-.258**	-.234	Weak

***. Correlation is significant at the 0.01 level (2-tailed).*
**. Correlation is significant at the 0.05 level (2-tailed).*

Table 11: Correlation Matrix Summary: Land Use

CATEGORY	***VARIABLE TESTED*** *Against Total Bikeshare Trips*	***CORRELATION BEFORE*** *Controlled for Poverty*	***CORRELATION AFTER*** *Controlled for Poverty*	***STRENGTH*** *of Relationship to Total Trips*
Destinations *(5 variables)*	Points of Interest - Culture	.382**	.357	Weak
	Points of Interest - Total	.250**	.226	Weak
	Points of Interest - Food	.198**	.177	Very Weak
	Points of Interest - Education	.125	.093	Very Weak
	Points of Interest - Health	.066	.011	Very Weak
Land Use *(11 variables)*	Gross activity density (employment + housing units)	.392**	.388	Weak
	Gross entertainment employment density (jobs/acre)	.332**	.350	Weak
	Gross retail employment density (jobs/acre)	.340**	.345	Weak
	Employment and household entropy	.327**	.340	Weak
	Gross employment density (jobs/acre)	.342**	.339	Weak
	Gross residential density (housing units/acre)	.358**	.329	Weak
	Employment entropy	.329**	.324	Weak

	(denominator set to observed employment types in the census block group)			
	Gross office employment density (jobs/acre)	.305**	.304	Weak
	Gross service employment density (jobs/acre)	.303**	.288	Weak
	Gross population density (people/acre)	.241**	.201	Weak
	Gross industrial employment density (jobs/acre)	.162*	.199	Very Weak

***. Correlation is significant at the 0.01 level (2-tailed).*
**. Correlation is significant at the 0.05 level (2-tailed).*

Table 12: Correlation Matrix Summary: Urban Design

CATEGORY	***VARIABLE TESTED*** *Against Total Bikeshare Trips*	***CORRELATION BEFORE*** *Controlled for Poverty*	***CORRELATION AFTER*** *Controlled for Poverty*	***STRENGTH*** *of Relationship to Total Trips*
Topography *(1 variable)*	Elevation Change (average)	-.426**	-.413	Moderate
Lighting *(2 variables)*	Pedestrian Lighting (16' and below in height)	.270**	.243	Weak
	Street Lighting (total)	.161*	.125	Very Weak
Canopy Cover *(1 variable)*	Street Trees	.076	.025	Very Weak

***. Correlation is significant at the 0.01 level (2-tailed).*
**. Correlation is significant at the 0.05 level (2-tailed).*

Table 13: Correlation Matrix Summary: Transportation

CATEGORY	***VARIABLE TESTED*** *Against Total Bikeshare Trips*	***CORRELATION BEFORE*** *Controlled for Poverty*	***CORRELATION AFTER*** *Controlled for Poverty*	***STRENGTH*** *of Relationship to Total Trips*
Mode (Walking) *(1 variable)*	Walk to Work	.471**	0.477	Moderate
Mode (Transit) *(11 variables)*	Aggregate frequency of transit service per square mile	.438**	0.402	Moderate
	Proportion of employment within 1/2 mile of fixed-guideway transit stop	.395**	0.42	Moderate
	Aggregate frequency of transit service within 0.25 miles of block group boundary per hour during evening peak period	.334**	0.324	Weak
	Proportion of employment within 1/4 mile of fixed-guideway transit stop	.304**	0.318	Weak
	Subway to Work	.208**	0.226	Weak
	Train to Work	.178*	0.159	Very Weak
	Transit to Work	0.134	0.132	Very Weak
	Distance from population weighted centroid to nearest transit stop (meters)	-0.122	-0.11	Very Weak
	WMATA Metrorail Stations	0.101	0.146	Very Weak

	Bus to Work	-0.074	-0.091	Very Weak
	Average Daily Boardings, WMATA Metrobus (80th percentile)	0.062	0.036	Very Weak
Mode (Bicycling) *(2 variables)*	Bicycle Lanes	.396**	0.388	Weak
	Bike to Work	0.15	0.146	Very Weak
Mode (Car) *(4 variables)*	Zero Car Households	.297**	0.302	Weak
	One Car Households	.200**	0.226	Weak
	Motorcycle to Work	.178*	0.187	Very Weak
	Drive Alone to Work	-.162*	-0.158	Very Weak
Mode (Carsharing) *(1 variable)*	Carsharing Locations	.270**	0.298	Weak
Mode (Telecommute) *(1 variable)*	Work from Home	.183*	0.155	Very Weak
Mode (Carpool) *(1 variable)*	Carpool to Work	-.151*	-0.207	Weak
Mode (Taxi) *(1 variable)*	Taxi to Work	.149*	0.14	Very Weak
Traffic Volume *(1 variable)*	Average Annual Daily Traffic Volume (AADT) (2010 estimate, in thousands)	.052	0.051	Very Weak

***. Correlation is significant at the 0.01 level (2-tailed).*
**. Correlation is significant at the 0.05 level (2-tailed).*

HIERARCHICAL STEPWISE REGRESSION

After producing a controlled and uncontrolled correlation matrix, I employed multiple regression to narrow the 84 original independent variables down to a more parsimonious, refined, and causal set of predictor variables. This finalized list of independent variables, referred to in the literature as "determinants of ridership," will be used in Chapter 10 to estimate ridership at bikeshare stations in low-income areas (Buck et al., 2011).

I used the SPSS software to enter the independent variables into block groups, which are inter-correlated predictor variables. In this model, my block group variables were organized and selected according to the seven correlation matrices in Table 7 through Table 13, namely: (1) Income, (2) Demographics, (3) Urban Design (4) Safety (5) Land Use (6) Connectivity and (7) Transportation. Only variables which correlated with bikeshare ridership at the .01 or .05 confidence level were included to create a parsimonious regression model. The syntax of this reduced regression model appears in Table 14 and the syntax of the full model it was compared to is in Appendix 2. This method follows a hierarchical regression model, whereby the researcher, instead of the computer, selects the order of entry for each block of variables in a multiple regression (Field, 2013). After the hierarchy is established between blocks, an algorithmic sequential testing procedure, known as a stepwise regression, removes variables from the model whose p-value exceeds the threshold limit (F<= .050 or >= .1) due to the inclusion of the proceeding variable (Field 2013). Variables that are entered in the beginning stages of this hierarchical stepwise regression will have a better chance of being retained, or will take precedence, over the next variable that follows in the model (Field, 2013). I entered the predictor variables that I wanted to control, namely the "income" block variables, into the model initially, followed by the remaining six block groups in descending order of their correlation coefficients' strength (Tables 7-14). In that way, the observed effects of these block groups on bikeshare ridership, detailed in Table 14 and Appendix 2, can be said to be independent of the "Income" block group's impact.

Table 14: Parameters of Hierarchical Stepwise Regression (Significant variables only)*

Syntax of Hierarchical Stepwise Regression	***Notes:***
REGRESSION /MISSING LISTWISE /STATISTICS COEFF OUTS R ANOVA COLLIN TOL **/CRITERIA**=PIN(.05) POUT(.10) /NOORIGIN	Regression **thresholds** (Stepwise Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100)
/DEPENDENT Trips	Dependent Variable = **Total Ridership**
/METHOD=STEPWISE Avg_PctUne Avg_E_MEDW Avg_E_LOWW Avg_Med_Sa Avg_PctSub Avg_PctSam Avg_NumOcc Avg_PctOwn Avg_fs_cli Avg_tanf_c	Block #1: **Income**
/METHOD=STEPWISE Avg_PctAsi Avg_PctWhi Avg_PctBla Avg_Pct25a Avg_PctFam	Block #2: **Demographics**
/METHOD=STEPWISE Avg_Elev_C PedLighting AllStreetLighting	Block #3: **Urban Design**
/METHOD=STEPWISE BikeCrash PedCrash	Block #4: **Safety**
/METHOD=STEPWISE Avg_D1D Culture_Co Avg_D1A Avg_D1C Avg_D1C5_R Avg_D1C5_E Avg_D2B_E5 Avg_D2A_EP Avg_D1C5_O Avg_D1C5_S Avg_D1B Avg_D1C5_I	Block #5: **Land Use**
/METHOD=STEPWISE Avg_D4d Avg_Walk Avg_D4b050 BikeLanes Avg_AUTOOW Avg_AUTO_1 Avg_Motorc Avg_Drove Avg_Carpoo CarSharing Avg_Taxi Avg_Work_a Avg_Subway Avg_Train	Block #6: **Connectivity**
/METHOD=STEPWISE Avg_D3a Avg_D3b Avg_D3bpo3 Avg_D3apo Avg_D3aao Avg_D3bpo4	Block #7: **Transportation**

** Correlation is significant at the 0.05 level (2-tailed)*

** Cases Used: Statistics are based on cases with no missing values for any variable used.*

** Variable codes in Syntax above (used in SPSS) can be found in Table 2*

The percent of variability in the dependent variable of Total Ridership that can be accounted for by all the predictor independent variables together, known as the R-squared value in this model, increased significantly with each variable included (Appendix 2). Specifically, only 20 percent of the variance in ridership could be accounted by the first iteration of the model, which only addressed income (Appendix 2). By the fifteenth iteration, 62 percent of the variability, or predictive power, could be explained by the block group variables selected in the stepwise regression (Appendix 2). The ANOVA results confirm that all models predicted Total Bikeshare Ridership to a statistically significant degree, seeing as the "Sig." or p-value column are all below .05 (Appendix 2). As seen in the Coefficients output in Appendix 2, several variables were flagged for having a high p-value (Sig.) and a high variance inflated factor (VIF) including: percent female-headed households (Sig. = .86, VIF = 6.64), pedestrian lighting (Sig. = .77), unemployment rate (Sig. = .13, VIF = 6.99) and cultural points of interest (Sig. = .06). This output suggests these five values are not significant to bikeshare ridership. The high VIF value of unemployment, female-headed households and also low and medium wage job sites suggests that these factors may be collinear, or inter-correlated such that it does not uniquely predict the dependent variable of bikeshare ridership (Field 2013). However, these factors may not be as collinear as they seem because they were also entered into the model as a control variable (Garbin n.d.). Further refinements of this model, therefore, could use the Ordinary Least Squares (OLS) Regression to compare the relative change in the R-squared value and the Significance value between the two models (Field 2013). The adjusted R-squared value on both a preliminary OLS model and the parsimonious Hierarchical Stepwise model suggests that 59% of the variation in bikeshare rides in 2014 can be explained by the income, demographic, topography, urban form, safety, land use and transportation variables combined.

Table 15: Stepwise Regression: Standardized Coefficients of Variables Entered into Model

Model	**Category**	**Variables Entered into Model**	**Standardized Coefficient**
#1	Income	Unemployment rate (%)(2012 ACS five-year estimate)	*-0.19*
#2	Income	Medium-Wage Job Sites (incomes $1250/month or more)	*0.70*
#3	Income	Low-Wage Job Sites (incomes $1250/month or less)	*-0.95*
#4	Income	Occupied housing units, 2010	*0.15*
#5	Income	Median home sales price, 2012	*0.13*
#6	Demographics	% Female-headed households (2012 ACS five-year estimate)	*0.02*
#7	Topography	Elevation Change (average)	*-0.18*
#8	Urban Form	Pedestrian Lighting (16' and below in height)	*-0.02*
#9	Safety	Collision Rate for Bicyclists (2014)	*0.17*

** Note: Stepwise Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100)*

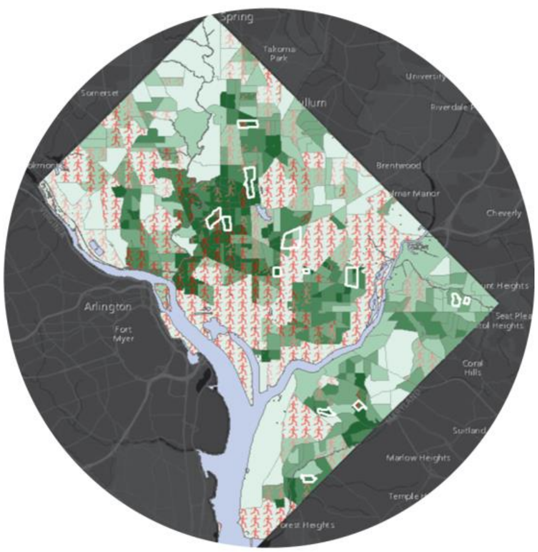
#10	Land Use	Gross retail employment density (jobs/acre)	*0.24*
#11	Land Use	Points of Interest - Culture	*0.15*
#12	Transportation	Walk to Work (2010 ACS, five-year estimate)	*0.17*
#13	Transportation	Train to Work (2010 ACS, five-year estimate)	*0.16*
#14	Connectivity	Network density in terms of facility miles of auto-oriented links per square mile	*0.20*
#15	Connectivity	Intersection density in terms of pedestrian-oriented intersections having three legs per square mile	*0.17*

8 Discussion of Trends

In summary, the Correlation Matrix and Bivariate Regression Scatterplots helped narrow down the original 84 predictors of bikeshare ridership at the station-level to 50 factors significant at the .01 level and a remaining nine variables significant at the .05 level for a two-tailed correlation (Table 7-Table 13). The Stepwise Regression model further reduced these variables to fifteen factors, organized in rank order by block and by correlation coefficient (Table 15).

These statistical tests revealed several key trends for bikeshare ridership in low-income areas, namely:

Figure 11: Expanding Outreach Efforts



On the map: Employment and Household Entropy was found to be a strong predictor of bikeshare ridership. Outreach efforts should identify community partners in the brightest red areas, where low-to-medium wage work sites (in red) may be otherwise overlooked and underrepresented due to a lack of residential density (in light green).

1. Top Predictors:
- Low-to-Medium Wages,
- Retail,
- Network Density,
- Unemployment,
- Topography

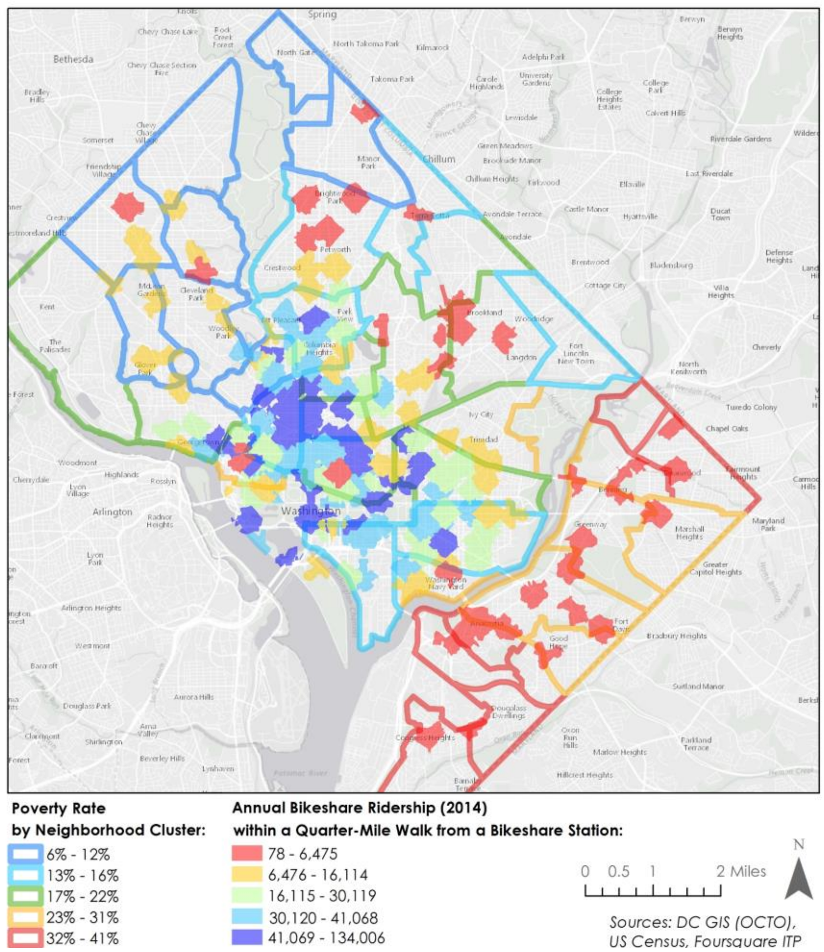
2. Moderate Predictors:
- Pedestrian-Oriented Intersections,
- Collision Rate,
- Walking and Trains,
- Cultural Facilities,
- Occupied Housing

3. Weak Predictors:
- Median Home Sales Price,
- Female-Headed Households,
- Pedestrian Lighting

Income and Demographics:

Low-wage work sites, paying less than $1,250 a month, as well as unemployment rates, strongly negatively correlated (-.95 and -.19, respectively) with bikeshare ridership. Medium-wage work sites, paying more than $1,250 a month, in contrast, were highly positively correlated (.70) with bikeshare ridership. Occupied housing units were moderately positively predicted bikeshare ridership at the station-level (.15). Median home sales price positively and weakly related to bikeshare ridership at the .13 level. Bikeshare ridership is lowest in the urban periphery and in high poverty areas, with approximately 2,000 annual trips or fewer coming to or from, and rarely between, the 21 stations east of the Anacostia River in Wards 7 and 8 (Figure 12 and Figure 13).

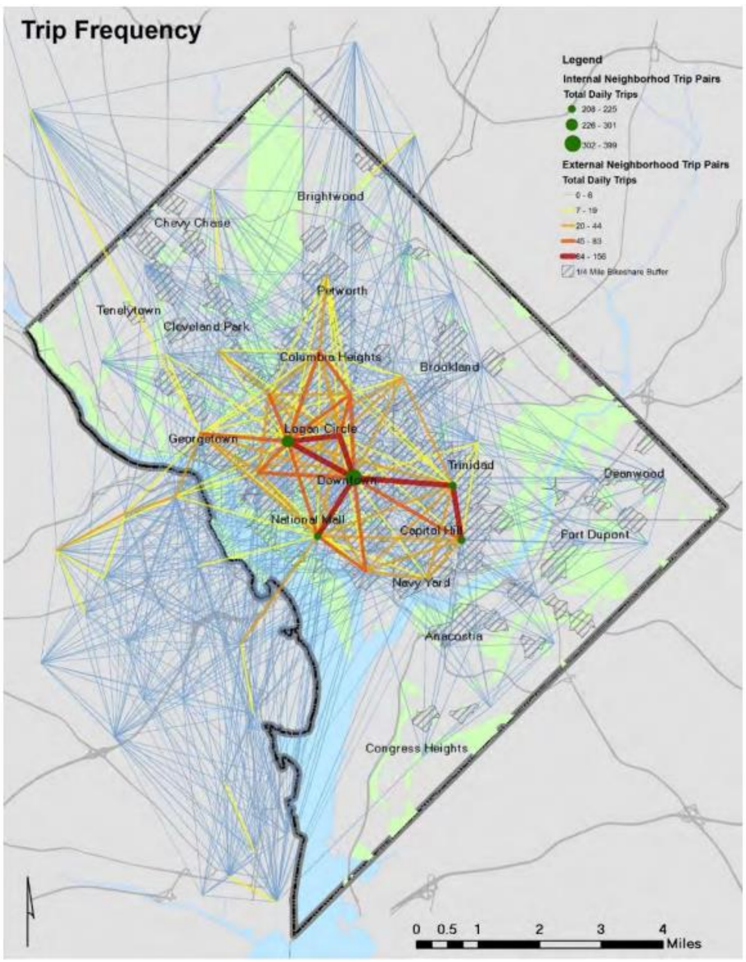
Figure 12: High Poverty, Low Bikeshare Use (2014)



These findings echo Kodransky & Lewenstein's 2014 study of Capital Bikeshare ridership garnering only 38 bikeshare members making 946 trips from low-income area's seven bikeshare stations. This is in stark contrast to the 1,317 members in wealthier zip codes of the city who have made 24,271 trips from one station alone, DuPont Circle, as of April 11, 2011 (Kodransky & Lewenstein, 2014). An American University survey of 260 commuters between 2012 and 2013 revealed that residents of Wards 7 and 8, "earn less, travel longer and use public transit more than the city as a whole" (Bratman, 2014). Compared to higher-income residents in the same area, lower-income residents reported "spending nearly four hours more in weekly commutes" (Bratman, 2014). Fifty-five percent of those surveyed in Wards 7 and 8 reported strongly wanting their own car, and ranked bikesharing as their least desirable mode of transit (Bratman 2014).

Lastly, bikeshare trips were weakly correlated to female-headed households with a standardized coefficient of .02. This finding validates previous research showing that Capital Bikeshare members are more likely to be female, younger, and own fewer cars and bicycles (Buck 2013). Similarly, the proportion of female bikeshare members is greater than for private bike riding in Australia (Pucher, Greaves, & Garrard, 2010). The weakness of this correlation may be because men continue to outnumber women, comprising 55 percent of total Capital Bikeshare users (Buck et al., 2013).

Figure 13: Origin-Destination Bikeshare Trip Pairs (2014)



Source: Foursquare ITP, 2015,
DC Capital Bikeshare Development Plan

Topography, Safety, Urban Form, and Land Use:

Topographic differences, measured by the change in elevation, were highly negatively associated with bikeshare ridership at the -.18 level. This could be because bicyclists and bikeshare users alike are adverse riding to hills (Frade & Ribeiro, 2014; Jurdak, 2013). Areas where collisions are frequent for bicyclists were moderately positively related to bikeshare usage (.17). The literature review, in contrast, suggests collision rates would be negatively correlated with bikeshare ridership. This result for the District of Columbia may be because areas with high levels of bikeshare use increase the crash exposure rates for cyclists, and not because crash rates are higher in these areas.

Less speculatively, Washington, DC's bikeshare membership is lowest in Wards 7 and 8, which are home to nearly half of the most dangerous intersections in the city, have the highest concentrations of poverty, and are 96 percent and 94 percent African-American, respectively (Figure 12)(DC Trust, 2011)(Kodransky & Lewenstein, 2014)(Hughes 2015).

Additionally, system-wide, Capital Bikeshare has recently been shown to have a causal effect in reducing traffic congestion by two to three percent on streets where bikeshare stations are present

(Hamilton & Wichman, 2015). Although researchers note that traffic diverts to neighboring roads without bikeshare stations, the results suggest that bikeshare has a traffic calming impact on city streets, which may enhance road safety (Hamilton & Wichman, 2015).

Instead, this moderate positive correlation between safety and ridership could be explained the large increase in the number of new carless households. After Capital Bikeshare was introduced in 2010, bicycle use, as a mode share, rose at over twice national rate from 2010 to 2012 (up 32% versus 15%) (Buck 2014). As Capital Bikeshare expanded, the number of car-free households in Washington, DC grew by 14.3 percent, from 35 percent to 37.9 percent, some by choice and others by economic circumstance (Chung 2014). By contrast, the District added only 1,662 car-owning households between 2010 and 2014, an increase of just 1.0 percent (Chung 2014). The safety in numbers phenomenon states that a rise in the amount of cycling may lead to an increase, but not a proportional rise, in the number of injuries for Washington, DC's growing alternative commuter population (Elvik, 2009).

Pedestrian lighting, defined here as the presence of light posts shorter than sixteen feet, was the lowest correlated variable in the model (-.02). The negative correlation was not expected, as street lighting provides a sense of safety and street enclosure, but the relationship is very weak in any respect. Perhaps this is because pedestrian, human-scale, lighting tends to be placed in upper-income areas looking at the original dataset in ArcMap. Therefore, pedestrian lighting is slightly negatively correlated because of the effect of the strongly negatively associated low-income wage sites variable at the station-level.

Gross retail density had a strong, positive effect, with a standardized coefficient of significance at .24. Cultural points of interest had a moderate positive impact on ridership with a beta weight of .15. This confirms previous research findings and suggests that a diversity land uses, especially those featuring art, culture, and small business, has a role to play in attracting the short trips most conducive to bikeshare (Rixey 2013) (Buck et al, 2013) (Fishman 2015).

Transportation and Connectivity:

Walking to work (.17) and taking the train to work (.16) proved to be the most significant predictors of bikeshare ridership out of a possible 22 transportation related factors (Table 15). Their positive, moderate association with annual bikeshare trips is confirmed by research on bikeshare and mode split. A multi-city analysis of bikeshare's overall impact on changes to vehicle miles travelled (VMT) shows that bikeshare reduces car use, even after factoring in the distance covered by redistribution and maintenance trucks (Figure 3, Fishman et al., 2014a). Montreal bikeshare users possessing a driver's license had 1.5 times greater odds of using bikeshare (Bachand-Marleau et al., 2012). This research suggests that bikeshare users, even those with access to a vehicle, are more likely to be multimodal commuters.

This positive association between bikeshare, walking, and rail travel is not limited to adult commuters. Research suggests children from low-income and minority households, particularly

African-Americans and Hispanics, are more likely to bike or walk to school than whites or higher-income students (McDonald 2008). Velib, the bikeshare operator in Paris, has piloted a special bikeshare for children in France with success called P'tit Vélib. The P'tit Vélib program was in response to a study indicating half of Parisian children learn to cycle outside of the city and also to a January 2012 City Hall survey which found that 86 percent of Parisian families were interested in a children's cycle hire service (Coldwell 2014).

Lastly, there is a moderate positive correlation between bikeshare ridership and intersection density in terms of pedestrian-oriented intersections (.17). The EPA defines "pedestrian-oriented" as blocks with three or more sides, a speed limit less than 30 miles per hour, pathways and/or trails (Ramsey and Bell, 2014). In this definition, highways, tollways, highway ramps, ferries, parking lot roads, tunnels, and facilities having four or more lanes of travel in a single direction are excluded (Ramsey and Bell, 2014). Network density in terms of facility miles, including auto-oriented links, proved more strongly positively related to bikeshare ridership (.20). These findings echo the aforementioned research about the importance of safety and traffic calming to bikeshare users perception of safety (Hamilton & Wichman, 2015) (DC Trust, 2011) (Kodransky & Lewenstein, 2014) (Hughes 2015).

Connectivity ranks as a top concern for bikeshare members in many of the surveyed 1,055 cities operating bikeshare (Meddin & DeMaio, 2016) (Fishman 2015). In 2013, for example, approximately half of Capital Bikeshare's 11,100 members were emailed a survey about their bikeshare ridership, with a response rate 34 percent (LDA Consulting 2013). Sixty-nine percent of those respondents said that "getting around more easily, faster and shorter" as "very important" in their motivation for bikeshare use (LDA Consulting 2013). Similarly, Montreal respondents living within 500 meters of a bikeshare station were 3.2 times more likely to have used bikeshare (Bachand-Marleau, Lee, and El-Geneidy, 2012). These findings are consistent with earlier studies of the Capital Bikeshare program, similar surveys of bikeshare users in London, multiple cities in North America, Melbourne and Brisbane (Transport for London,2014) (Shaheen et al., 2013) (Fishman, Washington, Haworth, & Mazzei, 2014).

Surveys of those who choose not to use bikeshare are not commonly done, however one was completed with a small sample size (n = 60) in Brisbane regarding their CityCycle bikeshare program. In focus groups, those surveyed with no known connections to bikeshare said their major barrier was mainly that driving was too convenient and also that docking stations were considered to be too far from respondents' homes (Fishman 2015). This finding is consistent with previous studies that suggest bikeshare members are more likely to live in close proximity to a bikeshare station (Bachand-Marleau et al.,2012) (Goodman & Cheshire, 2014) (Fishman et al., 2014; 2015).

9 FINDINGS & RECOMMENDATIONS

To address these findings proactively, the District Department of Transportation (DDOT) and Capital Bikeshare community partners should:

Recommendation 1:
Leverage intra-agency connections in **safety outreach** and communications through the Vision Zero Working Group.

a. Partner #1: Vision Zero Working Group

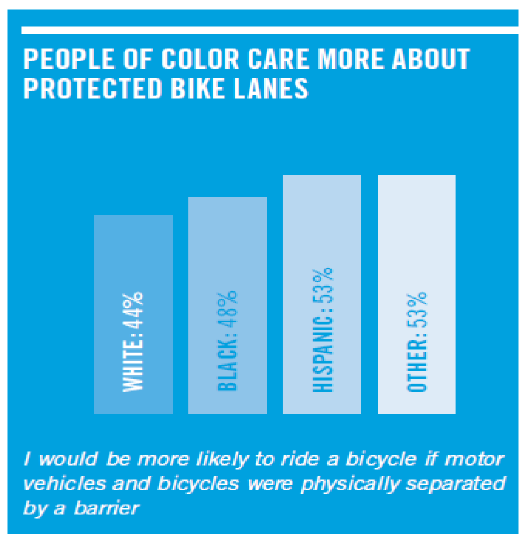
1. Why should they play a role?

   a. **Finding:** Traffic collisions involving bicyclists correlated highly in the bivariate regression model (accounting for 38 percent of the variation in bikeshare ridership at the 99 percent confidence level, even when holding poverty constant (Table 9).

   b. **Finding:** Out of a possible 84 factors tested, traffic collisions involving bicyclists were statistically one of the 16 most salient variables in predicting ridership (with a Beta Weight of 1544.4, Appendix 2).

   c. **Literature:** Washington, DC's bikeshare membership is lowest in Wards 7 and 8, which are home to nearly half of the most dangerous intersections in the city, have the highest concentrations of poverty, and are 96 percent and 94 percent African-American, respectively (Figure 12)(DC Trust, 2011)(Kodransky & Lewenstein, 2014) (Hughes

Figure 14: Advocating Safety



Source: Survey by Breakaway Research Group, 2014.

2015). Additionally, Ward 8 doubled its homicide rate from 2013 to 2015 (Azar 2015).

i. Nationally, people of color and low-income pedestrians are killed or injured at disproportionate rates caused by dangerous road design and bad drivers (Governing, 2014). Specifically, neighborhoods with high concentrations of poverty and people of color have double the fatality rates compared to their wealthy counterparts (Governing, 2014).

ii. People of color said protected bicycle lanes would make them "more likely to ride a bicycle" (48% African-American, 53% Hispanic out of 16,19 adults surveyed in 2014) (Figure 14).

iii. No one has died to date due to a bikeshare ride, with over 23 million bikeshare rides tallied since the first system launched in the United States in 2007 (Goldberg, 2014).

d. **Literature:** The perception of safety or lack thereof is a major determinant of cycling in studies across the United States, Australia, and the United Kingdom (Gardner,2002) (Horton, Rosen, & Cox, 2007) (Fishman, Washington, & Haworth,2012b).

2. What to do about it?

a. **Action #1.1:** Traffic safety data, graphic renderings and outreach meetings could integrate a discussion about safety on Capital Bikeshare.

i. Questions in **outreach materials** should be posed positively, for example: "What would it take for you to feel safe and secure riding Capital Bikeshare a few days a week or month?"

b. **Action #1.2: Protected bicycle lanes** and **traffic calming** features should be introduced in bikeshare service areas that facilitate travel between common trip origin and destination pairs, as mapped in Figure 13.

i. Prioritize the installation of bicycle facilities in areas with high collision rates and high concentrations of poverty to address existing safety and equity concerns (Table 7 and Table 9)(Governing, 2014)(Breakaway Research Group, 2014).

Recommendation 2:

Integrate Capital Bikeshare into the DC Office of Planning's **design review** process and the EPA **Environmental Justice** Working Group's programs.

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b. Partner #2: EPA Environmental Justice Coordinator with Partner #3: DC Office of Planning

1. Why should they play a role?

a. **Finding:** Urban design elements, especially Pedestrian Street Lighting (below 16 feet in height) and connectivity/urban design elements, like Pedestrian-Oriented, Three-legged Intersection Density levels, were found to be predictors of bikeshare ridership using the Hierarchical Stepwise Regression (Appendix 2).
b. **Finding:** When controlling for poverty, the Bivariate Analysis also found the variation in bikeshare ridership could be explained by Pedestrian Street Lighting (24%, Table 12) and Pedestrian-Oriented, Three-legged Intersection Density (35%, Table 8).
c. **Finding:** Land use variables, especially cultural destinations (by 36%), employment and housing entropy (concentration relative to study area)(by 34%), occupied housing units (by 16%), percent female-headed households (by -23%), median home sales price (by 22%) and gross residential density (by 33%) all proved salient in predicting bikeshare ridership in a controlled Bivariate Analysis. They also proved significant in Multilinear Regressions (Appendix 2).
d. **Literature:** The Office of Planning's "DC Vibrant Streets Toolkit" and "Design and Streetscape Guidelines" mention the importance of pedestrian-oriented lighting in creating a perception of safety.
e. **Literature:** However, the District Department of Transportation also must plan and approve such lighting according to their own rigorous design standards.
f. **Literature:** The Office of Planning's "Comprehensive Economic Development Strategy." "Retail Action Strategy" and "Creative Placemaking" initiative all point to the need for inclusive arts, culture and community and economic development

2. What to do about it?
   a. **Action #2.2:** Include Capital Bikeshare planning and outreach when conducting **design reviews** of new and proposed real estate developments, especially on topics highly correlated with ridership such as: street lighting height, affordable housing or community/economic development.

   b. **Action #2.3:** Capital Bikeshare should also be a part of the Region 3 Environmental Justice mitigation process as link to smart growth, addressing job/housing imbalances, social equity, environmental justice, public health or community and economic development.

      i. **Example**: **Ward 7 & 8 EPA Environmental Justice Working Group** consists of approximately 40 organizations including: the District Department of the Environment (DDOE), the US Department of the Interior, the Department of Labor (250 Jobs Corps Center trainees) and other community-based organizations. Their stated goals of, "green economy/jobs, children's environmental health (through a 'healthy homes, healthy schools and healthy child care program') and contaminated properties" (outlined in a March 2010 report) could be a common platform to connect the District Department of Transportation with new local community partners, who may be interested in Capital Bikeshare's (1) the access to green jobs bikeshare provides directly and indirectly (2) green infrastructure management around stations and rights-of-way (3) new community partners program offering free or reduced price bikeshare memberships as well as outreach and support. The EPA supervisor for this project also advised the data collection phase of this report. His contact is Reginald Harris (harris.reggie@epa.gov) at 215-814-2988.

Recommendation 3:

Identify new ways to reach **financially burdened residents** and workers using the DC Office of Tax and Revenue and the Federal Financial Institutions Examination Council data to increase access to affordable Capital Bikeshare resources for those who need it most.

c. Partner #4: DC Office of Tax and Revenue with the
d. Partner #5: Federal Financial Institutions Examination Council

1. Why should they play a role?

a. **Finding:** Factors related to financial vulnerability, such as predatory subprime lending rates (by -.25%), median sales price (by 30%), TANF recipients (by 31%) or food stamps (by 27%) and number of home sales (by -14%) are weak-to-moderately correlated with bikeshare ridership in the Bivariate Analysis (Tables 7-13).

b. **Finding:** Out of the original 84 variables, low-wage (by 27%) and medium-wage (by 31%) job sites were both positively correlated with bikeshare ridership in the bivariate model, and also were strong predictors on the hierarchical stepwise regression (Appendix 2).

c. **Literature:** The DC Office of Tax and Revenue collects and analyzes the housing data, while the Federal council analyzes predatory lending (Table 2). The Federal Deposit Insurance Corporation (FDIC) collects city-wide statistics on the banked and underbanked, including the reasons why and how groups of different demographics came to be without a secure line of credit (Valenti 2015).

d. **Literature:** Trends in Capital Bikeshare user surveys suggest that current membership is not proportionate to the population, with 80 percent of members were white, 80 percent had an income of $50K or more, and 95 percent had at least a 4-year college education (LDA Consulting, 2013)

2. What to do about it?
   e. **Action #3-1:** Include Capital Bikeshare membership as part of the **EBT or TANF card** benefits, a reduced-fair SmartTrip card or the DC One Card. This would expand access for the elderly, the poor, students and other traditionally underserved populations.
      i. **Example:** The Los Angeles Metro plans on allowing bikeshare users to pay for their trip using a **Transit Access Pass (TAP)** card for the standard $1.75 base transit fare. This 2015 Fehr and Peers study accesses the feasibility of this and other payment alternatives for bikeshare.
      ii. **Example:** Research from the National Association of City Transportation Officials (NACTO) suggests that fare payment options should include a cash option and be marketed as dollars per month to reflect how people budget and spend (NACTO, 2015).
   f. **Action #3-1:** Strategize how to guide the discussion about financial barriers for the **unbanked and underbanked** in the city to help expand access to Capital Bikeshare and the wider sharing economy.
      i. By 2018, 42 percent more low-income residents are forecasted live within a quarter mile of a new or existing bikeshare station (Foursquare, 2015)

Recommendation 4:

Foster new **community** partnerships to promote equity in bikeshare **access**, **mobility** and **public health** in across all eight wards of the District of Columbia.

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e. Partner #6: The District Department of Health & Human Services

1. Why should they play a role?
   i. **Findings:** Bikeshare stations with the highest concentrations of poverty, a measure highly correlated with health, education and social outcomes, are also the stations with the lowest concentrations of trips to a statistically

significant degree in both bivariate and hierarchical regression analysis (Figure 12 and 13)(Table 7 and 15).

ii. **Literature:** Bikeshare has been shown to increase public health. In London, men's major benefit was estimated to come from reductions in ischemic heart disease, whereas women have been found to be more likely to benefit from reductions in depression (Woodcock et al., 2014). Woodcock et al. proved these benefits using trip data to model the health impacts of the bikeshare via comparison to a scenario in which bikeshare did not exist.

1. In that London study, the greatest health benefits were projected to be from an increase in middle-aged and older people using bikeshare (Woodcock et al., 2014).

iii. **Literature:** Bicycling as a whole, is becoming more diverse. Between 2001 and 2009, cycling rates rose fastest among African Americans (by 100%), Hispanics (by 50%), and Asian Americans (by 80%). Those three groups also account for a growing share of all bike trips, rising from 16 percent in 2001 to 21 percent in 2009 (Pucher 2011)(League of American Bicyclists 2013).

1. Data from the U.S. Census Bureau indicate that these growth trends have continued, particularly among those with low household incomes and those who self-identify as Hispanic, Some Other Race, or Two or More Races (McKenzie 2014). This increasing diversity in bicycling demographics has been referred to by some as the "New Majority" (League of American Bicyclists 2013; Taylor 2013; Lugo et al. 2014).

2. This is bolstered by the growing trend in the United States that values access over ownership (Earley, 2014). Owning a car may be no longer viewed as a critical need by many city dwellers who prefer paying for and using vehicles only when needed (Earley, 2014). Combined, these trends suggest that there is potential to attract a great diversity of ethnic groups to bikeshare.

2. What to do about it?

a. **Action #4-1:** The Department of Health and Human Services curated many of the datasets I used in calculating health, service, arts, education, and recreation, religious and cultural facilities. This geocoded data can be added to DDOT's growing community partnership database for more robust and context-sensitive outreach.

ii. **Example:** DDOT's new "**Prescribe a Bike**" program, where community clinic doctors will assign a wellness coordinator to patients recover from cardiovascular disease, can benefit from additional contacts in the health and human services nonprofit, religious and civic institutions social and human capital.

c. **Action #4-2:** There is a lack of **open data** on cardiovascular disease incidence rate in the District of Columbia. A working group with the DC Department of Health and Human Services should be formed to geocode this data in order to target outreach about Capital Bikeshare's role in addressing this pressing public health crisis, which disproportionately impacts low-income communities (Foursquare ITP, personal communication, February 16, 2016).

i. This measure can also serve as a way to **monitor and evaluate** community partnership program with pre and post implementation public health data.

f. Partner #7: Non-traditional partners

3. Why should they play a role?

a. **Findings:** As illustrated in Figures 11, 12 and 13, areas with the highest need for greater transportation access are the areas where bikeshare has the fewest users.

b. **Literature:** Only 3 percent of Capital Bikeshare members are African-American, compared to 8 percent for general bicycle riders in the D.C. area (Buck et al., 2013), despite African-Americans making up some 50 percent of the Washington, D.C. population (United States Census Bureau, 2013). Eighty-eight percent of respondents to a Transport for London identified as being white (Transport for London, 2014), compared to 55 percent for the general London population (Office of National Statistics, 2014).

i. Focus groups with low-income residents of Philadelphia, Pennsylvania reported feeling excluded by mainstream advertisements that lacked "people who look like us." They suggested that bikeshare marketing materials should portray a diversity of ages, genders and ethnicities so that "people in Fortune 500 companies to supermarket workers" would be able to see themselves using the system (Hoe and Kaloustian, 2014).

c. **Literature:** Users and would-be users value bikeshare's spontaneity and policies should seek to minimize hurdles associated with becoming bikeshare users (Fishman et al., 2012a).

    i. These informational hurdles must be addressed in order to expand bikeshare access to older age groups, people of lower-incomes and limited language skills.

d. **Literature:** Actual usage of bike-share, car-share, and ride-share systems alike by low-income individuals has been minimal (Berman, 2013; DDOT, 2007; Golub, 2007; Fuller et al., 2011). The for-profit operators do not have stated goals of high usage by low-income individuals per se.

    i. New York and Philadelphia bikeshare stations have ongoing partnerships with community-based organizations and "community ambassadors" made up of local residents with close ties to the community to organize events and promote the bikeshare system (Indiego 2015) (Kaufman et al., 2015).

4. What to do about it?

a. **Action #4-3:** Establish new community partnership working groups as Capital Bikeshare expands into low-income communities to develop a coordinated outreach strategy

    i. Toole Design Group call this strategy a "**meeting in a box**" (Alia Anderson, personal communication, January 2016).

    ii. This would contain social media soundbites, infographics, photographs and statistics tailored to the Capital Bikeshare station near each partner.

        1. Standardized "Action Plan" templates, powerpoints and checklists, such as the "Community Toolbox" provided online by the University of Kansas, could be used to monitor and evaluate the progress of each community partnership Capital Bikeshare forms.

iii. These new partners would be responsible for encouraging **community leaders**, such as church pastors or local teachers, in leading group bikeshare rides and bikeshare station safety audits.

1. This could be coordinated with DDOT's Safe Routes to School coordinator and DC's Office of Arts and Humanities.

2. **Example:** Chicago bikeshare features a Design-a-Divvy art contest with online teacher resources for students to design wraps for bikeshare bikes and to learn about cycling safety. Charlotte's B-Cycle bikeshare hosts an annual back-to-school group ride (Corbin, 2015).

b. **Action #4-4:** Incorporate innovative and unconventional outreach methods to reach a more diverse audience, such as **Limited English Proficient learners**, **seniors** and **low-literacy residents**.

i. **Example:** Bring a creative Participatory Planning approach into community meetings. Here is an overview:

1. The **charrette** facilitator asks attendees to create their ideal neighborhood block or the site of their fondest childhood memory using found and recycled objects. Individuals briefly present their creations and then work in teams to reimagine a specific neighborhood block.

2. This technique allows participants of all ages and language abilities to visually communicate with one another, practice consensus and compromise and use their lived experiences to imagine a safer, more aesthetically pleasing and more accessible neighborhood.

3. Throughout the charrette, planners could ask participants to focus on bicycling, walking and bikesharing in each scenario created.

ii. **Example:** Team up with local community theatre groups and drama departments at universities and high schools to start a **"People's Planning School"** and a **"Theatre of the Oppressed"** workshop series. These approaches have been used by nonprofits such as Pacoima Beautiful and the East Los Angeles Community Corporation when working on Environmental Justice cases in historically disadvantaged communities.

1. These unconventional artistic programs and "urban planning 101" studios and seminars have empowered community residents in Los Angeles to become more civically engaged and proactive in urban planning policy implementation.

c. **Action #4.5:** Include equity considerations apart of day-to-day operations, outreach and marketing:

i. **Example:** Philadelphia's IndieGo bikeshare has make a strategic commitment to feature people of different genders, ethnicities, languages and different age groups in bikeshare **marketing and advertising** materials (Hoe and Kaloustian, 2014).

ii. **Example:** The City of Philadelphia hired an **Access Manager**, Claudia Setubal, who is embedded in the bikeshare operations offices. She created a cash membership program and analyzes data to understand usage patterns. She developed a Bikeshare Ambassador Toolkit to guide local residents hired to host context-sensitive outreach and educational events (Indiego 2016).

iii. **Example:** Nike's recent sponsorship of BIKETOWN bikeshare in Portland, Oregon has "contractual obligations to ensure that 50% or more of the **jobs** that BIKETOWN creates go to people from underrepresented communities. The jobs will pay a minimum of 150% of the state's minimum wage (Community Cycling Center, 2016)."

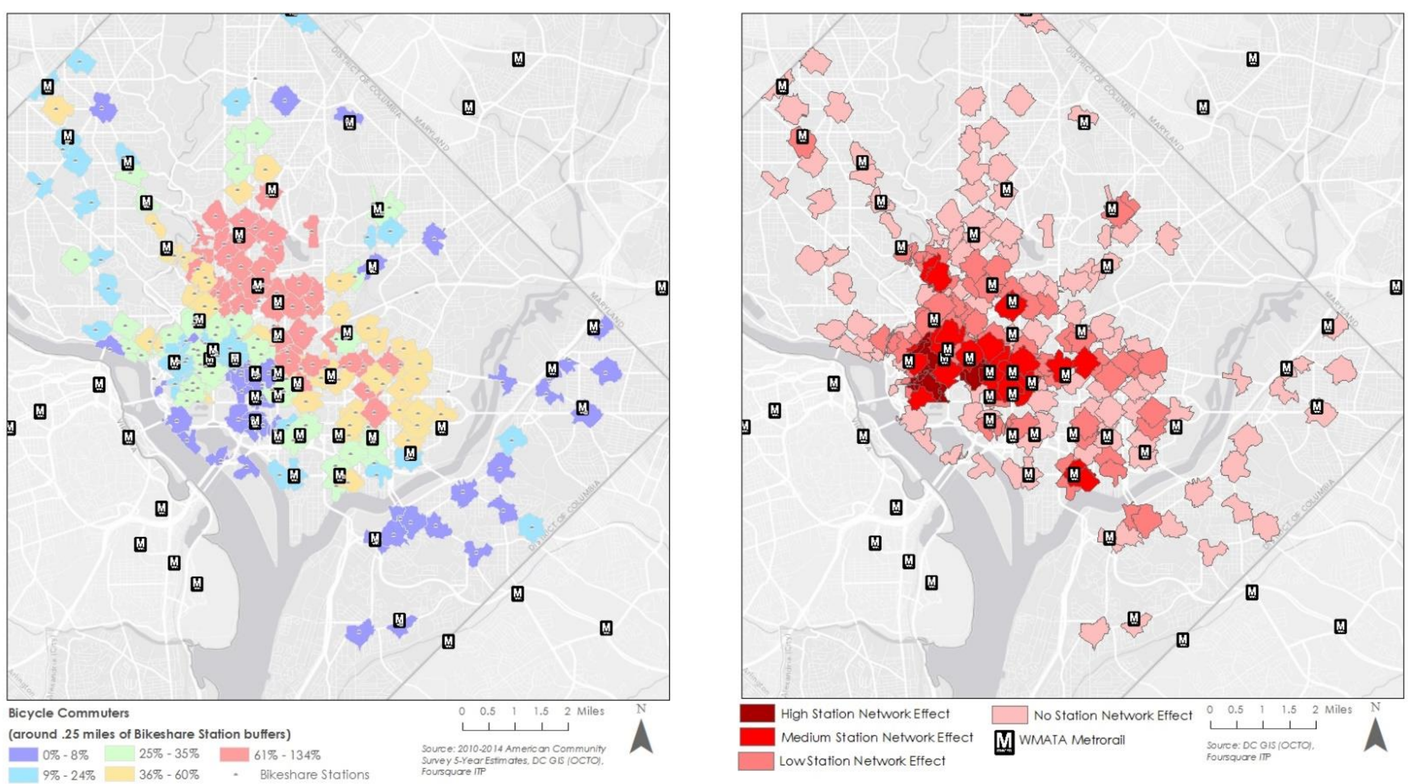
10 DATA LIMITATIONS

It should be noted that due to privacy reasons, the majority of the data collected are not available at a granular level, but at a census block group level. In a personal communication this July with an EPA staff member, I was told that analyzing Capital Bikeshare ridership using these data would be, "Analyzing a pinpoint problem with a blunt tool." Additionally, there currently does not exist any survey of non-Capital Bikeshare users to corroborate my results. Lastly, this dataset does not consider the relative amount of funding, staffing, and services available to introduce bicycling and bikeshare into low-income areas, beyond the pilot program the District Department of Transportation recently launched with the Washington Area Bicyclist Association. Therefore, it should be noted that this study and bikeshare may not be able to adequately address the deep-seated and systematic financial, structural, and informational/cultural gaps between the wealthier and poorer areas of the city.

11 APPENDIX 1: GEOSPATIAL ANALYSIS CONTINUED

I used ArcGIS to visualize the geographic distribution of certain dependent variables which several studies suggested highly correlated with bikeshare ridership in my literature review. One such variable, examined by R. Alexander Rixey of Fehr & Peers, was *station network effects*, or the impact of high, medium and low connectivity between bikeshare stations within a 500 to 1,000 feet distance. Geospatial analysis results from ArcGIS, shown in Figure A1 below, reveal there is potential to improve poor network effects, or zero bikeshare stations in the 500 feet range, in high poverty areas as Capital Bikeshare expands over the next three years. Another variable I mapped was *mode share to work*, which includes commute by taxi, transit, carpool, bicycle, walking, driving and teleworking from home. The map below in Figure A1 demonstrates that bikeshare is high even in high poverty areas east of the Anacostia River and also in areas farther away from the WMATA subway, suggesting that bikeshare could compliment the first and last mile for low-income workers and household's daily commute.

FIGURE A1: Bicycle Modal Split to Work and Station Network Effects by Bikeshare Service Area Buffer



12 APPENDIX 2: REGRESSION OUTPUTS (SPSS)

Note: All SPSS output tables of the Stepwise and Ordinary Least Squares Regression Models can be found in this online workbook (anyone with this link can comment): https://docs.google.com/spreadsheets/d/1tB9eHI_cu_qKKgFlftzm4pZ1JFWbe5YW-xCfaboMmZg/edit?usp=sharing

MODEL SUMMARY (Hierarchical Stepwise Regression)

Table 16: Parsimonious Model Summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.444[a]	.197	.193	20507.396	.197	44.438	1	181	.000
2	.512[b]	.262	.254	19712.830	.065	15.885	1	180	.000
3	.536[c]	.287	.275	19435.531	.025	6.173	1	179	.014
4	.561[d]	.315	.300	19102.031	.028	7.305	1	178	.008
5	.577[e]	.333	.314	18902.223	.018	4.783	1	177	.030
6	.596[f]	.355	.333	18635.114	.022	6.110	1	176	.014
7	.646[g]	.418	.394	17763.363	.062	18.699	1	175	.000
8	.660[h]	.435	.409	17540.555	.018	5.474	1	174	.020
9	.708[i]	.501	.475	16532.895	.066	22.857	1	173	.000
10	.732[j]	.535	.508	16007.695	.034	12.538	1	172	.001
11	.740[k]	.547	.518	15848.296	.012	4.477	1	171	.036
12	.758[l]	.575	.545	15393.664	.028	11.250	1	170	.001
13	.765[m]	.585	.553	15257.286	.010	4.053	1	169	.046
14	.782[n]	.611	.579	14810.614	.026	11.347	1	168	.001
15	.790[o]	.624	.590	14619.448	.012	5.422	1	167	.021

ANOVA (Hierarchical Stepwise Regression)

Table 17: Parsimonious Model ANOVA

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	18688590821.464	1	18688590821.464	44.438	.000[b]
	Residual	76120142533.005	181	420553273.663		
	Total	94808733354.470	182			
2	Regression	24861513604.347	2	12430756802.173	31.989	.000[c]
	Residual	69947219750.123	180	388595665.278		
	Total	94808733354.470	182			
3	Regression	27193300061.283	3	9064433353.761	23.996	.000[d]
	Residual	67615433293.187	179	377739850.800		
	Total	94808733354.470	182			
4	Regression	29858745249.663	4	7464686312.416	20.457	.000[e]
	Residual	64949988104.806	178	364887573.623		
	Total	94808733354.470	182			
5	Regression	31567686188.132	5	6313537237.626	17.670	.000[f]
	Residual	63241047166.338	177	357294051.787		
	Total	94808733354.470	182			
6	Regression	33689659671.483	6	5614943278.580	16.169	.000[g]
	Residual	61119073682.987	176	347267464.108		
	Total	94808733354.470	182			
7	Regression	39589747582.786	7	5655678226.112	17.924	.000[h]
	Residual	55218985771.684	175	315537061.552		
	Total	94808733354.470	182			
8	Regression	41273965799.020	8	5159245724.878	16.769	.000[i]
	Residual	53534767555.450	174	307671077.905		
	Total	94808733354.470	182			
9	Regression	47521496279.971	9	5280166253.330	19.317	.000[j]
	Residual	47287237074.499	173	273336630.488		
	Total	94808733354.470	182			
10	Regression	50734369586.244	10	5073436958.624	19.799	.000[k]
	Residual	44074363768.226	172	256246300.978		

	Total	94808733354.470	182			
11	Regression	51858922996.659	11	4714447545.151	18.770	.000[l]
	Residual	42949810357.811	171	251168481.625		
	Total	94808733354.470	182			
12	Regression	54524699534.819	12	4543724961.235	19.175	.000[m]
	Residual	40284033819.651	170	236964904.821		
	Total	94808733354.470	182			
13	Regression	55468104035.926	13	4266777233.533	18.329	.000[n]
	Residual	39340629318.544	169	232784788.867		
	Total	94808733354.470	182			
14	Regression	57957212206.772	14	4139800871.912	18.873	.000[o]
	Residual	36851521147.698	168	219354292.546		
	Total	94808733354.470	182			
	Regression	59116112591.570	15	3941074172.771	18.440	.000[p]
	Residual	35692620762.900	167	213728268.041		
	Total	94808733354.470	182			

Table 18:

Model		B	Std. Error	Beta	t	Sig.*	Lower Bound	Upper Bound	Zero-Order	Partial	Part	Tolerance	VIF**
15	(Constant)	-3546.52	7285.44		-.49	.63	-17929.94	10836.91					
	Points of Interest - Culture	556.19	290.4	.15	1.92	.06	-17.14	1129.52	.38	0.15	.09	.35	2.83
	Unemployment rate (%)(2012 ACS five-year estimate)	-821.83	534.69	-.19	-1.54	.13	-1877.44	233.78	-.44	-0.12	-.07	.14	6.99
	Pedestrian Lighting (16' and below in height)	-8.30	28.88	-.02	-.29	.77	-65.32	48.72	.29	-0.02	-.01	.64	1.57
	% Female-headed households (2012 ACS five-year estimate)	21.63	119.24	.02	0.18	.86	-213.79	257.04	-.28	.01	.01	.15	6.64
	Low-Wage Job Sites (incomes $1250/month or less)	-18.50	4.62	-.95	-4.00	.00	-27.62	-9.37	.29	-0.30	-.19	.04	25.03
	Gross retail employment density (jobs/acre)	2575.50	728.38	.24	3.54	.00	1137.49	4013.51	.37	0.26	.17	.48	2.08
	Elevation Change (average)	-246.25	79.74	-.18	-3.09	.00	-403.68	-88.83	-.43	-.23	-.15	.67	1.49
	Medium-Wage Job Sites (incomes $1250/month or more)	7.05	2.42	.70	2.92	.00	2.28	11.82	.34	.22	.14	.04	25.83
	Occupied housing units, 2010	.99	.35	.15	2.85	.01	0.30	1.67	.18	.22	.14	.80	1.25

Model		B	Std. Error	Beta	t	Sig.*	Lower Bound	Upper Bound	Zero-Order	Partial	Part	Tolerance	VIF**
15	Network density in terms of facility miles of auto-oriented links per square mile	1537.68	554.33	.20	2.77	.01	443.28	2632.07	.26	.21	.13	.44	2.28
	Collision Rate for Bicyclists (2014)	1421.06	533.16	.17	2.67	.01	368.46	2473.66	.40	.20	.13	.55	1.81
	Network density in terms of facility miles of auto-oriented links per square mile	1537.68	554.33	.20	2.77	.01	443.28	2632.07	.26	.21	.13	.44	2.28
	Train to Work	*1143.49*	*434.25*	*.16*	*2.63*	*0.01*	*286.16*	*2000.82*	*0.18*	*0.2*	*0.13*	*0.64*	*1.57*
	Median home sales price, 2012	0.01	0.01	0.13	2.54	0.01	0	0.02	0.31	0.19	0.12	0.82	1.22
	Walk to Work	26.45	10.79	0.17	2.45	0.02	5.16	47.75	0.5	0.19	0.12	0.49	2.06
	Intersection density in terms of pedestrian-oriented intersections having three legs	112.26	48.21	0.17	2.33	0.02	17.08	207.44	0.36	0.18	0.11	0.42	2.39

COLLINEARITY DIAGNOSTICS (Hierarchical Stepwise Regression)

Table 19: Parsimonious Model Collinearity Diagnostics

Model	Dimension	Eigenvalue	Condition Index	Constant	Unemployment	Medium-Wage Job Sites	Low-Wage Job Sites
15	1	10.31	1.00	0.00	0.00	0.00	0.00
	2	1.86	2.35	0.00	0.00	0.00	0.00
	3	1.10	3.06	0.00	0.00	0.00	0.00
	4	0.50	4.52	0.00	0.00	0.01	0.01
	5	0.48	4.65	0.00	0.01	0.00	0.00
	6	0.44	4.83	0.00	0.01	0.00	0.00
	7	0.31	5.80	0.00	0.00	0.00	0.00
	8	0.26	6.33	0.00	0.00	0.00	0.00
	9	0.20	7.23	0.00	0.00	0.00	0.00
	10	0.17	7.81	0.00	0.00	0.00	0.00
	11	0.14	8.62	0.00	0.01	0.01	0.01
	12	0.10	10.05	0.00	0.00	0.00	0.00
	13	0.09	10.91	0.00	0.00	0.00	0.03
	14	0.03	20.26	0.31	0.25	0.05	0.06
	15	0.02	24.81	0.52	0.70	0.01	0.02
	16	0.01	29.21	0.17	0.01	0.91	0.87

Continued:

COLLINEARITY DIAGNOSTICS (Hierarchical Stepwise Regression)

Table 19: Parsimonious Model Collinearity Diagnostics

Collinearity Diagnostics[a]

Variance Proportions							
Occupied housing units, 2010	Median sales price, 2012	% Female-headed households (2012 ACS five-year estimate)	Elevation Change (average)	Pedestrian Lighting (16' and below in height)	Collision Rate for Bicyclists (2014)	Gross retail employment density (jobs/acre)	Points of Interest - Culture
.00	.00	.00	.00	.00	.00	.00	.00
.00	.00	.00	.02	.00	.00	.01	.01
.00	.00	.00	.00	.01	.05	.01	.00
.00	.00	.00	.01	.11	.00	.02	.01
.00	.01	.01	.01	.00	.00	.08	.00
.00	.01	.01	.21	.03	.00	.13	.03
.01	.01	.01	.01	.28	.13	.18	.01
.01	.01	.00	.00	.01	.67	.22	.00
.17	.05	.00	.44	.12	.06	.05	.01
.02	.06	.00	.01	.30	.00	.10	.03
.00	.01	.00	.01	.04	.02	.00	.84
.37	.48	.00	.06	.06	.00	.07	.01
.07	.09	.00	.01	.01	.03	.03	.03
.05	.08	.47	.21	.04	.01	.01	.01
.27	.17	.45	.01	.00	.01	.05	.01
.01	.02	.04	.00	.00	.00	.03	.01

Walk to Work (2010 ACS, five-year estimate)	Train to Work (2010 ACS, five-year estimate)	Network density in terms of facility miles of auto-oriented links per square mile	Intersection density in terms of pedestrian-oriented intersections having three legs per square mile
.00	.00	.00	.00
.00	.02	.00	.00
.00	.07	.07	.00
.04	.11	.08	.00
.01	.23	.09	.01
.00	.03	.00	.00
.00	.07	.13	.00
.04	.16	.00	.00
.01	.01	.05	.01
.56	.08	.07	.01
.12	.00	.08	.00
.17	.01	.02	.00
.01	.14	.12	.56
.01	.03	.08	.03

MODEL SYNTAX ALTERNATIVE (Hierarchical Stepwise Regression)

Table 20: Alternative Parameters of Hierarchical Stepwise Regression (Full Model – including all variables)

Syntax of Hierarchical Stepwise Regression	***Notes:***
REGRESSION /MISSING LISTWISE /STATISTICS COEFF OUTS R ANOVA COLLIN TOL **/CRITERIA**=PIN(.05) POUT(.10) /NOORIGIN	Regression **thresholds** (Stepwise Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100)
/DEPENDENT Trips	Dependent Variable = **Total Ridership**
/METHOD=STEPWISE Avg_E_LOWW Avg_E_MEDW Avg_PctUne CheckCash Avg_fs_cli Avg_tanf_c Avg_NumOcc Avg_PctSam Avg_PctVac Avg_PctOwn Avg_sales Avg_PctSub Avg_Med_Sa Avg_PctAnn Poverty_Concentration Pov_DummyVar	Block #1: **Income**
/METHOD=STEPWISE Avg_PctBla Avg_PctWhi Avg_PctHis Avg_PctAsi Avg_PctFam Avg_Pct25a	Block #2: **Demographics**
/METHOD=STEPWISE PedLighting AllStreetLighting Avg_Elev_C Trees	Block #3: **Urban Design**
/METHOD=STEPWISE V_Crime_To Homicides Assault Robbery SexualAbuse PedCrash BikeCrash	Block #4: **Safety**
/METHOD=STEPWISE Health_Cou Culture_Co Food Edu_Count Fac_Count Avg_D1A Avg_D1B Avg_D1C Avg_D1C5_R Avg_D1C5_O Avg_D1C5_I Avg_D1C5_S Avg_D1C5_E Avg_D1D Avg_D2B_E5 Avg_D2A_EP	Block #5: **Land Use**
/METHOD=STEPWISE Avg_D3a Avg_D3aao Avg_D3amm Avg_D3apo Avg_D3b Avg_D3bao Avg_D3bmm3 Avg_D3bmm4 Avg_D3bpo3 Avg_D3bpo4 NtwkEffect	Block #6: **Connectivity**
/METHOD=STEPWISE Avg_Drove Avg_Carpoo Avg_Transi Avg_Bus Avg_Subway Avg_Train Avg_Taxi Avg_Motorc Avg_Bike Avg_Walk Avg_Work_a ADB_80pcl Avg_D4a Avg_D4b025 Avg_D4b050 Avg_D4c Avg_D4d CarSharing RailStn BikeLanes Avg_AUTOOW Avg_AUTO_1	Block #7: **Transportation**

** Cases Used: Statistics are based on cases with no missing values for any variable used.*
** Variable codes in Syntax above (used in SPSS) can be found In Table 2.*

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