Planting Lime at the Station: Building a Theoretical Docking Station Network to Analyze the Spatiotemporal Characteristics of Dockless Bikeshare in Seattle

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Abstract

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Bikeshare systems are a well-established component of urban transportation systems, however until recently they have almost exclusively relied on permanently placed docking stations. In recent years, privately operated dockless, or “free floating”, bikeshare systems have proliferated throughout urban areas. Seattle presents a rare example of a large city that does *not* have a docked bikeshare system, and exclusively features vendor operated dockless bikeshare. Docked and dockless bikeshare have been frequent research subjects, but how dockless bikeshare behaves in a city where it is the only bikeshare system available remains largely unconsidered. To study that question, I use the spatial distribution of Capital Bikeshare stations in Washington D.C. to develop a theoretical network of docking stations in Seattle. Using Lime, Seattle’s largest dockless bikeshare vendor, I calculate net flows of bikes within Seattle’s “station” network and perform the same calculations on Capital Bikeshare’s real flows of bikes between stations. In doing so, I allow for a direct comparison between Capital Bikeshare and Lime on the (dis)similarities of the spatiotemporal characteristics of their bikeshare flows. I find that the two systems exhibit different dynamics, with Capital Bikeshare producing strong commuting flows in and out of the Central Business District, as well as statistically significant relationships to a variety of built environment and demographic variables. Lime’s Seattle fleet, however, does not demonstrate the same spatiotemporal patterns, and does not share the same relationships to the measured variables.

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Chapter 1: Introduction

In 2017, Seattle divested from Pronto, its docked bikeshare system. While the distribution of stations was quite unbalanced, favoring downtown, Capitol Hill, and the University District at the exclusion of other areas, the City of Seattle had preexisting plans for system expansion (Fucoloro, 2017). In shutting down Pronto, Seattle became the first major city in the United States to shutter an established docked bikeshare system. In its place, the Seattle Department of Transportation and Mayor Ed Murray pursued a dockless, free-floating bikeshare model operated by private vendors (Fucoloro, 2017). In the intervening years, several cities have made similar decisions, most notably San Diego (Bowen, 2019) and Minneapolis (Felegy & Sepic, 2023). At face value, whether a shared bicycle is docked at a station or freely parked within a service area has little bearing on the individual rider, and may actually be more convenient. As long as a prospective rider is able to rent a bicycle within walking distance of their trip origin, and end their trip a convenient walking distance from their trip destination, the system functions well. In practice, however, the differences between dockless and docked bikeshare have implications for level of service, use of urban space, and the ability of local governments to leverage bikeshare systems to achieve policy goals.

The implications and outcomes of docked and dockless bike share systems have been explored to a great deal in the academic literature, but research directly comparing docked and dockless systems with the goal of exploring their differences is limited. Researchers have extensively studied the relationship between docked bikeshare trips and population density (Tran et al, 2014), distance from the Central Business District (Faghih-Imani & Eluru, 2014), land use characteristics (Wang et al, 2015), and public transit stations (Tang et al, 2024; Martin & Shaheen, 2014). Authors have investigated the same relationships within dockless bikeshare systems, though the literature is less deep, owing to the recency of modern dockless bikeshare systems. Several authors have compared docked and dockless systems within the same city (McKenzie, 2018; Lazarus et al, 2020), as well as comparisons between systems across cities (Meng & Brown, 2021). Little is known, however, about how dockless systems operate when they are the sole bikeshare system available in a city, particularly in the Western urban context. Much of what we know about dockless bikeshare comes from cities like Washington D.C. that have dominant docked bikeshare systems (McKenzie, 2018), suburban cities and towns (Gehrke, 2021), or densely built cities like Singapore (Zhu et al, 2020), whose urban form does not map onto American cities outside of New York.

Dockless bikeshare is an attractive option for city officials interested in promoting sustainable transportation but wary of tight budgets and inflating infrastructure costs. Traditional docked bikeshare systems cost their host cities tens of millions of dollars to build and improve (Government of the District of Columbia, 2022), and require substantial funding for ongoing system build-out (2022). While a fully developed docked system partially fund itself with membership sales, per-trip fees, and sponsorship deals, this revenue is not usually sufficient to cover all costs (Goldbeck, 2022). In contrast, dockless bikeshare vendors will gladly pay annual permit fees to secure operating rights in high demand areas, allowing the city to establish a new revenue stream at little to no financial cost (SDOT, 2023). Weighing these two options, local governments would surely be interested in the option that allowed them to make money without committing any of their own. In addition to cost, program operations are also a key point of difference. The majority of publicly operated bikeshare systems rely on private firms to manage the day to day operations of the system (Goldbeck, 2022). The largest, Motivate, is owned by Lyft, and has exhibited generally poor performance since its purchase (Office of the Comptroller, 2023). That performance is perhaps indicative of Lyft's commitment to Motivate, as they have recently begun to float the idea of selling the firm (Griswold, 2023). If Lyft was to leave the bikeshare market, cities would be left having to take on citywide operations and logistics work at significant cost. Considering that scenario, why not outsource bikeshare services directly to the private sector? Docked bikeshare systems have proven to be valuable tools to supplement transit service (City of Boston, 2022), advance equity goals (DDOT, 2019), and increase access to zero emission transportation. They clearly support commuter activity (Goldbeck, 2022), and can extend the reach of limited transit systems (Metro Bike Share, 2024). Given the inherent costs and present instability of docked bikeshare systems, one of the only factors preventing dockless bikeshare systems from being preferable to docked is the lack of knowledge on their ability to replicate the proven benefits of docked systems. Seattle presents the ideal environment in which to explore this gap in the literature—Seattle has an urban form broadly analogous to other American cities, with pockets of high density residential and business land use, clearly defined commercial corridors, and broad swaths of low-density residential neighborhoods. It has a centrally located Central Business District and bicycle infrastructure that facilitates bikeshare use. With seven years having gone by since the switch from docked to dockless, Lime and its smaller competitors are no longer novelties, and are well integrated into the urban transportation system. Lime is clearly the dominant bikeshare system in Seattle, with a fleet comparable in size to Portland's BikeTown system and a vehicle similar in size and appearance to those of docked systems. The impact of Seattle's hills is mitigated by Lime's electric pedal assist motors, which allow riders to travel up to 15 miles per hour with ease (SDOT, 2023). The main difference, then, is that Lime is dockless, and Capital Bikeshare, the comparison system I chose, is not. On its face, the two systems appear quite different. Capital Bikeshare's service area covers three states and has over 5,000 bikes available to rent (Goldbeck, 2022). Lime offers service within Seattle, but not outside its borders, and during its peak deployment had 2,059 bikes available to rent (SDOT, 2024). Not all Capital Bikeshare bikes are located within the District of Columbia, however, and bikes in other municipalities, such as Alexandria or Bethesda, tend to stay there (Goldbeck, 2022). The real value offered by Capital Bikeshare is the extent of its service area. With over 350 stations throughout the District, Capital Bikeshare data captures arrival and departure trends from a wide variety of land use types and population densities. The District's urban form varies significantly, with outer neighborhoods demonstrating the single family homes characteristic of many Seattle neighborhoods, while neighborhoods closer to the urban core exhibit mixed use density, with rowhouses and low-rise apartment buildings dominating the landscape. The two cities are quite similar in population, with Seattle at 749,256 residents (US Census Bureau, 2024) and the District of Columbia at 671,803 (US Census Bureau, 2024A). While the District is not a perfect match for Seattle by any means, no city would be, owing to the uniqueness of Seattle's dockless-only bikeshare system. What Capital Bikeshare does provide is a known quantity with broad similarities, and excellent geographic coverage that allows for precise analysis of how land use and demographic factors affect bikeshare flows, and a spatial structure that can be used to create a theoretical system of docking stations in Seattle.

In this thesis I ask the following question–to what extent does Lime Bike in Seattle exhibit the spatiotemporal characteristics of a built-out docked bikeshare system? This question is explored through flows, or the net change in available bikes at the station level across a defined time frame. By analyzing the (dis)similarity of bikeshare flows within similar areas between Capital Bikeshare and Lime Bike, and by analyzing each system's respective relationship between bikeshare flows and selected built environment variables, I am able to determine their (dis)similarity. To make the direct comparison feasible, I use the spatial characteristics and arrangement of Capital Bikeshare's docking stations to create a broadly similar network in Seattle, to which I aggregate Lime Bikes and calculate flows. I hypothesize that despite its status as the dominant bikeshare service in Seattle, Lime Bike flows will *not* exhibit similar spatiotemporal characteristics as Capital Bikeshare, but that the two systems may share similar relationships with the built environment, particularly during the afternoon demand peak when trips are not constrained by morning commute dynamics.

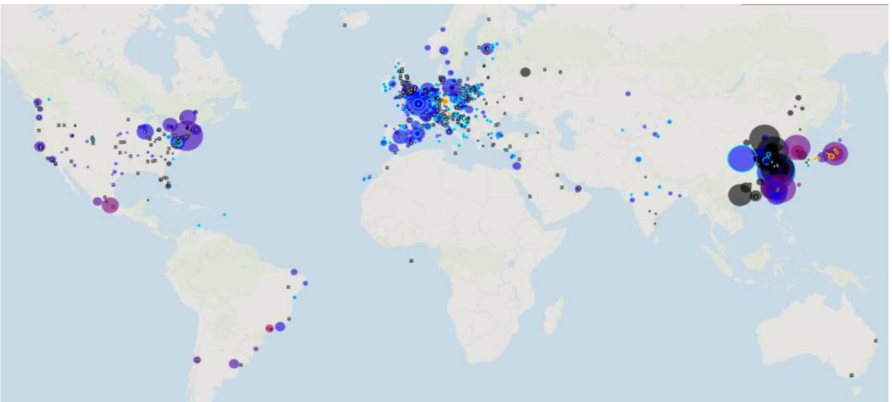
Chapter 2: Bikeshare in Context

Before analyzing Seattle's dockless bike share system further, we must contextualize the two bikeshare systems being compared in this thesis within the broader bikeshare ecosystem. This chapter begins with an overview of the two bikeshare systems compared in this thesis, followed by an exploration of the development of bikeshare systems and their diffusion across the world, the origins of dockless bikeshare, and the specific history of bikeshare in Seattle as it made the transition from a docked to dockless system.

Modern Bikeshare Systems

Every modern bikeshare system functions on the same basic model: standardized bicycles, typically with colorful branding or sponsored logos, are available to rent for low cost at convenient locations around a city. Renting a bicycle is a quick process, typically consisting of either an in-app purchase or processing an electronic payment at a kiosk. These locations are typically high demand areas, such as commercial corridors, in the central business district, by transit stations, or on university campuses (OOMAP, 2023). Many publicly owned systems offer membership programs that reduce point of sale and hourly costs in exchange for an annual payment, effectively creating two different ridership classes–those who ride frequently (members) and those who ride infrequently or randomly (casual riders). In a docking station-based system, trip origins and destinations are constrained by station locations. A prospective rider must have a station within convenient walking distance at the trip origin and have a station within convenient walking distance of their trip destination. Therefore, bikeshare systems operate most efficiently when stations are frequently and densely distributed throughout the city, maximizing both station and trip destination accessibility. Beginning in 2016, dockless or “floating” bikeshare systems operated by private companies began to appear and rapidly grew in popularity (NACTO, 2017). In a dockless system, bikes can be left anywhere within the company’s service area, though typically rules are in place that attempt to prevent bicycles from blocking sidewalks or ending up in water features. Bikesharing, both docked and dockless, has proven popular internationally, with large docked systems operating in New York, Montreal, London, Paris, Beijing, Mexico City, and many more (OOMap, 2023).

Figure 1: Bikeshare Systems Worldwide By Size



(OOMap, 2023)

Origins and Diffusion of Docked Bikeshare

Modern bikeshare systems are broadly considered to have originated in Western Europe in the second half of the 20th century. Researchers have broken the history of bikeshare into four distinct periods, which are detailed below (DeMaio, 2009).

First Generation Systems

The first known bikeshare proposal is the White Bicycle Plan, presented in 1965 by a Dutch Anarchist group called the Provos seeking to improve urban life in traffic-choked Amsterdam (DeMaio, 2009). The popular history (as relayed by many academics) presents a simplified version–that the Provos painted 50 bikes white and left them unlocked around Amsterdam, conveying the impression that bikesharing had whimsical origins that ultimately were naive to the realities of urban life. In reality, the original proposal is much more in line with the scale of a modern bikeshare system, and included elements of pedestrianization, radical traffic control, and large-scale mode shift to bicycle transportation in the dense urban core. After the plan was rejected, the Provos went ahead with 50 “White Bicycles”, in many ways analogous to the modern pilot program approach. While the plan ultimately failed due to theft and conflict with police and city government (Shaheen et al, 2010), the White Bicycle Plan is far more modern than often given credit for, and presents clear parallels to bikeshare systems today. The White Bikes program inspired other First Generation systems, including GreenBikes in Cambridge, UK, Yellow Bikes in La Rochelle, France (2010), and several smaller domestic examples in the United States.

Second Generation Systems

The Second Generation systems improved on earlier iterations by adding specialized docking stations to organize and secure bikes when not in use (DeMaio, 2009). The Second Generation is generally thought to have begun in 1995, when Copenhagen's City Bike Foundation introduced 1,100 branded bikes stored at coin operated stations (DeMaio, 2009). In the United States, Minneapolis and St Paul implemented the Yellow Bike program in 1996, which was followed by the launch of similar Second Generation systems in Madison (1995), Olympia (1996), Austin (1997), Princeton (1998), and Decatur (2002) (Shaheen et al, 2010). Earlier efforts to trace the history of bikesharing largely ignore the history of bikeshare in East Asia, where several cities experimented with Second Generation systems. From 1999 to 2004, Singapore operated TownBike, a Second Generation system. Taito Bicycle Sharing opened as a pilot program in the Japanese city of Taito in 2002, running until 2003. In 2005, Beijing opened a privately operated Second Generation system featuring 8,000 bicycles across 100 stations, though the system entered bankruptcy in 2009 (2010).

Third Generation Systems

Third Generation systems, defined by their electrified stations and payment kiosks, sturdier bicycle models, and larger scale began to appear in 1998, when the billboard and advertising company Clear Channel launched SmartBike in Rennes, France. To use the system, riders had to apply for a Smart Card, which would grant free bicycle use for three hours. The first major successes of the Third Generation both come from France, with Velo'v launching in Lyon in 2005 with 1,500 bicycles and Paris launching Velib in 2007–five years later Velib had 20,600 bicycles across 1451 docking stations, making it the largest bikeshare system in Europe, a designation that it retains today (Shaheen, 2010). In Taiwan, Kaohsiung City and Taipei both launched large bikeshare systems in 2009. The largest scale, and one of the most successful, Third Generation bikeshare system was Hangzhou's, in China. Operated by Hangzhou's public transit agency, it featured 40,000 bicycles across 1,600 stations at time of launch. Other notable Third Generation bikeshare systems in China include Beijing, with 10,000 bikes across 1,000 stations, and Shanghai with 7,200 bicycles across 80 stations. These three cities additionally present a case study of differential system design, with Hangzhou favoring a citywide station distribution, Beijing clustering stations around metro stops, and Shanghai using bikeshare to extend the range of its metro system (Tang et al, 2011). In the United States, the first Third Generation system was Capital Bikeshare, at the time SmartBike, in Washington D.C. In 2008, SmartBike opened with 120 bicycles across 10 stations (Hamilton, 2020). In 2010 the system was shut down in favor of implementing the more advanced Capital Bikeshare, but it served as an important proof of concept for bikeshare in the District of Columbia. In Seattle, the Pronto system opened in October, 2014, featuring 500 bicycles across 50 stations (Peters and Mackenzie, 2019). The development of Third Generation systems in the United States is also notable for the role played by dedicated bikeshare planning and operation firms, namely Alta Bicycle Share (later Motivate), and B-Cycle, as well as PBSC. B-Cycle and PBSC provide bikeshare bikes and docking stations (Lyft, 2022), while Motivate manages daily system operations –Motivate was bought by Lyft in 2018 in an effort to diversify holdings (Teale, 2018). Uber, Lyft's rival in the ridehailing space, is heavily invested in Lime, owning 33% of shares and allowing Lime to display their vehicles within the Uber app (Dillett, 2020). While not the focus of this thesis, the increasing dominance of docked (Lyft) and dockless (Uber) bikeshare markets by competing ridehailing companies is worth further study.

Fourth Generation Systems

Three key developments characterize the Fourth Generation bikeshare system: transit integration, electric assist bikes, and experiments with hybrid systems that allow dockless parking. Docked bikeshare systems have become increasingly integrated with public transit systems in a variety of ways, including partnerships that provide free bikeshare rides as a reward for upgrading to a new transit card (WMATA, 2021), offering free bikeshare memberships during transit line shutdowns (City of Boston, 2022), or even building bikeshare systems specifically to extend the reach of a limited subway system (Bicycle Transit Systems, 2016). E-Bikes first began to appear in public bikeshare fleets in 2016 (PBSC, 2019), with systems like Capital Bikeshare adding significant numbers of e-bikes to its fleet in 2018 (Goldbeck, 2022). More recently, systems such as Divvy (Chicago), Capital Bikeshare, and Portland's BikeTown have experimented with self-locking mechanisms on E-Bikes that allow them to be parked away from docks anywhere within the service area (Jin, 2024). These hybrid systems offer increased user flexibility while maintaining the benefits of a docked system.

Dockless Bikeshare

App-based dockless bikeshare originated in China between 2014 and 2016, and rapidly grew in popularity shortly thereafter. In 2014, students at Peking University launched what may have been the first true dockless bikeshare system, intended for internal university use (Gu et al, 2019). The following year, two companies, MoBike and Ofo, were founded with the intention of providing dockless bikeshare services at scale. In 2016 MoBike began operations in Shanghai (2019). By 2017, dockless bikeshare had exploded in China, with 23 million bikes across 57 operators, peak daily ridership of 70 million trips, and combined ridership of 17 billion trips, all within under two years of operation (2019). In 2017, dockless vendors began operating in the United States, with Ofo and MoBike, as well as domestic vendors Lime, Spin, and Jump competing for dominance (2019). Throughout 2017, over 57,500 dockless bikes were introduced to American cities–more than doubling the number of bikeshare bikes in service, and representing 44% of the total bikeshare bikes in service nationwide. Dockless vehicles were largely a novelty when introduced, with no precedent, and often the presence of an already established docked bikeshare system, dockless vehicles initially experienced low ridership, accounting for only 4% of total ridership, indicating significant oversupply (NACTO, 2017). In several cities, vendors did not have municipal approval to deploy their vehicles, leading to conflict with city level Departments of Transportation that led to confused and halting rollouts (2017). Bicycle clutter and competing vendor/city goals quickly became visible issues, leading many cities to adopt more restrictive policy frameworks to govern dockless vehicles (Wood and Hamidi, 2019). In the United States, the majority of dockless bikeshare operators also operate shared e-scooter fleets, which are typically the main revenue generator for vendors. The early 2020s have proven to be a period of consolidation for dockless mobility firms, with many leaving key markets or declaring bankruptcy, leaving Lime as the dominant player in both dockless bikeshare and e-scooters (Hamilton, 2023) .

Bikeshare in Seattle

In 2014, Puget Sound Bikeshare, a nonprofit organization, opened Pronto, a Third Generation docked bikeshare system developed and built by Alta Bikeshare (Alta, 2014). The system featured 500 bikes across 50 stations, with service provided in the Central Business District, South Lake Union, Belltown, Uptown, Capitol Hill, Eastlake, the U-District, and the University of Washinton's campus (Peters & Mackenzie, 2019). Service was quite geographically limited, though Puget Sound Bikeshare had plans to quickly expand and add 600 bikes and 60 docking stations (2019). In 2016, the City of Seattle bought all Pronto assets and solicited bids for system expansion, selecting Bewegen to provide 1,200 electric assist bikes and 100 stations in what would be a complete revamp of the system (Fucoloro, 2016). Before the plan could proceed, Mayor Ed Murray shut down the process in January 2017 citing high costs (Peters and Mackenzie, 2019). In March 2017 Pronto officially ceased operations, and shortly thereafter dockless operators began to approach SDOT for permission to begin operations (2019). The timing of Pronto's shutdown was fortunate–SDOT was able to see the immediate impacts of domestic dockless bikeshare, particularly the issues peer cities experienced with unreliable vendors and vehicle oversupply. As a result, the SDOT put forward a novel pilot and permitting structure that set requirements for vendors to be considered for approval (SUMC, 2019).

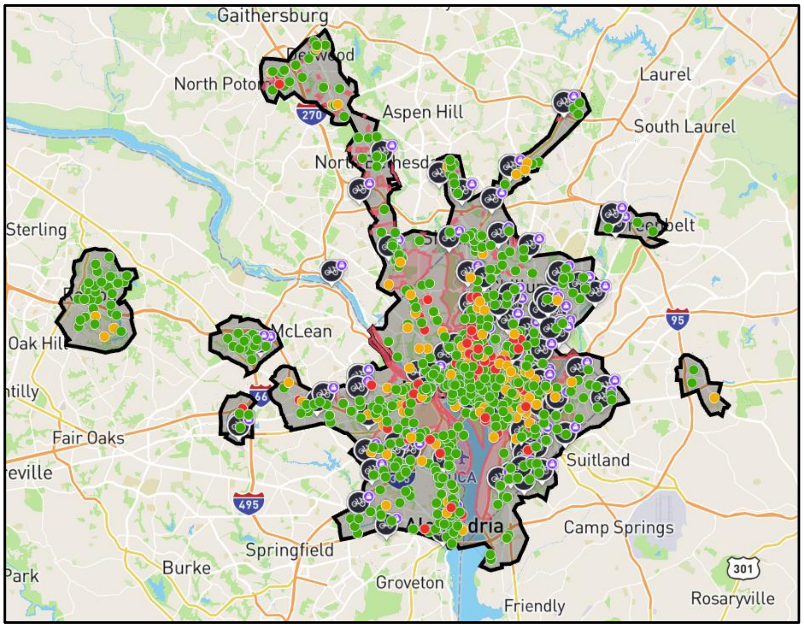
SDOT began its dockless pilot program in July 2017, allowing Lime, Ofo, and Spin to operate a capped number of dockless bicycles within Seattle's public right of way (SMUC, 2019). At the end of the six month pilot, SDOT evaluated outcomes on criteria including geographic coverage, safety, compliance with parking rules, accessibility and ADA compliance, and public opinion (2019). During the six month window, dockless bikeshare in Seattle recorded 468,976 rides, almost 300,000 more than Portland's Biketown system in the same time frame (SDOT, 2017). Following the end of the pilot program, SDOT updated permit requirements to reflect pilot outcomes, and formalized the permit-based approach, codifying various requirements that vendors would need to abide by for consideration to operate within Seattle.

In 2020 Lime bought Jump, then its largest bikeshare competitor, becoming the dominant bikeshare system in Seattle, and transitioning its bikeshare fleet to the bulkier e-bike model formerly used by Jump. In 2021, Veo entered the market, offering a hybrid vehicle that would be more accurately referred to as a sitting e-scooter, but still retained operable bike pedals (SDOT, 2021). From 2021 until 2023, the bikeshare market in Seattle remained largely stable, with Lime deploying 1,700 bikes on average in 2022, to Veo's 1,300. The two companies recorded 79,000 and 57,000 rides in June of that year, respectively (SDOT, 2024). 2023 saw a significant consolidation in favor of Lime, with 117,000 trips in June, compared to Veo's 51,000 (2024). This shift was fueled by a reduction in Veo's fleet to 975 vehicles, and an increase in Lime's to 2,505 (2024). Bird introduced their own e-bike model in Fall 2023, however their e-bike market share was marginal, recording 2,000 rides in October 2023 compared to Lime's 73,000 (2024). By October 2023, the window this study focuses on, Lime had clearly achieved dominance in the Seattle market, and could accurately be referred to as Seattle's bikeshare system (Hamilton, 2023).

Capital Bikeshare

Capital Bikeshare was one of the first major bikeshare systems in the Untied States, first opening in 2008 as SmartBike, a limited system that served as proof of concept for a larger offering. In 2010, the District of Columbia worked in conjunction with Arlington, VA, to issue an RFP for bikeshare system development, selecting Alta Bikeshare to design the system, and PBSC to provide physical infrastructure (Vanderbilt, 2013). In 2015, DDOT announced an expansion plan to add 99 stations to the network. Currently, Capital Bikeshare has over 360 stations throughout Washington, and is currently in the closing stages of an expansion plan with the goal of every resident living within a quarter mile of a docking station (DDOT, 2019). Capital Bikeshare is one of the most successful bikeshare systems in the country, recording 4,469,358 total rides in 2023, and setting a single day record on March 16th, 2024, with more than 20,000 rides on a single day (Vigliotti, 2024). Capital Bikeshare offers both traditional bikeshare and electric pedal assisted bikes, or e-bikes, which make up just over half of all trips (Littauer, 2024). System ridership is dominated by annual members, who make up 72% of all riders (2024).

Figure 2: Capital Bikeshare Regional Station Map



(Capital Bikeshare, 2022)

Lime

In 2017, Neutron Holdings incorporated in California with the intention of offering dockless bikeshare services to the American market (Kolodny, 2017). Operating under the name Lime, the company's first dockless bike was nonmotorized and featured a five spoke wheel design modeled after the sections of the fruit sharing the same name (2017). To use Lime, users would download the smartphone app, locate a vehicle on the in-app map, and scan a QR code on the bike to unlock the vehicle. This would cause the onboard wheel lock to disengage, after which the user's rental period would begin. In early 2017 Lime secured $12 million in funding, followed by a $50 million funding round over the summer (2017). Lime quickly upgraded their bike to a more traditional multi-spoke model, and in 2018 deployed an electric assist motor model (Rose Dickey, 2018). Initially in competition with Ofo, MoBike, Spin, Jump, and Lyft, all of whom provided dockless bike share services, Lime emerged as the strongest micromobility provider, in large part powered by the financial success of its e-scooter fleet (Hawkins, 2023). In 2023, Lime announced its first profitable year, and that Fall "declared victory" in the ongoing competition for dominance of the domestic dockless micromobility market (2023). After acquiring competitor Jump in 2020, Lime modeled their e-bikes after Jump's distinct, boxier bike model, resulting in the design seen today (Fucoloro, 2020). The most recent model, deployed in Seattle in May 2024, includes a throttle that allows users to operate the electric motor without actively pedaling (Schlosser, 2024). During October 2023, the study window for this thesis, Lime had 1,735 bikes deployed within Seattle. During peak deployment in mid-summer, Lime has almost 3,000 bikes available to rent within Seattle city limits (SDOT, 2024). These numbers outclass Portland's Biketown system to the south (2,000) (Biketown, 2024), Vancouver across the border to the north (2,500) (MoBi, 2024), and comes close to matching Philadelphia's IndeGo (3,500) (IndeGo, 2024). In Washington DC, Lime operates as a clear second option to Capital Bikeshare (Goldbeck, 2022), and its dynamics reflect that, with trips mimicking the behavior of casual riders of Capital Bikeshare (McKenzie, 2018). As the majority of large American cities have well funded docked bikeshare systems, it is rare to find an example of dockless bikeshare operating in a vacuum. What characteristics a bikeshare system exhibits in such a scenario, such as demand peaks, trip length, and origin/destination points, are largely unknown. Considering the different typologies of docked bikeshare systems, and how Lime compares to them in terms of service area, bike availability, and demand profile, is a necessary first step in assessing the system dynamics of Lime in Seattle, and the extent to which the bikeshare system performs like a fully built-out docked bikeshare system.

Figure 3: Lime Bikes Parked in Seattle

(Feeney, 2024)

Chapter 3: Bikeshare System Typologies and Dynamics

In this chapter, I attempt to describe the development patterns of docked bikeshare systems and define the typical system dynamics of a “mature” or built out bikeshare system. It is these defined characteristics that makes the comparison between a docked and dockless bikeshare system possible, allowing us to analyze system dynamics against a set of expectations. Bikeshare is governed by the same basic constraints as other transportation systems–regardless of how the rider may perceive it, physical distance and time form a “space-time prism” that sets boundaries for the set of locations an individual can travel (Hägerstrand, 1970) . As with other modes of transportation, it is reasonable to assume that bikeshare trip generation is affected by the “3Ds”, Density, [land use] Diversity, and [pedestrian friendly] Design, with certain locations being more attractive than others, such as restaurant lined commercial corridors or downtown central business districts, allowing for the association of urban features with trip demand (Cervero & Kockelman, 1997).

Two prominent studies have attempted to create system typologies, one internationally (O’Brien et al, 2014) and one domestically (Kou & Cai, 2019). O’Brien et al describe systems by their “compactness ratio”, or the relationship between station density and total urban area, the variation in available bicycles throughout the day, and the spatiotemporal trip demand throughout the day. The authors create six typologies: two peak weekday, one peak weekend; two peaks across the entire week; more than two peaks on weekdays; two peaks with high inter-peak usage; high weekend use; and a single peak on all days of the week (2014). Capital Bikeshare and BlueBikes fall into the first category of systems with two distinct weekday commuter peaks, followed by a single peak on weekends (2014). Kou and Cai created typologies by analyzing trip duration and distance, finding that in larger systems with frequent docking stations, trip distance and duration are broadly similar, while smaller or less built out systems experience greater variance (Kou & Cai, 2019). Following the work of O’Brien et al and Kou & Cai, I demonstrate that docked bikeshare systems of a certain service shed and density–referred to here as “complete” systems–have clear spatiotemporal characteristics that systems with fragmented, unbalanced, or limited service areas do not share. These clear spatiotemporal characteristics support the use of flows as the independent variable in my research; if systems of a certain type behave in a certain way, such as demand peaks during morning and afternoon commutes, then these trends would be reflected in the flows of vehicles expressed as a trip origin and destination site characteristics, and other built environment and demographic characteristics.

Bikeshare Trip Production: Theoretical Framework

Once an individual is open to riding bikeshare for a trip, the next question is whether there is a station within convenient walking distance. If there is not a station within convenient walking distance of a trip origin or destination, the trip will either not occur or be made via a more flexible mode of transportation. Because docking station locations are so deterministic of system activity, their spatial distribution and frequency have important implications for system dynamics. If a commuter's apartment had three or more bikeshare stations within walking distance, they would have more of an incentive to ride than someone who had only one station that was a slightly inconvenient distance away. On a larger scale, the distribution of land uses, and land use intensity permitted, determine the magnitude and direction of flows. Generally speaking, American cities follow a spatial model wherein a majority, or plurality, of employment is located within the Central Business District, which is then surrounded by a mix of commercial land uses and apartments, followed by less dense housing approaching the urban boundaries. Low density areas with cheap land may be filled in by industrial or warehousing land use, and major institutions such as universities or large employers are scattered throughout. Population density would tend to be highest in mixed use areas that permit apartment development, and lower in low-rise and single family housing zones (Lewis et al, 2013). Within that model, the general types of trip an urban resident might take have distinct spatial and temporal characteristics. Commuters leaving for work in the morning depart from residential areas and travel to the Central Business District or another commercial zone. At lunchtime, they may venture into the commercial zone for lunch, or travel throughout the day to attend in-person meetings at a different location. After the end of the workday, they may return to a residential area, or attend a function elsewhere downtown or along a commercial corridor. Theoretical daily schedules and locations for three different individuals, their implications for travel origin and destinations, and the decision to ride bikeshare or not, are included below to illustrate this dynamic.

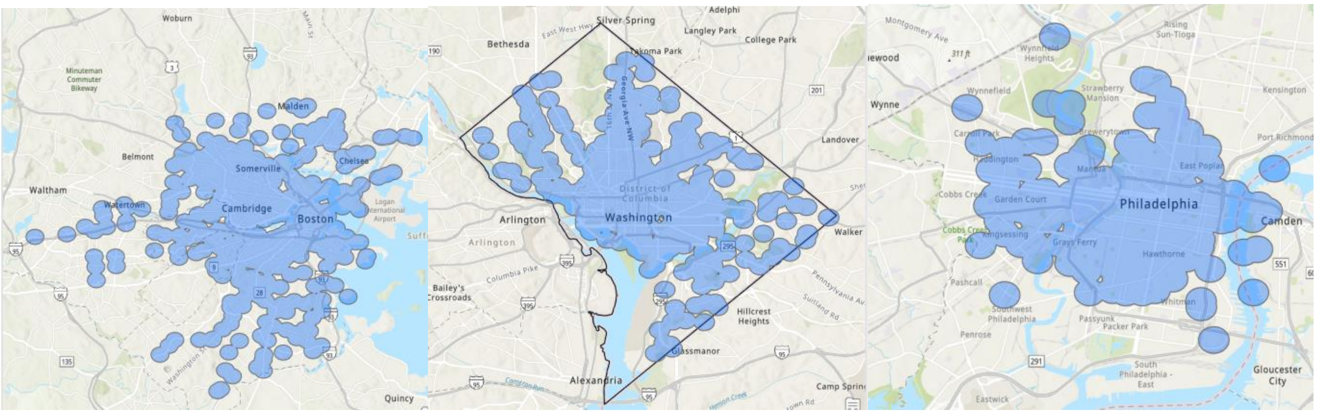
Table 1: Bikeshare Trip Production

Individual	Person A (Bikeshare member)	Person B (Casual rider)	Person C (Student membership)
Employment	Office Worker	Restaurant Worker	Student
7:00-9:00	**Residential to CBD** for the start of the workday. **Rides bikeshare** due to convenient station locations.	No Travel	**Mixed Use to Major Institution** for morning class. **Rides bikeshare** because of free student membership.
Noon	CBD to Mixed Use for lunch, then back to CBD	**Residential to Mixed Use** for start of shift	**Major Institution to CBD** for internship. Takes transit to avoid arriving sweaty.

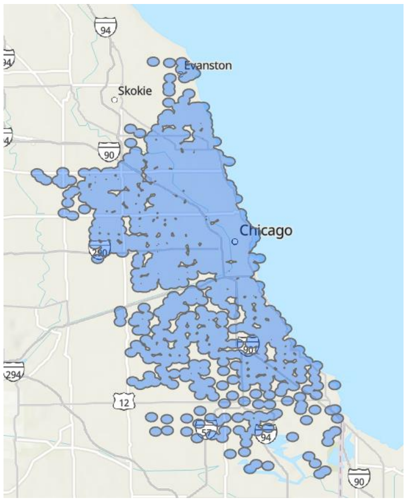
		Does not ride bikeshare, rides transit for faster travel.	
4:00-5:00	**CBD to Mixed Use** to meet friends for dinner, **Takes subway** to get to dinner on time.	No Travel	**CBD to Major Institution** for class. **Rides bikeshare** due to convenient station location and reduced time pressure.
5:00-7:00	**Mixed Use to Residential** to return home **Rides bikeshare** due to lack of time pressure and convenient station location.	**Mixed Use to Mixed Use** to meet friends at a bar. **Rides bikeshare** due to lack of acute time pressure and convenient station location.	**Major Institution to Mixed Use** to return home. **Rides bikeshare** because of free student membership.

Taken individually, these three individuals exhibit different schedules with different spatiotemporal arrangements. Aggregated across all bikeshare riders over a sufficient period of time, however, clear patterns would become apparent that characterize systems. These patterns are produced by the interaction of trip demand with the spatial distribution of the bikeshare system. At a certain threshold of development, where X number of stations are located within Y distance of Z population share, spatiotemporal patterns assume the same appearance across cities (O'Brien et al, 2014). While these patterns are most visible in spatiotemporal variation, they are also present within non-spatial trip characteristics (Kou & Cai, 2019). Consider the spatial arrangement of stations in Boston and its immediate surroundings (BlueBikes), Philadelphia (InDego), Chicago (Divvy), and Washington D.C. (Capital Bikeshare). In Washington DC, Philadelphia, Chicago, and much of the Boston metropolitan area, bikeshare station service areas cover significant portions, if not the majority, of the city's geographic extent. As a result, the average resident is likely to live within a station's service area–in this case defined as the 400 meter area surrounding the station. Because of the extent of the bikeshare system, the set of likely trip destinations throughout a week–work, groceries, a night out–are likely to be within a convenient distance of a bikeshare station as well. This allows the resident to use bikeshare as one might a bus that stops a few blocks away from their house, using it with regularity and establishing patterns. At scale, these patterns manifest in the variance of trip demand throughout the day, as well as the geographic flow of bikes between stations.

Figure 4: Service Areas of Capital Bikeshare, IndeGo, BlueBikes, and Divvy


Capital Bikeshare, Washington D.C.
IndeGo, Philadelphia, PA
BlueBikes, Boston MA

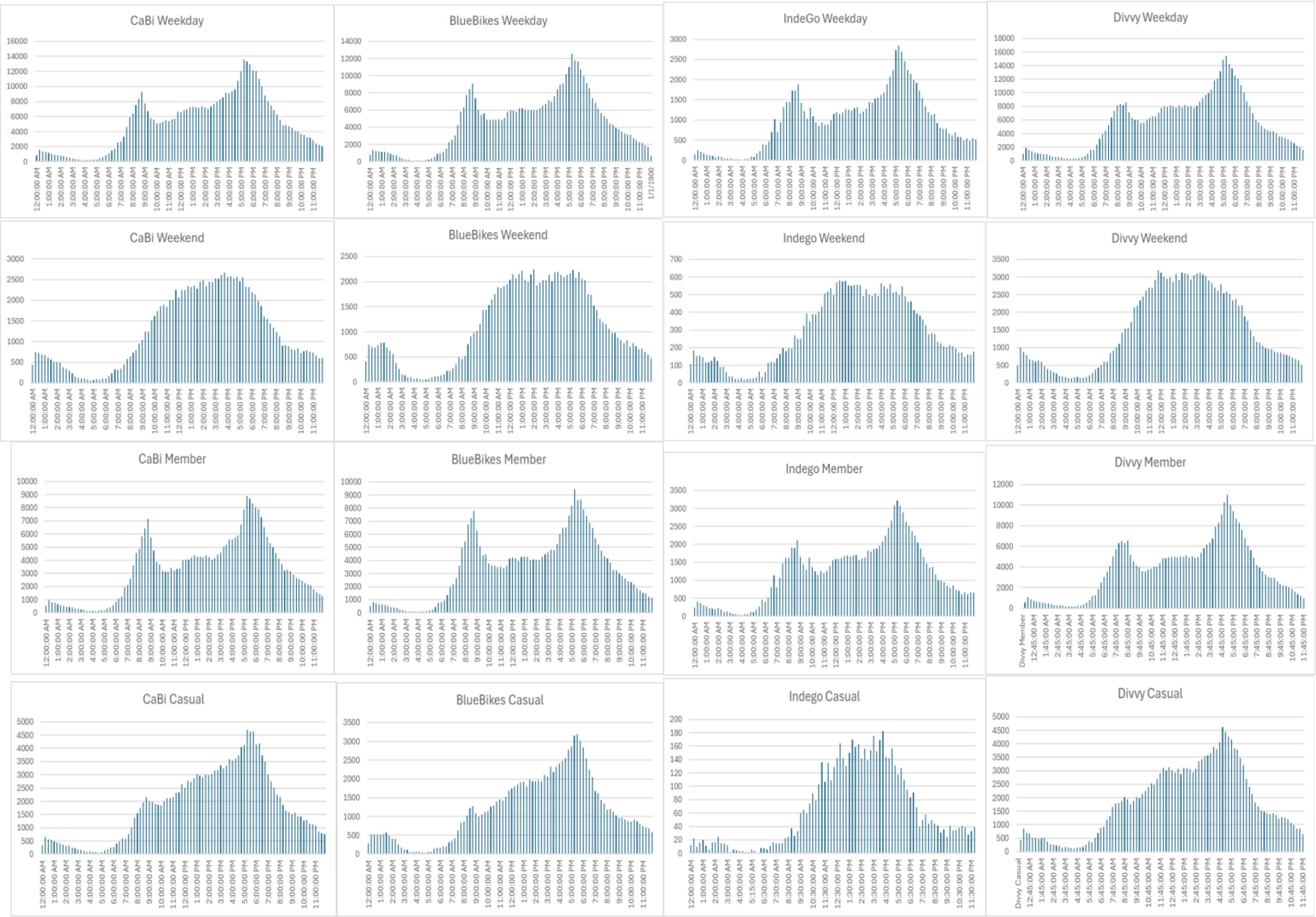
Divvy, Chicago, IL



Data sources: Capital Bikeshare, 2024; IndeGo, 2024; BlueBikes, 2024; Divvy, 2024.

The reach of each respective system and their station densities produces the following demand profiles, which exhibit two distinct demand peaks during peak AM and PM commute, and one single increasing demand peak on weekends. On weekdays, members exhibit the same two-peaked demand profile, while casual riders exhibit increasing demand throughout the day, resulting in a profile resembling weekend demand.

Figures 5-8: Weekday, Weekend, Member, and Casual Demand Profiles for Select Bikeshare Systems

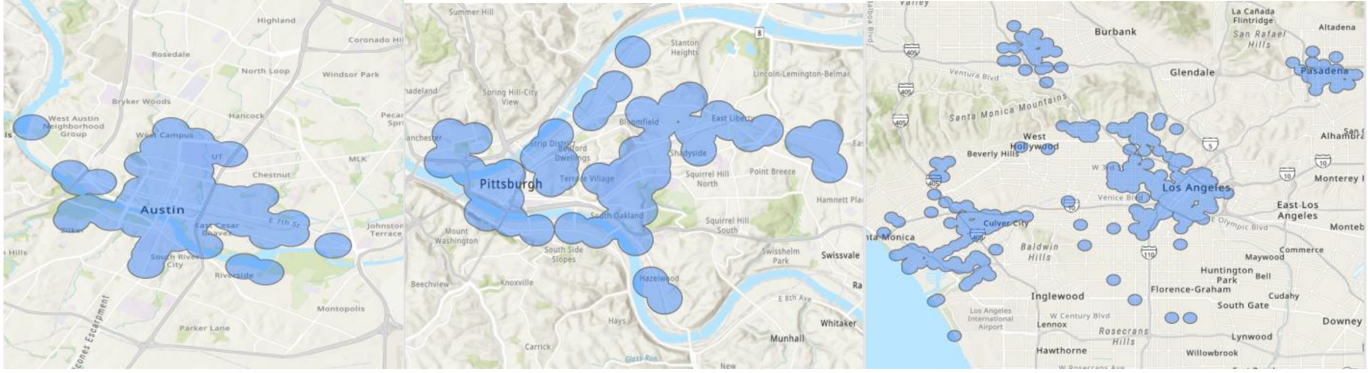


Data sources: Capital Bikeshare, 2024; BlueBikes, 2024; IndeGo, 2024; Divvy, 2024

The clear similarities between these systems validates in part my selection of a single system, Capital Bikeshare, with which to build a theoretical bikeshare network with which to analyze Lime Bike in Seattle. If system density and coverage are the key predictors of utilization, as O'Brien et al and Kou & Cai argue, then a system that originates in the density of a built-out bikeshare system could be expected to allow for the most accurate direct comparison between docked bikeshare and dockless bikeshare systems. Examining the temporal variation of trip starts across the aforementioned systems and three less dense, more fragmented, or unbalanced systems—LA's Metro Bikeshare, Pittsburgh's POGOH, and Austin's MetroBike, we can see the distinct character of a built out system, the similarities between built out systems, and the stark differences in trip patterns between developed and underdeveloped systems. The following maps display bikeshare stations buffered with a 500 meter (CITE) service area, illustrating how much of the city has access to the bikeshare system. Comparing the demand profiles of complete and incomplete bikeshare systems, it is clear that complete systems produce more consistent trip patterns, as the demand profiles of MetroBike, POGOH, and

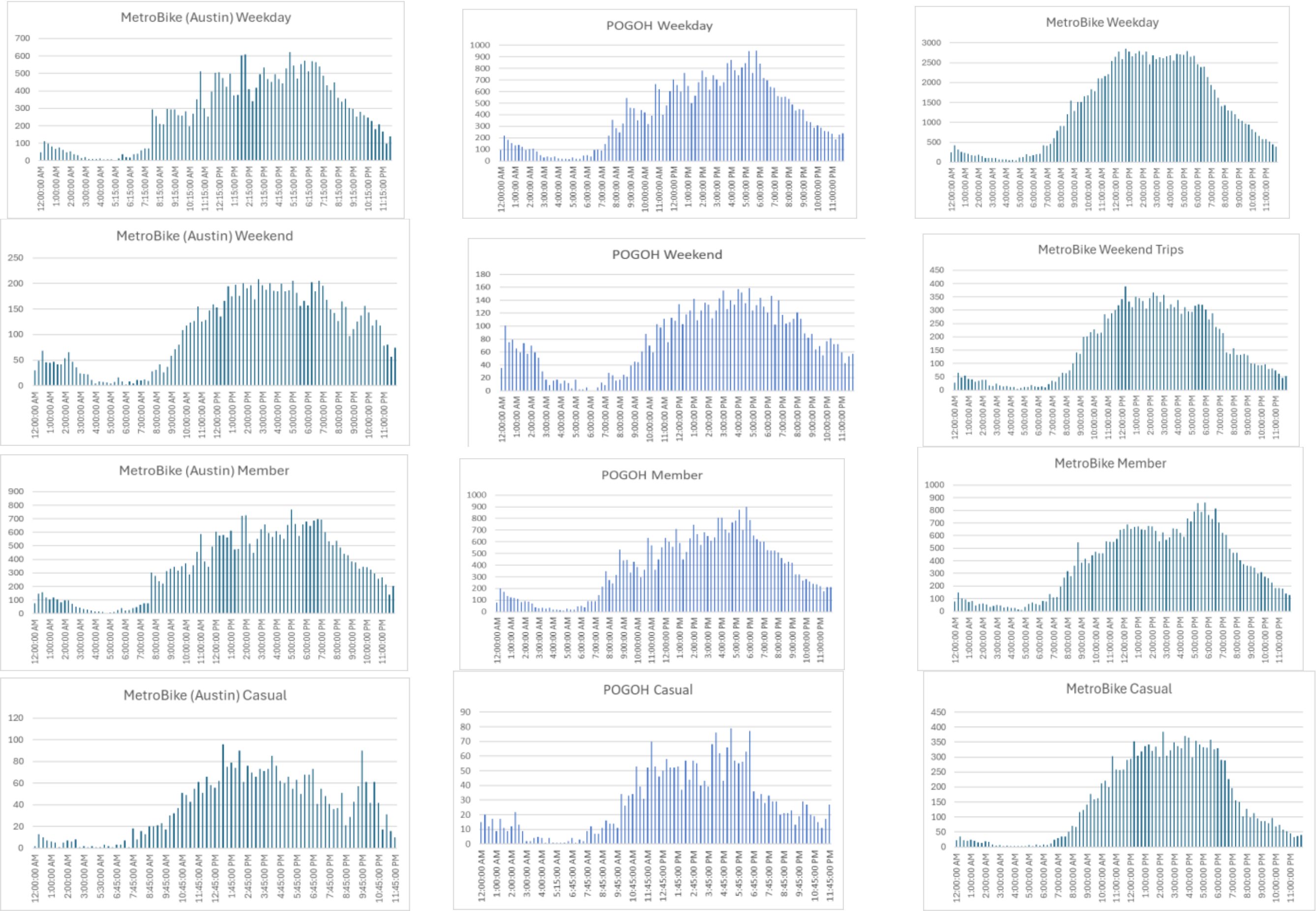
MetroBike LA resemble the casual or weekend ridership demand profiles of the previously discussed systems.. This is somewhat intuitive–if a mode of transportation can be used across the city, it will be used more consistently than one that can only be used in a limited number of places.

Figure 9: MetroBike, POGOH, and MetroBike LA Service Areas


MetroBike, Austin, TX
POGOH, Pittsburgh, PA
Metro Bike, Los Angeles, CA

Data sources: Austin Open Data, 2024; POGOH, 2024; Metro Bike LA, 2024

Figures 10-13: MetroBike, POGOH, and MetroBike LA: Selected Demand Profiles

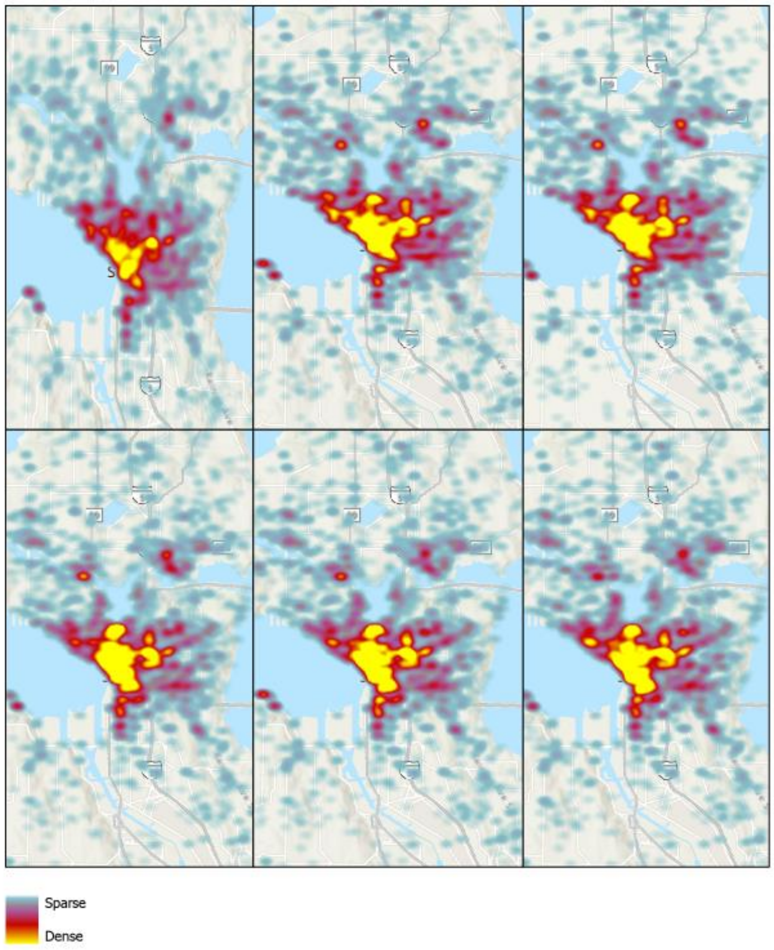


Lime Bike - Real Service Area

The impact of real service area on demand patterns is especially salient to the question of dockless bikeshare systems. In theory, the entirety of Seattle is Lime's service area. In reality, the service area is determined by the location of Lime Bikes, which are subject to change based on the last trip taken on an individual bike, Lime rebalancing behavior, and SDOT regulation. The following maps attempt to take stock of Lime's real service area, illustrating where bikes are most readily available at 8:00 am, 8:30 am, 9:00 am, 4:00 pm, 4:30 pm, and 5:00 pm. The first, included below, is a heat map symbolizing density, with warmer colors representing high density clusters of Lime Bikes and cooler colors representing low density clustering. The map(s) use data from October 4th, 2023, chosen as a day broadly representative of good conditions for bikeshare use. October 4th was a Wednesday, one of the days with the lowest telework rates in downtown Seattle (Commute Seattle, 2023), and weather was good, with no adverse effects from temperature, wind, or precipitation that might suppress ridership.

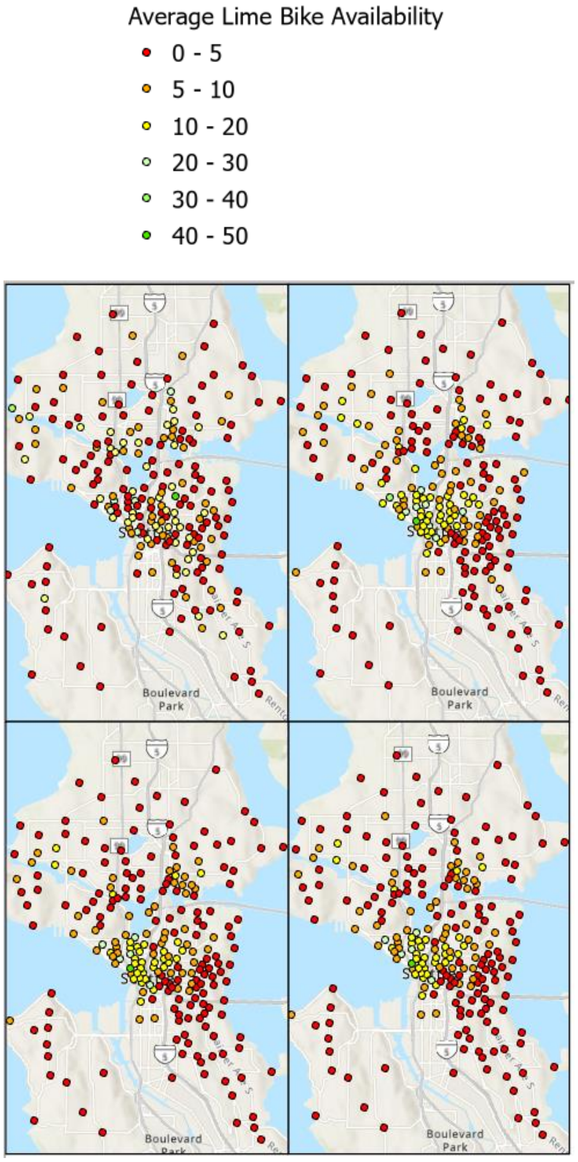
Figure 14: Lime Bike Availability Heat Map on October 14th, Selected Times

Heatmap of Lime Bike density in Seattle, October 4th, 2023.
Top: 8:00 am, 8:30 am, 9:00 am. Bottom: 12:00 pm, 4:00 pm, 4:30 pm.



Lime Bikes are present in limited numbers in West Seattle, Beacon Hill, Montlake, East Capitol Hill, North Capitol Hill, Greenlake, and other less dense neighborhoods north of the ship canal. Their concentration, and therefore level of service, is highest in the Central Business District, South Lake Union, Belltown, and along Capitol Hill's Broadway and Pike/Pine corridors. Bikes are also found in high concentration in the U-District, Fremont, and to a lesser extent in Ballard. The density of Lime Bikes in the CBD at 8:00 am is notable and unexpected. While clustering in the CBD is a common feature of docked bikeshare, it typically is found *after* the morning commute peak, around or after 9:00 am (Goldbeck, 2022). While the effects of the morning commute are visible in the expanding density at 8:30 am and 9:00 am, the preexisting concentration at 8:00 am may represent a lack of re-balancing to residential/commercial parts of the city where many morning commuters' trips originate. It is possible that I did not properly calibrate the ArcGIS Pro heat mapping algorithm, leading to the dense concentration of bikes downtown across both the AM and PM commuter peaks. To confirm that the heatmap's results were correct, I mapped average weekday bike availity at each "station" in my theoretical docking station network. This network has not yet been discussed in detail, so its use here is somewhat of a departure from the order of this thesis. Further context on the docking station network can be found in Chapter 5.

Figure 15: Lime Bike Availability at Station Level at Select Times of Day



Data source: Lime, 2023

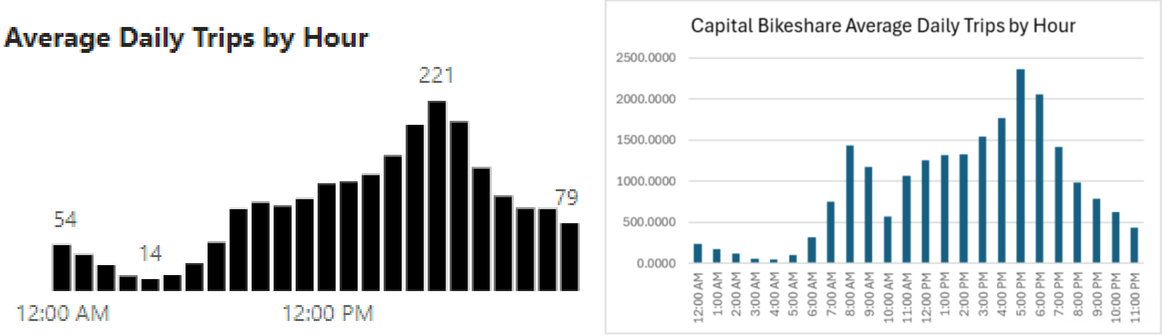
Considering the distribution of available bikes, average availability *does* seem quite concentrated in the Central Business District and restricted in neighborhoods outside of the CBD, which one could assume would impact trip flows, as prospective riders would need vehicles within convenient walking distance to take a trip. This distribution backs up the results of the heat mapping approach used on page 20—bikes concentrate downtown, and are either not rebalanced by Lime, or are not taken outside of that zone by normal trip activity. Availability outside the CBD may not be as dire as the availability maps make it seem, however. The deepest red symbology represents "stations" with 5 or fewer Lime Bikes available on average. Prospective riders within those areas could actually have good access to bikes, whether due to low competition or close geographic proximity. In some ways, these patterns are broadly similar to Capital Bikeshare's distribution on weekday afternoons. Following morning commute inflows, bikes are most readily available downtown, and can be difficult to find in less dense residential areas (Goldbeck, 2022).

With these apparent similarities between systems, at least in terms of the spatial distribution of available bikes, the most significant differences between Lime Bike and Capital Bikeshare may be the number of bikes available, with 1,731 bikes available in Seattle during October 2023 (SDOT, 2024) compared to several thousand in Washington D.C. (Capital Bikeshare, 2024), as well as the dockless character of Lime itself. Less significant, though perhaps relevant, differences include the association of Capital Bikeshare with a public service and Lime Bike as a privately operated venture, and the association of Lime Bike with Lime's e-scooter fleet, which may cause potential riders to think about the vehicles differently. Lime's Seattle fleet is entirely composed of e-bikes, though this may not be a significant difference in terms of trip demand. Comparing the demand profiles across e-bikes and "traditional" bikes in Capital Bikeshare, IndeGo, Divvy, and Citibike (BlueBikes did not offer e-bike service until recently), the demand profiles appear almost identical. On the impact of "docklessness" on system dynamics, one could point to a lack of certainty of vehicle availability as a unique characteristic. This may be true in low demand neighborhoods where only one or two Lime Bikes are available at any given time, however numerous Capital Bikeshare stations experience such significant demand that by 8:30 on a weekday morning, no bikes remain available (Goldbeck, 2022). The difference then, would be that static periods of high demand are easier to plan around than random or unknown demand–if one wanted to start a morning commute trip from a busy station they could simply leave earlier. Prospective Lime Bike riders, on the other hand, cannot control whether a bike would be within convenient distance of their trip origin.

Dockless Demand Profile

Fully built-out docked bikeshare systems provide service to a larger urban area, allowing prospective riders to choose bikeshare over transit, personal vehicles, walking, or riding their own bicycle. As a result of the certainty of access provided by a dense system covering a large service area, riders can use bikeshare for more than just leisure trips, and can use it for time restricted trips such as commuting. At scale, these trends become apparent in the two peaked weekday demand profiles shown in the previous section. While Lime's API data does not include trip start or end times, SDOT does require all vendors to provide start and end times for internal use as part of their operating permit (SDOT, 2023). SDOT in turn provides a processed version of the data in a public dashboard on its website. Considering the average daily trips by hour, included below, we can see clear similarities and differences between Lime and Capital Bikeshare.

Figure 16: Lime Bike October 2023 Average Daily Trips by Hour vs CaBi October 2023 Average Daily Trips by Hour



(SDOT, 2024) (Capital Bikeshare, 2023)

Lime's demand profile demonstrates a clear PM peak, with the highest average daily trips occurring at 5:00 pm. This is consistent with what we have previously seen in the weekday and member demand profiles of the previously discussed "complete" bikeshare systems, and matches up well with Capital Bikeshare's corresponding demand profile from the same time frame. The plateau and slow build in demand from roughly 10:00 am onwards is also consistent with patterns exhibited by Capital Bikeshare. The major divergence, however, is the morning commute. While Lime Bikes do exhibit an increase in demand between 8:00 am and 9:00 am, demand does not peak, rather it enters into the plateau that holds until just after 12:00 pm. This is consistent with NACTO's observation that dockless bikeshare systems across the United States have asymmetrical demand peaks, with a marginal if nonexistent AM peak and a robust PM peak (NACTO, 2017). In contrast, Capital Bikeshare exhibits a sharp AM peak at 8:00 am, followed by an equally sudden decline until 11:00 am. The lack of an AM peak in Lime, and the presence of a robust AM peak in Capital Bikeshare, may mean that the spatial distribution of flows and their relationship(s) with built environment and demographic variables are dissimilar in the morning but similar in the afternoon.

In theory, dockless micromobility deployed at scale would provide the same benefits as docked bikeshare systems. If a prospective rider lived within a densely populated area downtown, there is a high likelihood that there would be a number of bikes within convenient walking distance of his apartment. In one scenario, the bikes would be at a docking station, in the other, the bikes would be distributed throughout his neighborhood. In the latter scenario, certain bikes may be a more convenient walking distance than in the former scenario, increasing ease of access. The location of those bikes, however, would not be guaranteed. From one day to the next, the average distance of those ten bikes from his trip origin would fluctuate, while the distance to the docking station would remain the same. The presence of the docking station too, would guarantee *some* degree of service, particularly if the system had active rebalancing activity throughout the day, as is common with most modern bikeshare systems (Goldbeck, 2022). As we have seen from the maps of Lime Bikes distributed throughout Seattle on October 4th, 2023, much of the city, particularly Urban Villages, has good access to dockless bikeshare. There are odd fluctuations in the expected bike locations, however, such as the concentration of bikes downtown *before* the morning commute peak. These fluctuations may be explained by the profit motive of the privately operated bikeshare vendor, however SDOT's permit conditions may influence bikeshare allocation, and therefore flows.

SDOT's Permitting Structure - Implications for System Dynamics

While SDOT does not directly control Lime's fleet, it can and does exert significant influence over vendor actions and deployments through its micromobility permitting document. As discussed in Chapter 2, all vendors seeking approval to operate in Seattle must comply with permit requirements such as implementing geofences, developing equity and engagement plans, and sharing data with SDOT (SDOT, 2023). As a result, the permit document shapes the form of dockless bikeshare in Seattle, mandating that bikes be distributed in certain areas and that vendors "rebalance" the system, relocating bicycles from low demand areas to high demand areas as needed (2023). With this in mind, it is worth considering whether any specific provisions of the permit document would significantly affect the character of dockless bikeshare, shaping it into something more akin to a docked system.

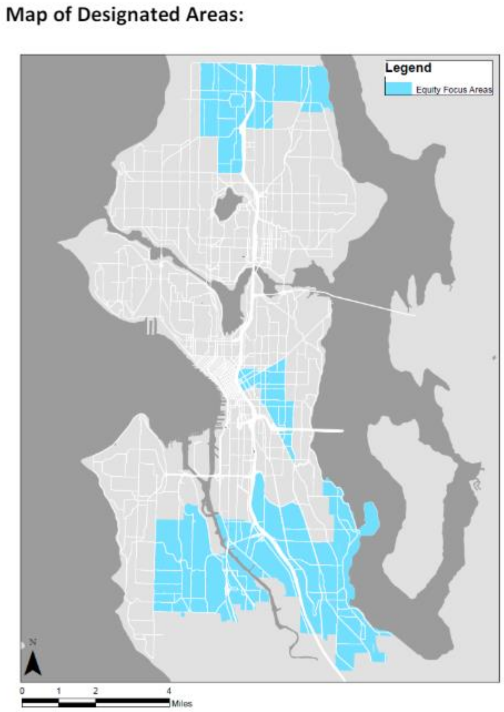
In 2019, SDOT mandated vendors provide live data feeds directly to the agency, instead of the University of Washington's Transportation Data Collaborative mediating the relationship (2020). SDOT required data be provided in the Mobility Data Specification, which lays out a bare minimum of categories of information that vendors must provide (2020). Public data would later be provided in the General Bikeshare Feed Specification (GBFS) data format, which is designed to provide public-facing access to micromobility data (Mobility Data, n.d.). By bringing data in house, SDOT increased their managerial capacity significantly, giving them fine grain data on vehicle position, usage, and distribution. One of the ways they used this data was tracking preferred parking locations and installing parking corrals, a kind of hybrid bike rack with wider spacing to accommodate bikeshare vehicles (SDOT, 2020).

Figure 17: Micromobility Corral

(Feeney, 2024)

Often placed in parking spaces, landscape features adjacent to sidewalks, or other non-sidewalk locations, corrals are specifically intended for dockless vehicles. Using parking demand data, SDOT was placing infrastructure analogous to docking stations, closely monitoring the locations and distribution of vehicles, and had the power to require vendors to adjust bicycle locations on-demand per SDOT request (2020). This process is remarkably similar to that used by the planners of docked bikeshare systems like Capital Bikeshare, who largely rely on demand data when placing new stations or expanding existing ones (Goldbeck, 2022). The difference between the two, however, is that SDOT does not require riders to park in corrals, and indeed many if not most riders do not. As a result, though the rationale and process behind these installations mirrors that of a docked bikeshare system, the outcome and impact on the system does not. The other policy relevant to the spatial distribution of Lime Bikes is SDOT's requirement that 15% of Lime's (and other vendors) total fleet be regularly rebalanced to Equity Focus Areas, which are delineated on the map below.

Figure 18: SDOT Designated Equity Focus Areas



SDOT designated Equity Focus Areas (SDOT, 2023)

The Equity Focus Areas broadly break down into three areas—the far north of Seattle by Northgate Mall and lightrail station, the far south of Seattle, including Rainier Valley, Othello, and South Park, and First Hill/Yesler Terrace. Mandating 15% of the bikeshare fleet be present in the far north or south of Seattle *would* be a significant distortion—these areas are low density, and consequently have lower demand compared to the high density urban core. However, the inclusion of First Hill/Yesler Terrace, a high density area close to the Central Business District and Capitol Hill, means that vendors could easily place the bulk of their equity deployment in a high demand area while remaining compliant with SDOT regulation. With that in mind, SDOT's Equity Focus Area policy may not cause much of a distortion of normal dockless bikeshare activity.

From reviewing SDOT's permit requirements, the distribution of bikes and service-sheds of Lime Bikes throughout Seattle, and the characteristics of Lime's average weekday demand profile, Lime *does* have many similarities with docked bikeshare systems in terms of management, but no one policy or regulation appears likely to make the system behave or operate like a docked bikeshare system. Lime's deployment in Seattle shares many spatial characteristics with Capital Bikeshare, such as broad availability in the morning and afternoon throughout much of the city, and provides a comparable level of service with regard to the number of bikes available. At the same time, it retains a distinctly dockless character with regard to the impact of policy and regulation on deployments and system operations, with SDOT allowing vehicles to park in a variety of locations and not requiring significantly different deployment strategies than vendors might otherwise employ. As a result, Seattle's Lime Bike network presents an ideal scenario to compare docked and dockless systems—broadly similar, but distinctly different in key ways. In the following section, I review the existing literature on spatial variation in bikeshare demand, the relationship between bikeshare demand and the built environment, and the similarities and differences between docked and dockless systems. In doing so, I provide support for my selection of variables used to analyze Lime's system dynamics in Chapter 5.

Chapter 4: Literature Review

Researchers have paid substantial attention to bikeshare despite its relatively young age, with interest rapidly growing with the popularity of Third Generation systems in the early 2010s (Shaheen et al, 2010). Early studies of bikeshare are often concerned with bikeshare rider profiles and trip characteristics, the built environment and natural factors that influenced trip generation, and the relationship between bikeshare systems and other modes, such as public transportation. As bikeshare proved itself a valid mode of urban transportation and not a novelty, researchers began to consider how different rider classes differed from one another, inter-system comparisons, and whether bikeshare could be leveraged to achieve policy goals. The soaring popularity of bikeshare in China in particular lead to a robust literature on the built environment and bikeshare (Guo et al, 2022), a trend that continued as dockless bikeshare systems exploded in Chinese cities from 2016 to 2017. In the United States, researchers were similarly interested in dockless bikeshare, studying the new phenomenon in comparison to existing docked systems and contrasting it with dockless e-scooters. Despite the significant interest in studying the relationship between trip production and the built environment, researchers have been unable to establish persistent causal relationships, leading to continued interest in that sub-topic in particular. This literature review is broken into three sections–the first covers literature docked bikeshare literature from 2010 to 2017, the second dockless bikeshare after 2017, and the third examines studies that directly compare dockless and docked bikeshare systems. Concluding the chapter is a summary of the studies with findings most important to this thesis.

Docked Bikeshare Literature: 2010-2017

Early research into bikeshare (2008-2012) tended to focus on user profiles, trip characteristics, and system dynamics—during this period, bikeshare was an entirely new mode in American cities, and was broadly new to North America as a whole, providing a blank slate for academics. Following the initial wave of studies, academics sought to decouple the relationship between the built environment and bikeshare activity, to better understand differences in member and casual rider behavior, and to assess the impact of bikeshare systems on transportation mode shift and equity.

Faghih-Imani and Eluru et al (2014) studied trip generation in Montreal's Bixi system, one of the oldest and largest bikeshare systems in North America. Using a series of linear regression models, they found that distance to the Central Business District had a significant negative correlation with bikeshare trips, indicating the trip generation inherent to its job and population density, that restaurant density, which exhibited a significant positive correlation in the afternoon, but a negative correlation for trip ends in the morning, and that universities and metro stations were also associated positively with bikeshare trips. The authors' findings regarding built environment factors and bikeshare flows are of critical importance to this thesis—commuting is known to account for a significant, in many cases majority, share of all trips. Assuming that the highest job density is found within the CBD, as is typical in North American city planning, then one would expect a bikeshare system with sufficient commuter access to exhibit strong flows into the CBD in the morning, and out in the afternoon. Their secondary finding on restaurants supports this, with a negative morning correlation that turns positive in the afternoon speaking to a likely shift in demand as workers leave the city center. In 2015, Faghih-Imani and Eluru later applied multinomial logit models to Chicago's Divvy bikeshare system, finding that areas of higher job density but lower population density resulted in higher trip flows during the morning peak, as well as low capacity stations located in high density areas predominantly served trips by system members, while high capacity stations in low density areas primarily were used by casual riders. The authors' findings on location appear to indicate the trip attraction effects of the central business district during the morning peak commute, while the station level findings indicate an association between casual riders and destinations such as large parks and other tourist attractions, which may be associated with lower population density.

Studying Capital Bikeshare, Buck and Buehler (2011) created half mile buffers around CaBi stations and used multiple regression models to identify significant variables in the built environment. The authors focused on liquor licenses (as a proxy for nightlife), bike lanes, intersection count, bicycle mode share, car ownership, transit stations, grocery stores, and demographic variables such as population and median income, finding the most significant positive relationships between the presence of bicycle lanes. Wang et al (2015) analyzed the impact of job and business density on bikeshare station trip levels in Minneapolis/St Paul's now defunct NiceRide system. This article is particularly noteworthy for its method of classifying the built environment—previous studies such as Buck and Buehler (2011) relied on built environment attributes such as the presence of bike lanes. Here, the researchers include a land use variable that models the (dis)similarity of land uses on a scale of 0-1, known as land use entropy, in addition to objective measures of active transportation infrastructure, job accessibility within a 30 minute transit ride from the individual bikeshare station, businesses within 0.16 miles categorized as "shopping" or "food", and a total count of businesses within the 0.16 mile buffer. Land use entropy revealed a weak negative relationship, however the presence and density of restaurants was found to be both statistically significant and positive, with each additional restaurant in the buffer zone increasing station level demand by almost 4.5%. Wang et al's finding on restaurant density mirrors that of Faghih-Imani and Eluru (2014), reproducing the relationship between certain points of interest and bikeshare demand. Land use entropy's weak correlation is unexpected, as is its negative sign, though this could be explained by the concentration of restaurants and nightlife, as well as large areas of the Twin Cities being devoted to solely residential use, increasing the chance that stations might be located in low entropy areas.

Noland, Smart, and Guo (2016) studied New York City's CitiBike and its station level trip generation, finding that population and job density have some predictive power for trip demand, that residential neighborhoods tend to be positively associated with member trips but negatively associated with casual trips, and a significant positive correlation between trip generation and proximity to bicycle infrastructure and subway stations. Noland et al's findings highlight two important characteristics of docked bikeshare systems: annual members and casual riders behave differently, and bikeshare is commonly used as a first mile/last mile solution that complements transit systems. Tran et al (2014) assessed the impact of the built environment on trip demand within the Velo'v bikeshare system in Lyon, France, finding that station size (capacity) and station density are both positively correlated with increased arrival and departure flows. Population density and job density were also significant and positively correlated. The researchers also find a significant difference between casual and longer term users, finding that casual users are more likely to take trips related to leisure and recreation, while long term members exhibit far fewer leisure trips. The primary conclusion by the researchers is that long term members can be expected to use bikeshare for commuting trips, while shorter term members have more diverse uses and are more likely to use bikeshare for leisure activities.

Wergin and Buehler (2017) analyzed Capital Bikeshare trips using GPS data to track routes selected by both members and casual users of the Capital Bikeshare system in Washington, D.C. Wergin and Buehler's study finds a significant preference among casual riders for trips to and around the National Mall, while members have a strong preference for trips to and within the Central Business District. In addition, casual trips tend to be slower moving and cover longer distances, while trips taken by members are shorter distance and shorter in duration. These findings support the broader idea that bikeshare members have distinct behavior from casual members or other modes of micromobility.

Rixey (2012) also studied Capital Bikeshare, as well as NiceRide (Minneapolis-St Paul), and B-Cycle (Denver), finding a significant and positive relationship between the number of stations within 3 miles and ridership, indicating network effects of station density. Rixey also suggests that bicycle infrastructure may be less influential on ridership than studies have indicated, and that population density and job counts have a statistically significant positive correlation with station level trip counts across all three systems. The finding that job density and population density have a positive relationship with demand across cities provides support for the conclusion that job density and population density may be good predictors of trip demand. Martin and Shaheen (2014) looked at the mode shift from public transit to bikeshare in Washington D.C. and Minneapolis, MN, finding that bikeshare associated decreases in transit use came from the denser urban core, while shifts towards transit associated with bikeshare were found in less dense peripheral parts of the city. Martin and Shaheen's research reveals more about how bikeshare use varies across urban form, with dense areas being associated with trip demand (substitution of trips for transit) and low density areas associated with trip chaining (first mile/last mile solution).

O'Brien, Cheshire, and Batty (2014) applied a big data approach to classify 38 bikeshare systems worldwide. Classifying bikeshare systems by geographic footprint, variation in trip start/end docks, and time of day and day of week trip rate variation, the authors develop a set of classifications to describe bikeshare systems. Dual demand peaks on weekdays and a single peak on weekends to indicate systems with robust commuter and leisure demand, double peaks across all seven days to indicate robust uptake among all workers, as non-traditional schedules are apparent; more than two peaks to describe commuting systems with robust underlying demand, and systems with high intra-peak usage to describe systems with predominantly "utility" users. The classification system presented in this paper is one of the first pieces of evidence that docked bikeshare systems have shared characteristics that can be generalized across systems, and, conversely, that a new type of bikeshare could be assessed as similar or different to existing systems through analysis of its demand curve and peaks.

Bikeshare in Seattle

A not insignificant amount of interest has been paid to Pronto, Seattle's former docked bikeshare system. Pronto was the first, but no the last, major city bikeshare system to be scrapped due to the costs of system maintenance and expansion. While much research interest has been in the factors that led to Pronto's termination, other researchers have used Pronto's trip data to investigate other subjects including built environment trip generation and transit integration.

Ding (2016) studied the relationship between Pronto ridership and weather patterns, finding that while rain decreased total trips, members of the Pronto system were more likely to ride in the rain than non-members using Pronto more casually, with 20% fewer casual users riding on days with moderate rain compared to annual members. Sun et al (2018) studied the processes necessary to successfully promote bikeshare systems, examining Seattle's former Pronto system using a mixed dataset consisting of trip counts, spatial data, and temporal factors such as weather. The researchers find that station location–particularly the impact of slope and elevation–was a key factor in Pronto's low ridership. The authors additionally identify potential competition for mode share with peak hour bus service, and find a unique travel pattern in the U-District where trip rates are unaffected by typical demand factors such as time of day or day of the week. Vieira Lopes (2022) studied the relationship between women's utilization of Pronto in Seattle and built environment factors including lighting, bicycle infrastructure, public transportation, green space, and points of interest, finding that women's mobility on Pronto was more significantly impacted by built environment factors than men's mobility. Peters and MacKenzie (2019) conducted a qualitative study of the factors contributing to Pronto's lack of success compared to other bikeshare systems, determining that the limited system scale and station density were major factors in the slow growth of the system; without easy citywide access, particularly in dense residential neighborhoods and commercial corridors like Fremont, Wallingford, Queen Anne, Central District, and Ballard, riders had limited access to preferred destinations, significantly reducing system utility. These findings are especially relevant to discussions of dockless bikeshare, as this is a problem that dockless systems are inherently predisposed to solve, as riders can, provided a bicycle is within walking distance, start and end a trip anywhere.

Docked Bikeshare Research After 2017

Research into the dynamics of docked bikeshare systems did not end after the introduction of micromobility. As successful bikeshare systems like Capital Bikeshare have continued expanding and introduced e-bikes to their fleets, researchers have continued to investigate user behavior, demand generation, and system characteristics.

Studying the relationship between lightrail ridership and bikeshare trip production in Minneapolis, Barber, Kopca, and Starrett (2018) found a significant positive correlation between train arrivals and trip starts at adjacent bikeshare stations, indicating synergy between the two systems, confirmed by the presence of a control group that did *not* demonstrate the same effects. In New York City, Campbell and Brakewood (2017) used bus stations within and outside of the Citi Bike service area to test the relationship between bus ridership and bikeshare trips, finding that the presence of bikeshare stations along bus routes *does* reduce ridership, though only by a small amount. Zhou and Cai (2018) studied the docked bikeshare systems of Seattle, Los Angeles, the Bay Area, Boston, Philadelphia, Washington DC, Chicago, and New York, finding that the systems do not share similar trip distribution patterns, both when analyzing system wide behavior and in breaking trips out into "commute" and "tourist" categories, potentially indicating the impact of built environment factors on trip generation—as each city in the study has different, at times significantly so, urban form, differences in land use distribution could explain the lack of shared patterns.

In Taipei, Liu and Lin (2019) studied the local docked bikeshare system, applying a hierarchical clustering and a multinomial logit regression model, finding strong correlation between peak weekday demand and trips originating and departing from the city center and along metro lines. The authors additionally find that travel to the downtown core is associated with mixed use and commercial areas, while more diffuse usage patterns are associated with leisure activities (proximity to parks) and that land use entropy is positively associated with bikeshare demand. The most recent study considered in this thesis comes from Tang et al (2024), who provide the most recent assessment of built environment associations with bikeshare demand, studying docked bikeshare systems in seven US cities. Analyzing Point of Interest data scraped from Google API, the researchers find that commercial POI have significant and positive relationships with bikeshare demand in Chicago and LA, and that all cities exhibit significant and positive relationships for public transportation coded locations. The differential results across cities are a potentially significant result in the literature, as there remains substantial uncertainty about which specific types of land use drive bikeshare demand. POI data provides one of the most interesting types of data, as restaurants have already been established as one of the correlates of bikeshare demand at certain times of day (Fagihih-Imani and Eluru, 2014). I considered using POI data in this thesis, but ultimately found it impractical. The chief method of accessing POI data is through the Google Places API, which allows users to run up to 1,000 free queries per hour, each of which will download the place names of specified types of places within a specified distance from a central set of coordinates. Using a Places query, researchers can calculate the number of restaurants within walking distance of a bikeshare station for instance, as Wang et al did in Minnesota (2015). The difficulty, however, is that running Places queries is time consuming and I was unable to find an efficient automation process to expedite data collection. This is part of what lead me to my zoning code based approach of accounting for land use, which I discuss further in Chapter 5.

Dockless Bikeshare System Characteristics

After 2017, researchers quickly began to publish articles on dockless bikeshare, focusing on its characteristics relative to docked bikeshare, competition with docked systems and other modes, and how its unique spatial dimension impacted trip generation. One particular area of interest was spatial equity, and the potential of dockless systems to fill gaps in the transportation ecosystem left unaddressed by docked bikeshare and the transportation system as a whole. One popular research area within the dockless vs docked literature is into which system provides better equity benefits—researchers have investigated spatial accessibility in underserved neighborhoods, the experiences of women with dockless bikeshare, and questioned whether dockless e-scooters provided better equity benefits as well. This is an especially salient research area as proponents of dockless bikeshare and scooter share argue that, because riders can theoretically start and end a ride anywhere, that dockless systems offer greater special access and, in turn, equity benefits, than docked bikeshare systems do. The following papers generally find greater spatial accessibility, but the equity benefits are less certain.

Mooney et al (2019) studied early models of dockless bikeshare in Seattle with a focus on spatial equity, finding that no sampled neighborhoods were “excluded” from bikeshare but that areas with higher availability tended to be more college educated, had higher incomes, and had greater levels of community resources, all of which are broadly in line with inequities identified in docked systems. Kutela et al (2023) surveyed 700 users of dockless bikeshare in Seattle to study perceptions of dockless bikeshare operators (at the time, Lime, Spin, and Ofo) compared to the former Pronto docked system, which Seattle had recently moved away from. Using data from Peters and MacKenzie (2019), the authors apply text mining and descriptive analysis approaches to the responses to two open ended survey questions, finding that female respondents tended to be more concerned with rider safety and more critical of dockless program shortcomings, while male respondents focused negative comments on price structures and vehicle quality. Additionally, many more female respondents preferred the Pronto docked system (56%) compared to male respondents (39%).

Jaller et al (2021) studied the differential equity impacts of docked and dockless bikeshare systems in Los Angeles and San Francisco, finding that dockless bikeshare in San Francisco had a significant proportion of bikes in “communities of concern” and had more rebalancing activities in those areas as well. In contrast, dockless bikeshare in Los Angeles appears to have a more tourist or leisure activity character, with the majority of bikes found in coastal areas and Santa Monica. As a result, Jump bike effectively provides better service to wealthy areas, while Metro Bikeshare services its entire service area roughly equally. Lazarus et al (2020) study the competition and complement between docked and dockless bikeshare in San Francisco between GoBike (docked) and Jump (dockless). The authors find that GoBike members exhibit 10% higher ridership during the morning period (12am-12pm), that Jump riders travel to a less clustered set of destinations, and that the destinations and trip characteristics of Jump riders appear to be similar to those of GoBike casual riders. Jump riders, whose fleet consisted entirely of e-bikes, also demonstrated greater willingness to travel uphill than GoBike riders. Meng and Brown (2021) assessed the equity benefits of three systems—docked, dockless, and hybrid—across 32 cities in the United States, finding that dockless systems offer increased spatial equity benefits in terms of service area, despite the fact that dockless and docked systems often overlap in their core service areas.

Bikeshare and Micromobility

Dockless mobility exploded in popularity (and availability) from 2017-2019. Beginning in 2017, dockless bikeshare services began to operate in U.S. cities, and e-scooters began to appear on city streets shortly after, with the first Bird shared e-scooters appearing in Santa Monica that fall (Etehad, 2018). Shortly thereafter, researchers began studying how e-scooters interacted with docked and dockless bikeshare, concentrating on mode shift between micromobility platforms and user behavior on new modes. McKenzie (2019) analyzed variation between docked bikeshare (CaBi) and dockless scootershare (Lime) in Washington, DC, finding that casual bikeshare ridership and scooter ridership share broadly similar spatiotemporal patterns, but that bikeshare members exhibit markedly different patterns of use. Bikeshare members exhibit a two peaked distribution on weekdays that indicates strong peak hour commute demand, while casual riders and scooter riders exhibit a normal distribution shifted towards a late-PM peak, and a clear tendency towards leisure and tourism trips based on origin, destination, and trip speed. Zhu et al (2020) focused on the spatiotemporal heterogeneity between dockless bikeshare and dock based scootershare in Singapore. The authors find increased utilization but shorter trip times for scootershare, and significantly higher instances of rebalancing among scootershare than bikeshare. Most notably, the authors find that dockless bikeshare is still preferred for commuting, indicated by peak hour demand, while docked scootershare is primarily used for recreational and off-peak trips.

In Chicago, Yang et al (2021) found that the introduction of scooter-share caused an average 10% decrease in bikeshare trips at the station level, that casual rider trips decreased by 34% compared to a 4% decrease for members, and that long duration trips experienced the most significant losses to e-scooters (20%). Younes et al (2020) studied how trip duration and trip counts vary throughout the day between dockless e-bike and e-scooter operators in Washington, D.C., finding that dockless micromobility user behavior mirrors that of casual ridership in docked systems, and has less in common with the user behavior of members of docked systems. McKenzie (2020) examined six different micromobility systems in Washington DC, finding that all six behave broadly similarly in terms of spatial distribution and temporal behavior. One finding of note to this thesis is that Jump, the only dockless bikeshare vendor operating in DC at time of publication, exhibits a two peak demand curve indicating demand spikes at peak commute, while the five scooter vendors exhibit an asymmetrical parabola shifted towards PM activity.

In 2019, two years after the local introduction of dockless bikeshare, Hirsch et al reviewed results of a Seattle Department of Transportation survey of 601 Seattle residents that covered familiarity with bikeshare, usage rates, and attitudes about dockless bikeshare. Through their analysis, the research team finds high rates of bikeshare uptake, with 33% of surveyed adults having used the dockless systems. 46% of those surveyed were classified as “Open Non Users”, respondents who did not use bikeshare but were aware of it, and were not opposed to using it in the future. The authors note that respondents currently using bikeshare were more likely to be white, young, and male, and that those classified as “Open Non Users" tended to be young as well.

Dockless Bikeshare and the Built Environment

Guo, Yang, and Chen (2022) reviewed bikesharing's relationship to the built environment, finding differential built environment impacts by world location. These effects include bikesharing being positively correlated with the presence of office space in East Asian cities but not North American cities; conversely, restaurants in North America and Europe are positively correlated, but restaurants in East Asian cities are not. On the differential built environment impacts between dockless and docked systems, the authors find that dockless bikeshare is associated with residential and industrial areas, particularly in East Asia. Dockless bikeshare additionally has a stronger association with bus service than docked bikeshare. A key finding relevant to this thesis is that docked bikeshare exhibits a negative relationship with proximity to city centers, so that docking stations in close proximity to the downtown core would be expected to have much higher demand for trip starts and ends than stations farther away. The authors explain this by the typical urban form of North American cities, which typically see significant decreases in population density and building height as one moves away from densely developed Central Business Districts. As a result of the decline in density, trip attractors and generators decline as well. Siting stations in these areas would lead to low ridership and minimal ROI, leading planners to locate stations in higher demand areas. This becomes a self fulfilling prophecy, with lower station density leading to lower bikeshare demand.

Gehrke et al (2021) studied Lime Bike trip generation in sixteen Boston suburbs not served by BlueBikes, finding positive and significant relationships between demand and population density, job density, transit stations, and that O/D patterns and rebalancing dynamics limited access in low income and racial minority communities. In contrast, zones within a 100m commuter rail walkshed were likely to have good e-bike availability, as were zones within municipalities that had been served by Lime for over a year. Sadeghinasr et al (2021) analyzed Lime Bike rider behavior in Boston, MA, finding the existence of an asymmetrical two peak demand curve that represents a hybrid of the expected demand curves for casual bikeshare and bikeshare members. The researchers additionally find spatial asymmetry, with over 40% of trips beginning in a commercial area or town center, that more trips are ended than started in residential areas, and more trips started than ended in commercial areas.

Zacharias and Meng (2021) study the environmental correlates of origin and destination location among dockless bikeshare vendors in Beijing, finding that protected bicycle facilities, metro stations, and "publicly oriented" points of interest are associated with increased activity, in addition to roughly equivalent dockless pickup and dropoff rates in sampled areas. Population density was not found to influence bikeshare demand, with demand varying significantly more than population density across sampled areas, which the authors hypothesize indicates the predominance of built environment factors in determining demand. Zhang et al (2021) studied dockless bikeshare in Singapore, finding that residential areas are the most frequent trip generators in the morning, and commercial or business areas the most common trip attractors in the same time frame. At the same time, commercial areas have a positive association with generation and attraction in the afternoon, and residential areas have a positive association as trip attractors. Zhou et al (2023) studied how the relationship between dockless bikeshare and transit varies across Beijing, finding that proximity to arterial roads, POI density, and presence of bicycle infrastructure influence successful integration with subway and bus modes, while population density, workplace density, and POI are impactful on integration with bus transit in particular. More broadly, Zhou et al find that while the relationship between these variables and bikeshare is consistent, the magnitude of that relationship varies significantly across regions of the city, pointing to variation in urban form as a likely confounding variable.

Docked Bikeshare vs Dockless Bikeshare

A subset of the literature on dockless bikeshare directly compares it to docked systems. Researchers typically compare systems within the same urban area, which allows for direct comparison of how demand, vehicle location, and trip characteristics vary across the same built environment and demographic characteristics. I would argue, however, that many authors do not consider the fact that the dockless system may have an entirely different user base (or potential user base) than the docked system, and that while the dynamics expressed by both systems may differ, it could be that there was never the potential for similar dynamics in the first place. This is true to an extent in Washington, D.C., where Lime Bikes largely do not compete with Capital Bikeshare for ridership (Goldbeck, 2022).

Qian et al (2020) contrasted the dockless and docked bikeshare levels of service offered in "communities of concern" in Chicago to illustrate differential potential to address equity concerns between the two models. The researchers find that dockless bikeshare had shorter "idle" times in CoC areas, greater rebalancing activity to CoC areas, and broadly higher availability of bikes. McKenzie (2018) compared Capital Bikeshare and Lime activity patterns within Washington DC, finding that the two modes exhibit differential temporal dynamics on weekdays but behave comparably on weekends, confirming findings of other studies. McKenzie also finds significant spatial variation, with Lime Bike trip density extending far beyond the CBD, while Capital Bikeshare trips are most densely clustered within and adjacent to the Central Business District. Reck et al (2021) studied interactions between docked bikes, dockless bikes, dockless e-scooters, and docked e-bike in Zurich, Switzerland, developing models for mode choice and assessing variations in usage rates. The authors find a significant commuter preference for docked bikeshare, a plateau effect at certain fleet density levels, indicating limits to consumer demand, and a preference for dockless e-scooters during off-peak hours, which could be assumed to represent leisure trips. Feng et al (2020) examined the relationship between publicly operated docked bikeshare and privately operated dockless bikeshare in London, finding as much as a 64% decrease in docked bikeshare activity at the station level due to dockless bikeshare competition within the service area. Peak demand experienced a significant reduction for trips beginning and ending in dockless deployment zones, indicating the potential for dockless bikeshare to absorb docked bikeshare trip demand. Li et al (2019) also studied the impact of dockless bikeshare on docked bikeshare in London, finding a 6% average reduction at the station level systemwide caused by the introduction of dockless vendors.

Zamir et al (2019) compared dockless bikeshare, dockless scootershare, and Capital Bikeshare in Washington, D.C., finding that dockless vehicle riders exhibited longer trips than casual CaBi riders but longer trips than members, aligning with results from comparable studies. Most interestingly, the researchers find that dockless micromobility ridership *does* exhibit the same characteristics as docked bikeshare with respect to weekday commuter peak, albeit with roughly 50% of the trip demand as Capital Bikeshare members (12% total trips and 6% total trips, respectively). Capital Bikeshare casual riders *do not* exhibit peak commute behavior, instead exhibiting slowly increasing demand throughout the day, peaking in the early evening. In Nanjing, China, Ma et al (2020) compared docked and dockless bikeshare dynamic using a mixed methods approach that leverages household travel survey data and bikeshare trip data, finding positive correlations in hourly use, but significant spatial heterogeneity in docked and dockless o/d pairs during the AM and PM peaks, as well as a relationship between "entertainment" points of interest and dockless bikeshare, but not for docked bikeshare. Ji et al (2020) confirmed Ma et al's findings of heterogentity in O/D locations, while adding the finding that trip duration and distance were broadly similar, but within that, docked users were more likely to account for longer duration and longer distance rides.

Table 2: Summary of Key Studies and Findings

Study	**Finding**
Faghih Imani & Eluru (2014, 2015)	Negative correlation between distance from CBD and trip flows at peak commute; positive correlation between restaurant presence and off-peak trip flows.
Tran et al (2014)	Positive relationship between station density, job density, population density, and trip flows. Demonstrated tendency of casual riders for "recreation" trips.
McKenzie (2018)	Differences in system dynamics between Lime and Capital Bikeshare: CaBi trips concentrated in and around CBD while Lime trips are more dispersed. CaBi and Lime exhibit different temporal behavior during weekdays, but similar temporal behavior on weekends.
McKenzie (2019)	Similarity between scootershare and casual Capital Bikeshare ridership, differential peak profiles, with CaBi exhibiting a two-peaked curve reflecting peak commute demand, and scootershare exhibiting a shifted peak towards afternoon and evening.
Zamir et al (2019)	Some similarity between CaBi commuter behavior and dockless micromobility, clear similarity between casual ridership and dockless micromobility.
Sadeghinasr et al (2021)	Lime Bike in Boston suburbs, finding an asymmetrical two-peaked demand profile similar in appearance to member demand in a docked bikeshare system. Trip starts tend to be in commercial and downtown areas, trip ends tend to be in residential areas.
Gehrke (2021)	Positive and significant relationships between bikeshare trip demand and population density, job density, and transit stations with Lime Bikes in suburban Boston.
Younes (2020)	Casual Capital Bikeshare ridership behaves more similarly to dockless micromobility than member trips in docked bikeshare.
Zhu et al (2021)	*Dockless* bikeshare used primarily for commuting, as evidenced by the two peaked demand profile, while *docked* scootershare is primarily used for off-peak and recreation trips.
Feng et al (2021)	If deployed at significant enough scale, dockless bikeshare systems are directly competitive with preexisting docked bikeshare.

Chapter 5: Methods

The goal of this thesis is to determine the extent to which the flow of bikes within Lime (Seattle), recorded across selected intervals of time, resemble the flows of Capital Bikeshare, a built-out bikeshare system that has been extensively studied by researchers. Flows of bikes are expressed as functions of built environment and demographic variables, each selected due to one or more authors finding them to be significant in docked or dockless bikeshare trip demand. The intervals of time chosen were carefully selected to illustrate known transportation behavior, and are included below:

- 8:00 am - 8:30 am, peak morning commute
- 8:30 am - 9:00 am, peak morning commute
- 4:00 pm - 4:30 pm, peak afternoon commute
- 4:30 pm - 5:00 pm, peak afternoon commute

Bikeshare Flows as a Unit of Analysis

To conduct my analysis I use the flows of bikeshare bikes, expressed as the net change in bikeshare vehicles at a station across two points in time. Docked bikeshare systems, largely because they are publicly owned, publish a large amount of data online on a monthly basis. This data includes the start and end time of individual trips, the start and end locations of trips, whether a trip was taken by a member or "casual" user, and whether an e-bike or a traditional bike was used (Goldbeck, 2022). Lime, as well as other micromobility vendors, do not provide such fine grain data for public use. Lime's API feed, available on the SDOT website, provides the latitude and longitude of bikes available for rent at the specific time the API feed is "called", whether a vehicle is an e-bike or e-scooter, and the time of the API call (SDOT, 2023). Lime Bikes do not have a unique identifier—while ID is a category included in the API call data, the ID is uniquely generated for each call, and cannot be used to track vehicles across points in time. As a result, I could not use trip start and trip end points in my research, or even trip start/end times, as Lime did not provide that information. What I was able to do, however, is calculate the net influx or outflow of bikes from discrete areas, in this case bikeshare stations. Within Capital Bikeshare, I was able to assign trip starts as outflows and trip ends as inflows at each station across two points in time. For example, if the station at Columbia Road and 16th St experienced 15 trip starts and 5 trip ends from 8:30 am to 9:00 am, I would compute a flow of -10 for that time period. As Lime only provides information on the number of available bikes, Lime flows were computed by taking the difference in available bikes between two points of time. Of course, as a dockless bikeshare system Lime does not utilize stations, complicating the calculation of flows at the station level. To address this, I used the spatial characteristics of Capital Bikeshare stations to develop a theoretical station network in Seattle, which I then aggregated available Lime Bikes to. This process, and its results, are discussed in the following chapter.

The development of a theoretical station network and calculation of flows also allows me to make a direct comparison between docked and dockless bikeshare systems without the two influencing each other. Several authors have presented comparisons between docked and dockless systems (McKenzie, 2018; Lazarus et al, 2020), however in each case the systems are either in direct competition, and thus influence each other, or are in separate cities operating under different conditions. A direct comparison between docked and dockless bikeshare systems that exist within the same city but simultaneously do not influence each other is largely impossible. To work around this problem, I have developed a theoretical network of docking stations based on the spatial distribution of Capital Bikeshare stations. I then overlay that network onto Seattle, aggregate available Lime Bikes to each station's service shed, and calculate net flows at the station level within the timeframes listed above. In doing so, I create a novel dataset that allows for direct comparison with Capital Bikeshare. Initially, I explored the possibility of creating an average of systems, for instance using the spatial characteristics of BlueBikes, CitiBike, IndeGo, and Capital Bikeshare to create my theoretical network, but ultimately I decided that I would prefer to make a comparison to a real system with real variables instead of an amalgamation that lacked any real defined characteristics.

Dates and Times Chosen

While the time constraints of thesis research partially dictated when and to what extent data was collected, the time frame in question, October 2023, was deliberately chosen for a number of reasons. Early Fall is one of the best times of year for accurate bicycle counts in the continental United States. Summer vacations have generally ended, and schools of all levels are back in session. As a result, commute schedules and modes normalize, giving researchers a more accurate picture of travel behavior. Additionally, extreme temperatures or weather conditions are typically less common in September and October than over the summer, removing one of the most common barriers to riding bicycles on a daily basis. For Seattle in particular, October made sense due to the University of Washington's academic calendar, which begins at the very end of September. Young people, college students in particular, are among the most frequent riders of micromobility (Mooney et al, 2019), so collecting data while UW students are commuting to and around campus on a daily basis was important for data accuracy. When selecting the specific hours of the day when I would collect data, I settled times that would allow me to capture morning and afternoon peak commute, or 8:00 am to 9:00 am and 4:00 pm to 5:00 pm. To that end, I downloaded live data detailing the locations of available bikes at 8:00 am, 8:30 am, and 9:00 am, as well as 4:00 pm, 4:30 pm, and 5:00 pm. I originally also downloaded data for 12:00 pm and 7:00 pm, intending to capture changes in bike locations between and after the commute peaks, but this data proved less useful than initially anticipated.

Comparison System Considerations

Several systems that would be obvious comparisons were not used, for reasons detailed below.

- **Portland, OR: Biketown.**
  After 2020, the Portland Bureau of Transportation adopted RideReport, a platform designed to process and present micromobility data for public consumption. Prior to 2020, trip data could be downloaded and aggregated at the monthly level. On RideReport, data can only be downloaded in quarters, and users must choose between Routes, which generates a file of the corresponding roads used by a trip, and Summary Statistics. Other data formats are not available, creating a level of data asymmetry that made comparison impossible (Biketown, 2024).
- **BlueBikes, Boston, MA.**
  BlueBikes extends across several jurisdictions, creating a metro area-wide system. While Capital Bikeshare does much the same, providing service to Arlington, VA, Alexandria, VA, Bethesda, MD, and other cities, flows *between* municipalities are marginal (Goldbeck, 2022). I was unsure of whether the same was the case for

BlueBikes, and given the close proximity and bike connectivity of Cambridge, Somerville, and Brookline, combined with each smaller municipality's limited GIS data, I decided to not use BlueBikes.

- **Minneapolis, MN: NiceRide**
  NiceRide was discontinued in November, 2022, due to a significant funding gap caused by the inability to secure a long term major sponsor. While their bike numbers mirror Lime's deployment in Seattle, and their land use pattern has broad similarities to Seattle's, 2023 data was not available for obvious reasons, and comparison across two different years felt inappropriate for this research question (Felegy & Sepic, 2023).
- **New York City, NY: CitiBike**
  CitiBike is a massive system, currently offering 33,000 total bikes across its service area (CitiBike, 2024). Comparing systems across an order of magnitude would be questionable in and of itself, but New York's population density and Manhattan's unique zoning/land use characteristics (at least in comparison to Seattle) complicate analysis of station siting and bikeshare flows.
- **Vancouver, BC: Mobi**
  If Portland is unavailable, Vancouver would appear to be the next best comparison for a Seattle bikeshare system. MoBi, however, has an uneven distribution pattern, potentially creating flows that would present significantly differently than those of Washington DC, Philadelphia, and Boston. Further complicating things, MoBi's monthly data automatically rounds trip start and end times to the closest hour, making it functionally impossible to calculate inter-hour flows using the historic dataset (Mobi, 2024)
- **Los Angeles, CA: Metro Bike LA**
  Metro Bikeshare is a fascinating case study of bikeshare system design. Operated by the LA County Metropolitan Transit Authority, Metro Bikeshare was explicitly designed as an extension of the LA Metro system (Bicycle Transit Systems, 2016). As such, it is the only bikeshare system that can claim to have a causal relationship between transit stations and bikeshare flows, as stations are planned in conjunction with transit planning efforts. Because of this departure in system design, it would not be accurate to compare Metro Bikeshare to other systems unless they were similarly designed (Bicycle Transit Systems, 2016).
- **Montreal, QC, Canada: Bixi**
  Bixi was one of the first and largest bikeshare systems in North America, and is widely regarded as one of its most successful. Its size–10,000 bikes across 900 stations–is significantly larger than Lime's fleet in Seattle or any of the comparisons used in this thesis (Bixi, 2024). Additionally, Bixi is decommissioned annually throughout Montreal's long winter season. While Bixi did recently begin offering Winter Bixi memberships with reduced numbers of bikes, the seasonal variation and fleet size are complicating factors. Additionally, while Montreal's land use regulations broadly mirror those of the United States, there is asymmetrical data availability that complicates analysis.

Creating a Theoretical Bikeshare Network: Extracting System Characteristics

Comparing dockless and docked bikeshare systems is inherently challenging due to the different units of analysis, especially if one seeks to analyze the relationship between trip demand or flows and the built environment. In a docked system, the characteristics of trip starts and ends are predetermined by station locations. In a dockless system, individual bikes are distributed in accordance with vendor deployment, permit requirements, and trip ends. There is no inherent unit of analysis, making it problematic to directly between dockless and docked systems. Researchers have worked around this problem by comparing the number or share of bikes within a discrete area, as Lazarus et al did when comparing dockless and docked bikeshare in San Francisco and Los Angeles. For citywide comparisons, however, a different approach is needed. This process is complicated by the fact that Capital Bikeshare and Lime publish their data in different formats. Capital Bikeshare publishes monthly data online that includes station origin, station destination, start time, end time, type of vehicle, and member status. Lime manages an Application Programming Interface (API) feed that is posted on SDOT's website. When users "call" the API using a string of code, the feed returns a JSON file, a type of data that can be read by a variety of different programs. Using another line of code, this data can be downloaded as a CSV file containing data including the coordinates of every inactive, or available, e-scooter and e-bike in Lime's fleet. The data does *not* include when a vehicle was last used, or where the origin of its last trip was, while Lime does record that data, it remains private and is generally only used internally, by SDOT, and with organizations partnering with Lime. This more specific data was *not* available for my research, so I relied exclusively on the simpler publicly available API data that provides the specific coordinates of Lime Bikes available to rent. There are several variables one could analyze in both docked and dockless systems, such as where bikes are located at set points in time. In docked systems, one can use the trip start time, trip end time, station origin, and station destination variables to calculate net arrival/departure of bikes within stations. Dockless bikeshare, if aggregated to a unit of analysis, can be analyzed in a similar way, calculating the net change in available vehicles at the unit of analysis across points in time. This variable, which I describe as bikeshare flows, allows researchers to analyze across both systems. Reviewing the literature, I was unable to find studies utilizing this type of comparison, potentially because finding a suitable unit of analysis to aggregate dockless bikeshare flows at can be complicated.

Considering the problem, I decided that the best way to capture flows in a manner that would allow cross-system comparison would be to create a theoretical network of docking stations to overlay onto available Lime Bikes in Seattle, set catchment areas that would allow me to assign Lime Bikes to stations, and use hour to hour measurements to calculate change in availability, or flows, within each station. This would allow me to match both the unit of analysis–the station–and the independent variable–flows at the station level. The problem, then, was to create a network that did not directly match Capital Bikeshare, as Seattle and Washington D.C. have different land area and topography, but one that shared enough characteristics that comparisons between the two would be salient. To generate the network, I used the following process:

1. The "GeoSphere" package in R allows users to perform a variety of spatial calculations that incorporate the curve of the Earth's surface (Hijmans et al, 2022). I used Geosphere to calculate the distance between each Capital Bikeshare station and a manually selected central point in Washington's central business district. The point, just north of the White House on Lafayette Square, is intended to be as close to central as possible without biasing downtown employment sub-regions such as the Capitol Building, the southwest concentration of federal agencies, or the northern Central Business District. This process resulted in a distance variable for each station.

2. Seeking to generate distinct zones for analysis, I used the R package "BAAMTools" which contains the "GetJenks" function. "GetJenks" allows users to calculate Jenks Natural Breaks (Rabosky et al, 2023). Jenks Natural Breaks are a cartographic approach to dividing a dataset that seeks to maximize the difference between classes and minimize the difference within classes (2023). As they seek out the natural break points in the data,

   Jenks Breaks are well suited for locating variations in spatial arrangement. I wanted to understand specifically where the spatial character of bikeshare station distribution changed, and calculated Jenks Breaks for station distance. My rationale for this is that bikeshare systems rely on station density to provide levels of service. Based on this, one may assume that densely grouped stations would have materially different demand characteristics than more dispersed stations. In a dense environment with high demand for trip starts and trip ends and unconstrained by topography, one would expect to find fairly dense distributions of stations, as demand would need to be captured in every direction. In less dense zones with lower demand, however, stations would be further apart both on the X and Y axis.

   Following that logic, I calculated five Jenks Breaks for distance from the central point chosen earlier, using the resulting distance breaks as radii to create four successive polygons centered around the chosen central point. I experimented with creating three, six, and seven breaks, ultimately finding that based on the urban form of Washington D.C. and the size of the polygons the breaks would produce, five appeared to be the most appropriate. My theory, that station characteristics would vary between Jenks categories, was proven correct by the variation in average station capacity, or number of bike docks. As each zone gets progressively further from the central point, the number of docks decreases as well. A table illustrating the four zones and their distance boundaries, share of stations located within, and average number of docks per station is included below.

Table 3: Capital Bikeshare Spatial Characteristics

Zone	Stations	Average Nearest Point (feet)	Distance Bounds (feet)	Share of Stations	Average Number Docks
1	131	465	0.000 - 6006.851	36%	21
2	114	1,003	6006.851 - 13334.424	32%	19
3	68	1,531	13334.424 - 22432.547	18%	17
4	47	1,939	22432.547 - 30116.658	13%	16

3. Within each zone, I used the "Near" tool to calculate the distances between stations. "Near" reads in a point dataset that contains location coordinates, and returns the minimum distance to another point for each point in the datatset. In this case, each point was a Capital Bikeshare station. Having assigned each station its respective distance to the nearest station, I calculated the average closest distance to nearest station per zone. This step concluded my spatial analysis of Capital Bikeshare. Next, I applied these spatial characteristics to generate an initial set of docking stations with which to create Seattle's station network.

Creating a Theoretical Bikeshare Network: Assigning Station Locations

4. To generate points, I created polygons that replicated the station density thresholds identified in the Capital Bikeshare system, using the distance bounds listed in the table above. While taking the spatial characteristics of one system and directly overlaying them onto another city is not a best practice, in the case of Seattle the boundaries of each zone broadly match up against breaks in the urban form. For example, applying the same

   distance bounds for Zones 1 and 2, 0 ft from central point to 6,007 feet from central point, and 6,007 feet to 13,334 feet, produces polygons that end where I5 separates downtown from Capitol Hill and at the eastern edge of Capitol Hill where residential character shifts towards almost exclusively single family homes and larger lot sizes, respectively.

5. Next, I calculated the total number of stations I would generate, as well as how they would be distributed across each zone. Within each Zone (Step 4), I randomly generated a set number of points that were constrained by a certain distance--average distance to the next closest point. Bikeshare systems commonly have a ratio of 2:1 docks per bike (Ursaki & Aultman-Hall, 2015). To generate a total number of docking spaces, I multiplied the average number of Lime Bikes deployed by Lime in Seattle in October 2023, 1,731, by 2, returning a total number of spaces to distribute, 3,462 in total. This step is what allowed me to “right size” my approach of transposing the spatial arrangement of Capital Bikeshare onto Seattle. By using the size Lime’s Seattle bikeshare fleet to determine the number of stations I would deploy, I ensured that I did not create too few or too many stations. Referring back to Capital Bikeshare’s share of stations within each zone, included in the previous table, and used each zone’s percentage share of stations to divide available docking spaces up between zones. Next, within each zone, I divided the number of docking spaces by the average number of spaces per station within each zone, rounding down to the nearest whole number to return the number of docking stations I would have available to distribute within each of the four zones.

   ArcGIS Pro allows users to randomly generate a set number of points, which in this case represent bikeshare stations. Users can constrain points by an average minimum distance between features, ensuring that a structure is preserved across the random generation. In this case, I used the average distance between Capital Bikeshare stations within each zone to constrain generation. For instance, this meant that points within Zone 1 were generated with a minimum distance of 465 feet. Using an average distance as the minimum does mean that points will be more spaced out than they would be if I had used the minimum distance of Capital Bikeshare, however using the minimum distance for each zone would have been more inaccurate, creating a network *denser* than Capital Bikeshare.

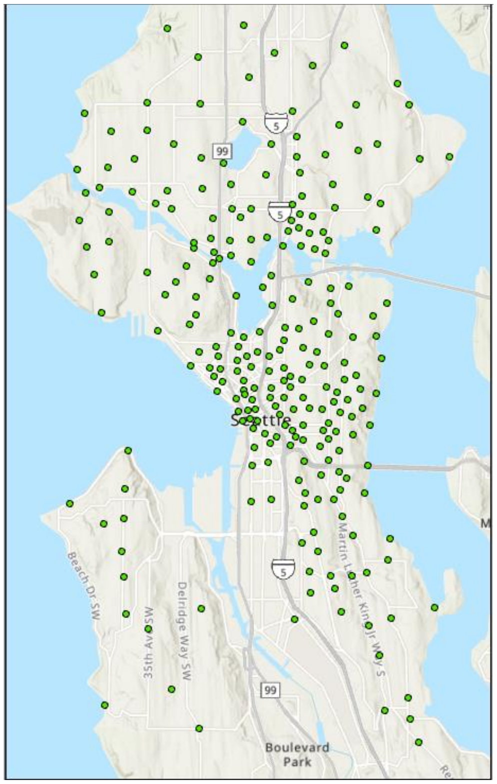
6. After generating points, I began the process of assigning them to locations. In this process I made an effort to move points as little as possible to maintain a degree of randomness as well as the structure ensured by minimum distances. As a rule, I did not move points between zones, and completed my first round of placements within each zone. The steps I took were as follows:
   a. Remove points located on water features.

    b. Remove points located within Seattle Parks, where Lime is currently not permitted to operate (SDOT, 2023).
    c. Relocate points placed within the center of blocks to block faces.
    d. Following NACTO guidelines, place points on the nearest sidewalk (where sufficiently wide), plaza, or streetscape (NACTO, 2016).
    e. In areas zoned as Neighborhood Residential, find the nearest intersection with a non-one lane road, or place points at the edge of the nearest park, school, or community center.
    f. Relocate points away from areas of steep incline, either uphill or downhill.

7. After distributing points, I assessed the network and examined station distribution within broad land use categories to ensure that roughly the same number of stations were distributed among residential, commercial/mixed use, and downtown areas in Seattle as were in Washington D.C. I additionally assessed station presence at Urban Villages, at the University of Washington and U-District, and at Link Lightrail stations. This step is a departure from the bounded random generation I had previously employed, but I believe it was necessary to accurately approximate a docked bikeshare network.
8. Seattle's Urban Village model concentrates development in and around commercial centers (Seattle OPD, 2005). Urban Villages have concentrations of restaurants, bars, and storefronts, and are typically located at the intersections of major roads. In producing my final network, I ensured each urban village had at minimum one centrally located station, adding points to the network where necessary to ensure this condition was met.
    a. Considering the distribution of Capitol Bikeshare stations relative to Metro stations in Washington, I ensured that each station had a bikeshare station within a quarter mile radius.
    b. The University of Washington would be a significant demand generator for bikeshare trips, and was the site of several Pronto stations (OOmap, 2023). The same could be said for the U-District, which is one of the most densely populated locations in the city. Additionally, university students are known to be frequent riders of micromobility (Hirsch, 2019). In light of these factors, I generated three additional stations within the University of Washington's campus.

In total, after removing impractically or impossibly placed stations, and making the aforementioned additions, I was left with a network totalling 240 bikeshare stations.

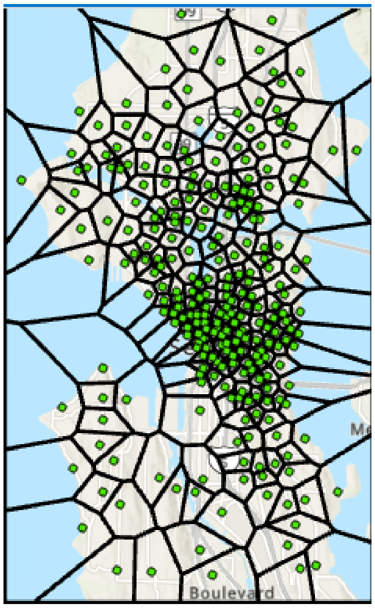
Figure 19: Seattle Docking Station Network: Final



9. Having produced a network of bikeshare stations, I next generated catchment areas within which to assign Lime bikes to stations. To do so, I generated a 500 meter buffer around each station. Many authors have studied bikeshare station service areas, commonly using 500 meters, or just over a quarter mile, as the convenient walking distance that would characterize a service area (Ursaki & Aultman-Hall, 2015). To generate the catchment areas themselves, I used ArcGIS Pro's "Pairwise Buffer" tool to produce 500 meter buffers around each station.

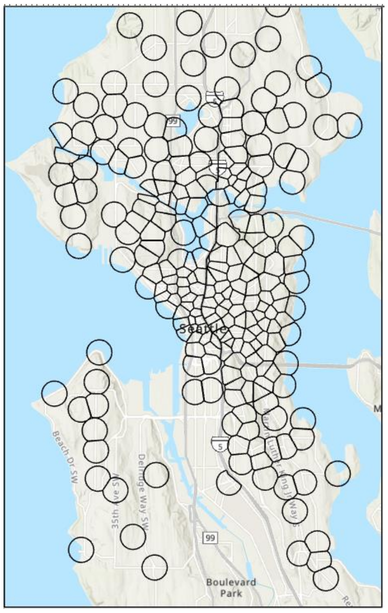
10. Catchment areas overlapped throughout the network, creating a challenge for assigning trips to stations. If a bicycle was located within two or more buffers, assigning it to a station would require trying to determine the rider's intended final location, impossible to do with GBFS data. Trips could be assigned to the nearest station, however this would need to take into account topography and built environment features in a way that ArcGIS Pro is not equipped to do. Recognizing this, I generated Thiessen Polygons around each station. Thiessen Polygons are a type of polygon generated around a point feature. Within the polygon, every potential location is closer to the generative point than any other point in the network and can be described as being within the point's service-shed (ESRI, 2024). Thiessen Polygons provide a practical way to separate overlapping station service sheds, especially in areas of high station density such as downtown.

Figure 20: Stations with Thiessen Polygons



11. In creating the Seattle network, I used the ArcGIS Pro tool “Pairwise Clip” to match station catchment zones to the extent of their associated Thiessen Polygon (Image A), or to match the Thiessen Polygon to the buffer area (Image B), whichever was allowed by the presence of other features. Images demonstrating the two processes are included below. When not constrained by overlapping service sheds, the Thiessen Polygon adheres to the circular shape of the service shed buffer, however when service sheds are constrained, the buffer conforms to the Thiessen Polygon. One significant downside of Thiessen Polygons, particularly in station dense areas, is that they create angular service sheds that do not accurately reflect service sheds or rider station preferences. This is largely unavoidable however, as alternatives would entail a complex optimization process to assign trips within overlapping station zones.

Figure 21: Station Catchment Areas Final



12. To assign Lime bikes to stations, I created points representing individual available bikes by using the Lime GBFS data I had previously pulled at set times of day from Lime's Application Programming Interface (API) feed located on the SDOT website. Each dataset contains the coordinates, expressed in latitude and longitude, of each Lime Bike not currently in use and available to rent. Lime Bikes currently in use are not included in the data due to data privacy concerns. When visualized on a map, each available bike is visible as a discrete point. Omitting live trips is not necessarily an issue, however, as Capital Bikeshare data does not include live trips either. My data was pulled at the following times: 8:00 am, 8:30 am, 9:00 am, 4:00 pm, 4:30 pm, and 5:00 pm. These times reflect changes in trip demand and trip character, including both peak morning commute, and peak afternoon commute. I filtered each dataset to only weekdays, and created CSV files that contained all bikes available at the respective time of day. Using ArcGIS Pro's XY Feature to Point tool, I generated points representing each bike. Once points were generated, I used the Pairwise Intersect tool to assign each point feature to the overlapping service shed associated with a station. Pairwise Intersect cross-checks two data features, returning the parts of them that overlap. This leads me to one of the more significant departures from reality in this analysis. Stations in the Seattle network have unlimited capacity, and do not have a set number of docking spaces assigned to them. The number of docks per station *were* used when reverse engineering the spatial characteristics of Capital Bikeshare, and I initially intended to include them in the network, but this proved too complicated. Assigning Lime trips to stations in the process I have used so far does not manipulate or edit the trips origins or destinations themselves. Assigning station capacity would create numerous scenarios where I would have been forced to change either the start or end location of a trip. Across tens of thousands of trips, this would have the potential to significantly distort flows, particularly as it could entail changing locations to a different land use, population density, or distance from the central point. This is more complicated by the fact that one cannot determine whether fluctuations in Lime bike counts within a "station" are more closely associated with the start or end of a trip. Compounding these concerns is the issue raised above with regard to Thiessen Polygons–assigning station capacity would necessitate a complex optimization process that I was not equipped to successfully complete.

13. With each station now having assigned an available number of bikes at different times of day, I could now calculate flows, or changes in available bikes, between intervals of time. I calculated the following flows: 8am to 8:30 am, 8:30am to 9am, 4pm to 4:30pm, and 4:30pm to 5pm. The result of this process was that I now had data that measured the same variable–bikeshare flows–at the same unit of analysis–the station–as Capital Bikeshare. Next, I needed to capture the built environment characteristics of stations in both systems, Capital Bikeshare and Lime.

Documenting Bikeshare Station Site Demographic and Built Environment Characteristics

Census Data

To access ACS data I relied on the TidyCensus R package, which interfaces directly with US Census Bureau API to download specified datasets (Walker & Rudis, 2024). Once I had downloaded the data, I subsequently cleaned it for tracts within the study area, and used the VLookup function in Microsoft Excel to associate population density with the tract that the respective Capital Bikeshare stations were located within.

Population Density

Several researchers have found correlation between population totals, population density, and bikeshare demand (Tran et al, 2014; Noland et al, 2016; Gehrke et al, 2021). This makes sense on an intuitive level–the more people there are, the more potential trips there would be. Additionally, in American cities, more densely populated areas tend to include commercial corridors that would serve as trip attractors. To collect population and population density I used the TidyCensus package, which allows users to interact directly with the US Census Bureau API (Walker & Rudis, 2024). I used TinyCensus to download population data aggregated to the Census Block Group level in both Washington D.C. and Seattle. I chose Block Group over Census Blocks due to blocks being too small to accurately capture the entirety of the built environment surrounding a station and due to data availability concerns at that level. Census Tracts have the opposite problem, being too large to capture fine grain differences in the built environment or demographic patterns. To calculate population density, I used the TIGRIS package to download the exact land area for each Block Group with the Coord function (2024), which I divided population by to produce population density. In both Washington and Seattle, high population density generally characterizes denser, more walkable urban form with more amenities and trip attractions. Seattle and Washington have significantly different typologies of density–Seattle's zoning code concentrates density in urban villages, generally characterized as densely built neighborhoods with a commercial core and the presence of mid–rise housing. Density also extends along arterial roads, though generally at lower levels than is found in an Urban Village. Outside of Urban Villages and arterial roadways, however, density rapidly decreases. Just one block off the main arterial in Wallingford, Eastlake, Ballard, and more, the form experiences a quick transition to single family homes and lowrise buildings. In Washington D.C. density is not as constrained, and single family homes are rarely found within two miles of the central business district. Instead, the built environment favors townhouses, which afford a significantly higher average residential zone population density than is found in Seattle. While Washington D.C. is home to several universities, none reach the scale of the University of Washington, and no neighborhood in D.C. comes close to the population density of certain U-District census tracts. Recognizing these differences, I classified both cities' population density variables by decile, or data broken into ten even groups, and coding the results in a range from 1-10. For example, the top decile of Seattle would represent the 10% most dense of all Block Groups, and each would be entered into my dataset with "10".

Land Use

Land use relates to both trip generation and trip attraction, and has been noted as one of the more significant variables in analyzing bikeshare system trends. Researchers have linked bikeshare flows to the presence of restaurants

(Faghih Imani & Eluru, 2014, 2015; Wang et al, 2015), office space and industrial land use (Guo et al,), and park land (Wang & Chen, 2020; Wergin and Buehler, 2017). Each of these land uses is linked to a city’s zoning code, with office space being concentrated in Downtown zoning, large parks often being zoned as “Open Space”, industrial land use exclusively existing in “Industrial” zoning, and restaurants being most common in “Mixed Use”, “Commercial” or “Downtown” zones. Common bikeshare trip purposes such as the morning or afternoon commute, traveling to after work dinner plans, or going to the park on a weekend all have distinct land use characteristics that allow researchers to infer trip purpose. Of the prior examples, their corresponding land use pairs could be assumed to be Residential - Central Business District, Central Business District - Residential, Central Business District - Commercial/Mixed Use, and Residential - Open Space/Unzoned. Seeking an objective measure of land use that could be used to compare across Washington D.C. and Seattle, I used a simplified version of both city’s zoning code to classify land use. A diagram summarizing how land use was simplified across both datasets is included below. Zoning variables are measured as individual binary variables, with “1” representing the zoning category being present and “0” representing an alternate zone. This classification was chosen to ensure zoning could be accounted for in linear regression models.

Table 4: Creating a Simplified Zoning Category

Washington DC: Zoning Boundaries (2016): “ZONE DISTR”	**Combined Zoning Variables**	**Seattle: Current Land Use Zoning Detail: “CLASS_DESC”**
Downtown Zone	**Downtown**	Downtown
Mixed Use Zone	**Commercial/Mixed Use: High Density**	Seattle Mixed
		Commercial/Mixed Use
Neighborhood Mixed Use Zone	**Commercial/Mixed Use: Low Density**	Neighborhood Commercial
Residential Apartment Zone	**Residential: High Density**	Multi Family
		Multi Family/ Residential/Commercial
Residential Flat Zone	**Residential: Low Density**	Neighborhood Residential
Residential Zone		
Unzoned	**Major Institutions**	Major Institutions
Production, Distribution, Repair Zone	**Industrial**	Industrial and Maritime
		Manufacturing and Industrial

Note: In DC, Unzoned denotes Federal land. Capital Bikeshare stations in Unzoned areas are exclusively found on the National Mall, which is why I reclassified it into Major Institutions

Presence of Transit Station

The relationship between both docked and dockless bikeshare systems and transit stations is well established in the literature. Connections between bikeshare and rail transit in particular have been established in Montreal (Faghih-Imani & Eluru, 2014), Washington D.C. (Buck & Buehler, 2011; Martin & Shaheen, 2014) New York City (Noland et al, 2016), as well as Chicago and Los Angeles (Tang, 2024). To capture the influence of Metro stations in Washington and Link stations in Seattle, I created quarter mile buffers around stations to identify stations in a transit station’s walkshed. Whether a station is located nearby transit or not is indicated by a binary variable, with “1” representing transit station and “0” representing no transit station. Bus stations are *not* included due to their significantly increased frequency compared to rail stations and frequent presence downtown and in commercial corridors. In a dockless system, bikes left adjacent to a bus stop could represent a first mile solution to reach the bus in the morning, or they could equally represent a trip that ended at a business adjacent to the bus stop. Transit stations, particularly Link stations, tend to take up more urban space than bus stations, and thus it is easier to determine the station's area of influence. Additionally, the relationship between rail transit and bikeshare is much better established in the literature than it is with bus systems.

Distance from City Center

Many authors have established that distance from the city center, or Central Business District (CBD), can be expected to have a significant negative correlation with bikeshare demand in the morning, or that as distance to CBD decreases, bikeshare trips increase and vice versa. This relationship has been established in Montreal and Chicago (Faghih-Imani & Eluru, 2014, 2015), Washington D.C. (Wergin & Buehler, 2017), several East Asian cities (Guo et al, 2018), Taipei (Liu & Lin, 2019), and Singapore (Zhang et al, 2021), among others. The most obvious explanation for this is that the majority share of jobs, particularly those that induce a typical AM/PM commute, are located in the CBD, and as a result commute flows would result in a share of bikeshare trip flows. In addition, the urban form tends to become denser the closer one gets to the CBD, increasing both trip generation and trip attraction in areas adjacent to and within the CBD. Both Washington D.C. and Seattle have zoned Downtown areas, however both cities' CBDs expand beyond those zoning boundaries. In Seattle, much of the CBD extends up into South Lake Union, which is zoned as Seattle Mixed, whereas in D.C. the CBD is asymmetrically shaped, with a private sector CBD just north of the White House and a government CBD stretching along Pennsylvania Avenue and located south of the National Mall. Ideally, I would have used a more precise replicable approach and calculated a central point of the Downtown zones. However, given classification difficulties and asymmetrical spatial organization, I selected each city's central point manually. In Washington D.C. the central point is within Lafayette Square at (38.898987, -77.036590) , and in Seattle the central point is at the intersection of 2nd and Union, or (47.608300, -122.337934). I calculated distance from the CBD with the "Near" tool in ArcGIS Pro, using the central point as the "Near" feature to compare all bikeshare stations to, producing a matrix of distances measured in feet.

Street Category

Less established in the literature, though still of interest, is street category. Both Seattle and Washington classify their city streets at five different levels, and though the names differ, they are easily reclassified into an ordinal variable from 1-5. The theoretical underpinning for considering street category is that certain street types are more conducive to biking than others. Experienced cyclists typically have a higher tolerance for traffic stress, that is, sharing the road with drivers without protected facilities, than non-cyclists. If Lime's ridership is heavily weighted towards casual riders, those who do not normally ride a bike or do not own a personal bicycle, their lower tolerance for traffic stress may show up here. Alternatively, it is possible that dockless bikeshare riders may be less aware of the risks of riding on city streets, resulting in a reverse of the expected effect.

Table 5: Street Classification

Washington D.C. Street Categories (OpenData DC, 2024)	Unified Categories	Seattle Street Categories (Seattle GeoData, 2024)
Local	1	Not Designated
Major Collector	2	Collector Arterial
Minor Arterial	3	Minor Arterial
Principal Arterial	4	Principal Arterial
Interstate	5	State Route/Freeway

Bicycle Lane Presence and Category

Buck and Buehler (2011) and Rixey (2012) both studied the effect of bike lanes in Washington D.C. on Capital Bikeshare ridership, finding a positive and significant relationship. Whether dockless bikeshare riders have the same preference for protected facilities as docked riders is largely unknown, though one would assume that the relationship would persist. Of note is that Washington D.C. has massively expanded its protected bicycle lane network since those authors conducted their research. Seattle has expanded its bike lane network as well, and has a more robust off-street network than Washington does, but overall Seattle has fewer protected on-road facilities than Washington does. I classify bike lanes on a scale from 0 to 3, with 0 representing no protected facility, regardless of whether a painted lane is present or not, 1 representing “soft” protection like flex-posts, 2 signifying protected on-road lanes with a hard barrier, such as parked cars or cement curbs, and 3 representing off-street facilities like the Burke Gilman Trail.

Table 6: Bike Lane Classification

Rating	Facility Type (Seattle GeoData, OpenDataDC, 2024)
0	No facility
1	Protected bike lanes - flex post
2	Protected bike lanes - hardened barrier
3	Off-street bicycle facilities

Proximity to a University

Bikeshare ridership is known to skew young, and the area immediately around universities generally has the highest concentration of young adults in a city (Hirsch, 2019). The effect of universities on bikeshare ridership is largely undocumented in the literature, though on paper it stands to reason that a large share of high propensity riders with schedules that necessitate frequent trips (to class, to internships, back to the dorms) would generate a clear affect on bikeshare flows. To account for universities, I buffered university campus boundaries in Washington D.C. and Seattle with a 400 meter walkshed. In Seattle, that includes the University of Washington, Seattle University, Seattle Pacific University, and North Seattle College. In Washington D.C. the included universities are Georgetown University, George

Washington University, Howard University, Gallaudet University, American University, the University of the District of Columbia, and The Catholic University of America (Google Maps, 2024).

Geospatial Analysis and Statistical Tests

With regard to my analysis, my intended methods when planning and conducting my research differed significantly from my ultimate approach. The main benefit of creating a system of bikeshare stations to "dock" Lime at was that it allowed a direct comparison between two systems using the same unit of analysis, the station. I initially planned to use two sample T-Tests extensively as part of this analysis, using Capital Bikeshare as the "control" sample and Lime as the "treatment" sample, and the respective bikeshare flows at the station level as the variable. Within each system I planned to use the R package "MatchIt" to create two samples that had similar characteristics with regard to station density, distance from urban core, as well as land use and demographic characteristics. The primary issue with this approach is that each sample would come from a different geographic area, however the fact that the Seattle station network was created based on Capital Bikeshare's spatial arrangement mitigated this to an extent. Ultimately, however, I did not include the T tests in my results section. There are two reasons for this—first, the tests did not tell us anything that the geospatial analysis in ArcGIS did not already reveal, and second, the tests, performed in R, generated statistically impossible degrees of freedom, leading to serious concerns about the suitability of T Tests for this analysis.

Similarly, I intended to extensively use regression models to assess the relationships of bikeshare flows in each system to built environment and demographic variables. As explained in the previous section, there is an extensive body of research proving the connection between such variables and docked bikeshare. As such, comparing the demonstrated relationships of a docked and dockless system might generate interesting and relevant findings. There were several issues with this approach, however. In building my models, I used flows as the dependent variable and built environment/demographic factors as the independent variables. Neither set of flows, Capital Bikeshare's or Lime's, is normally distributed. While non-normality is not necessarily a dealbreaker for linear regression, it is not ideal. More concerning, however, was the fact that the models with the highest predictive power, or R^2 values, were quite simple. The two models are included below.

Bikeshare Net Flow (Station Level) ~ Block Group Population Density + "Downtown" Land Use Category + Transit Station Proximity

Bikeshare Net Flow (Station Level) ~ Block Group Population Density + Distance from Central Business District

Given the simplicity of both models, there were concerns that missing variable bias could impact results. I attempted to correct this by exploring additional arrangements of the models that included more variables, however none could provide good predictive power. Another concern was that almost all model runs demonstrated significant heteroskedasticity, per the results of the Breusch Pagan Test. Both the heteroskedasticity of results and non-normality of the data appeared to be caused by outliers in the dataset. Normally, I would remove outliers, however in this case I found the outliers to represent real flows of bikes from stations in exceptionally high demand for trip starts or trip ends. Given the existing concerns about the regression models and T-Tests approach, I ultimately chose to use less complex methods and used a visual comparison of bikeshare flow maps, as well as a set of Pearson Correlation tests to examine the similarities and differences between Lime and Capital Bikeshare.

Visual Comparison of Bikeshare Flows

Using station location data from Capital Bikeshare, as well as the station network I created in steps 4-10 of the process described earlier in this chapter, I was able to use the "Join" tool in ArcGIS Pro to link bikeshare flows to their respective stations. I then created visualizations of the following bikeshare flows: 8:00 am – 8:30 am, 8:30 am – 9:00 am, 4:00 pm – 4:30 pm, and 4:30 pm – 5:00 pm. I then broke flows into five or six categories using Jenks Natural Breaks, which seek to maximize difference between categories while minimizing difference within categories. Seeking to make the maps more intuitive to viewers, I then slightly altered the break points, changing them to whole numbers or a single decimal place when possible. I additionally ensured that negative and positive flows were always in separate categories, allowing negative flows to be visualized in a Red – Orange – Yellow color scheme and positive flows in three intensifying shades of green. Using this color scheme allows users to compare flows at a glance even as the range of flows increases or decreases throughout the four times of day. The magnitude of flows varies significantly between times and across the two bikeshare systems. From 8:00 am to 8:30 am, for example, Capital Bikeshare's average weekday flows range from -5.64 to 7. Lime's, on the other hand, range from -4 to 2. From 8:30 am to 9:00 am, Capital Bikeshare's range rises to -9.6 to 10, while Lime's changes to -1 to 5.6. Because of these fluctuations, the number of flow categories visualized may change from map to map, and the same is true for the ranges of each category. The constant, however, is that positive flows are always visualized in green shades, and negative flows are always visualized on the yellow – orange – red spectrum. This is not a perfect solution to the problem of varied ranges and distributions of data, however it was the best solution I could identify that would preserve the visual legibility of the maps.

Pearson Correlation Tests

Pearson Correlation tests present a simpler way of evaluating the correlation between two variables than building linear regression models. Ideally, Pearson Correlation should be used with normal data, like the majority of linear regressions and related methods, however normality is not an absolute requirement for this approach. To gain a sense of how the bikeshare flows of Capital Bikeshare and Lime related to the built environment and demographic variables detailed above, I used Pearson Correlation to test bikeshare flows of each system against each measured variable. I conducted testing in R, which includes Pearson Correlation in its base set of statistical tools. A simplified version of the tests can be expressed as follows: Flows (Time Frame) ~ Variable. To simplify results, I included the results that were statistically significant ($p < 0.05$), as well as the equivalent results from the other bikeshare system, regardless of whether the corresponding results were significant or not. An example of this approach is included below.

Figure 22: Pearson Correlation Results Example

	Capital Bikeshare		**Lime**	
8:00 am - 8:30 am	**P Value**	**Coefficient**	**P Value**	**Coefficient**
Distance from CBD	1.31E-05	-0.2271678	0.9249	-0.00612887

In this case, Capital Bikeshare's results for Distance from CBD *are* statistically significant, however Lime's are not. Because one of the systems was significant however, the category is included for both. This is done to illustrate the similarities and differences between Capital Bikeshare and Lime. The following chapter presents the results of my geospatial analysis and Pearson Correlation tests. As these tests were conducted using spatial data, I also computed the Moran's Global Index for Lime and Capital Bikeshare flows to test for spatial autocorrelation, the results of which follow the Pearson Correlation tables.

Chapter 6: Results

The following pages present maps that detail the flows of Lime Bikes in Seattle, measured by change in available bikes at the station level, and Capital Bikeshare flows in Washington, D.C. Due to variations in the range of flows across measurement times and systems, the categories and their associated symbology varies between maps. For ease of visual legibility, red always represents the highest magnitude negative flow, while green always represents the highest magnitude positive flow. The maps begin on the following page and run through page 56. The results of Pearson Correlation and Moran's Global Index tests follow the map section.

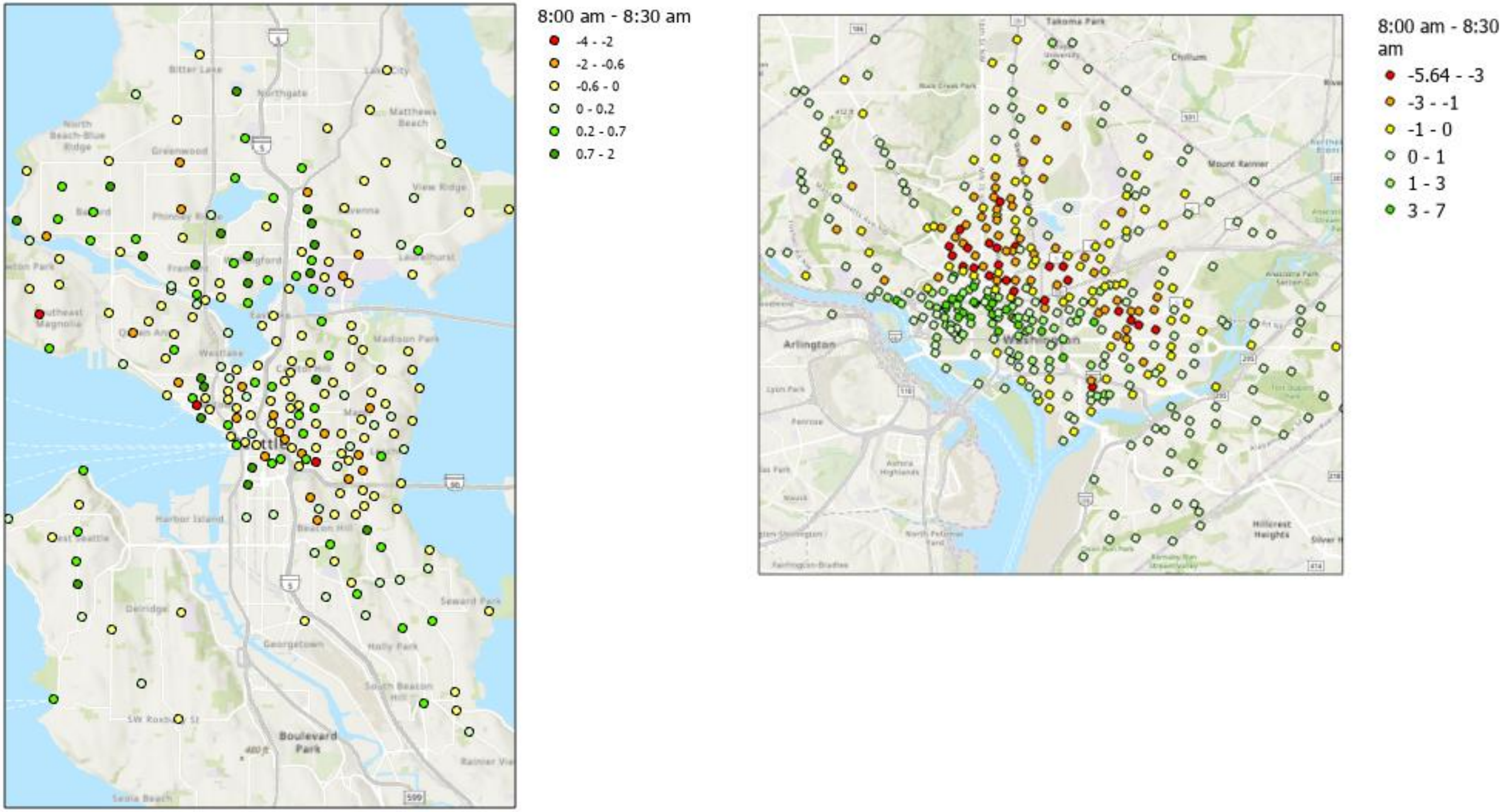


Figure 23: Lime (Seattle) and Capital Bikeshare average weekday flows from 8:00 am – 8:30 am

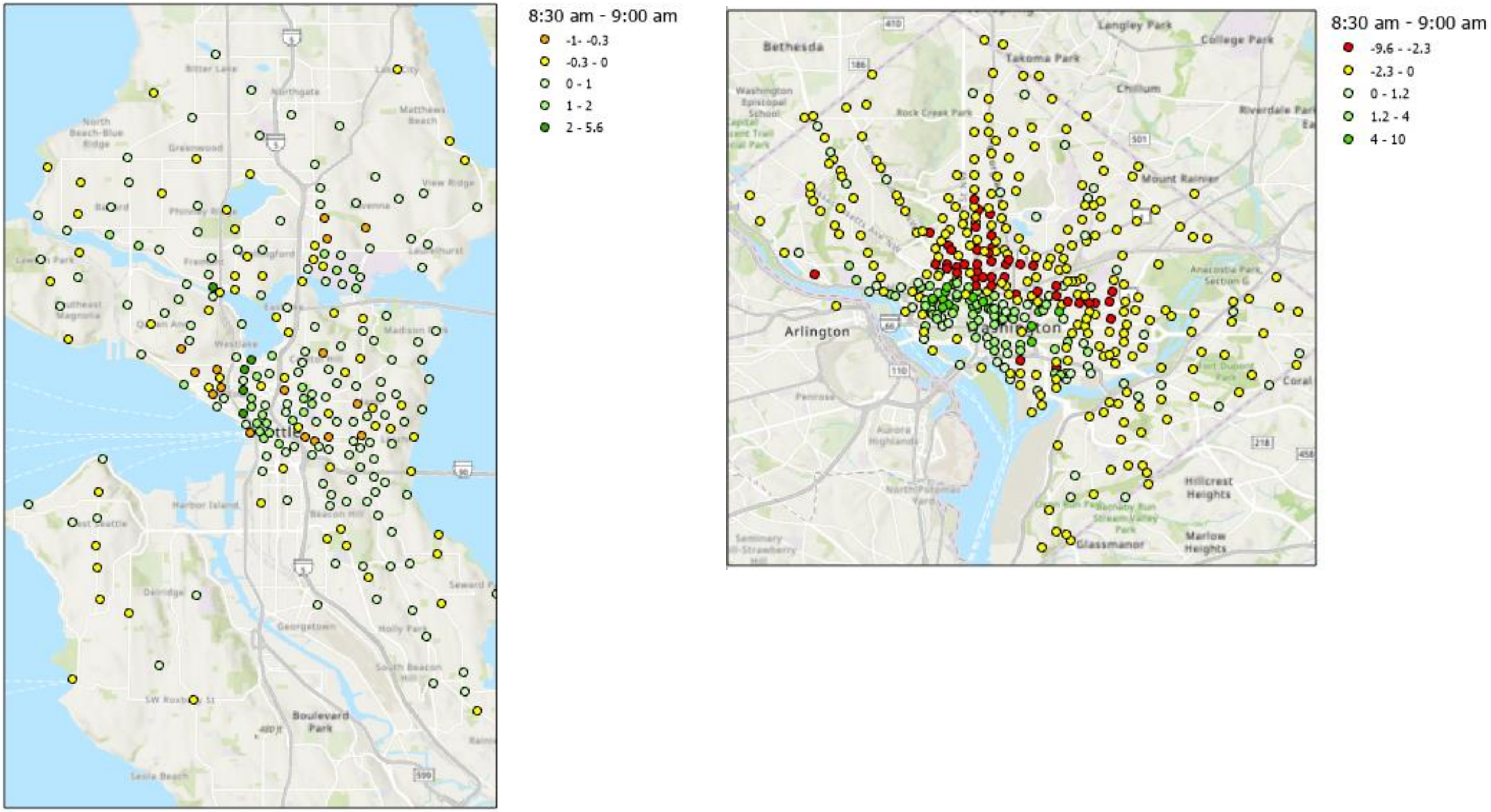


Figure 24: Lime (Seattle) and Capital Bikeshare average weekday flows from 8:30 am – 9:00 am

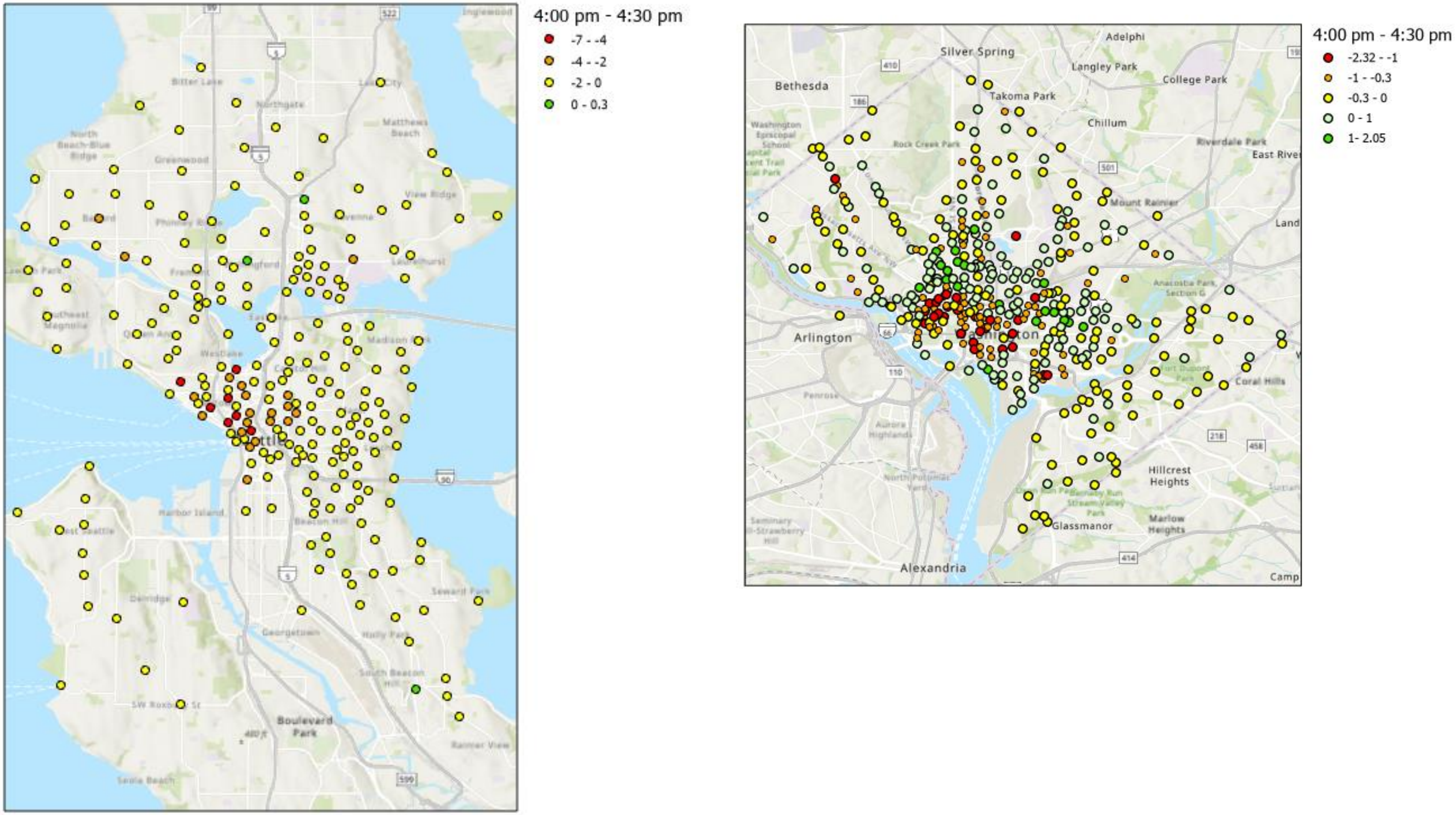


Figure 25: Lime (Seattle) and Capital Bikeshare average weekday flows from 4:00 pm – 4:30 pm

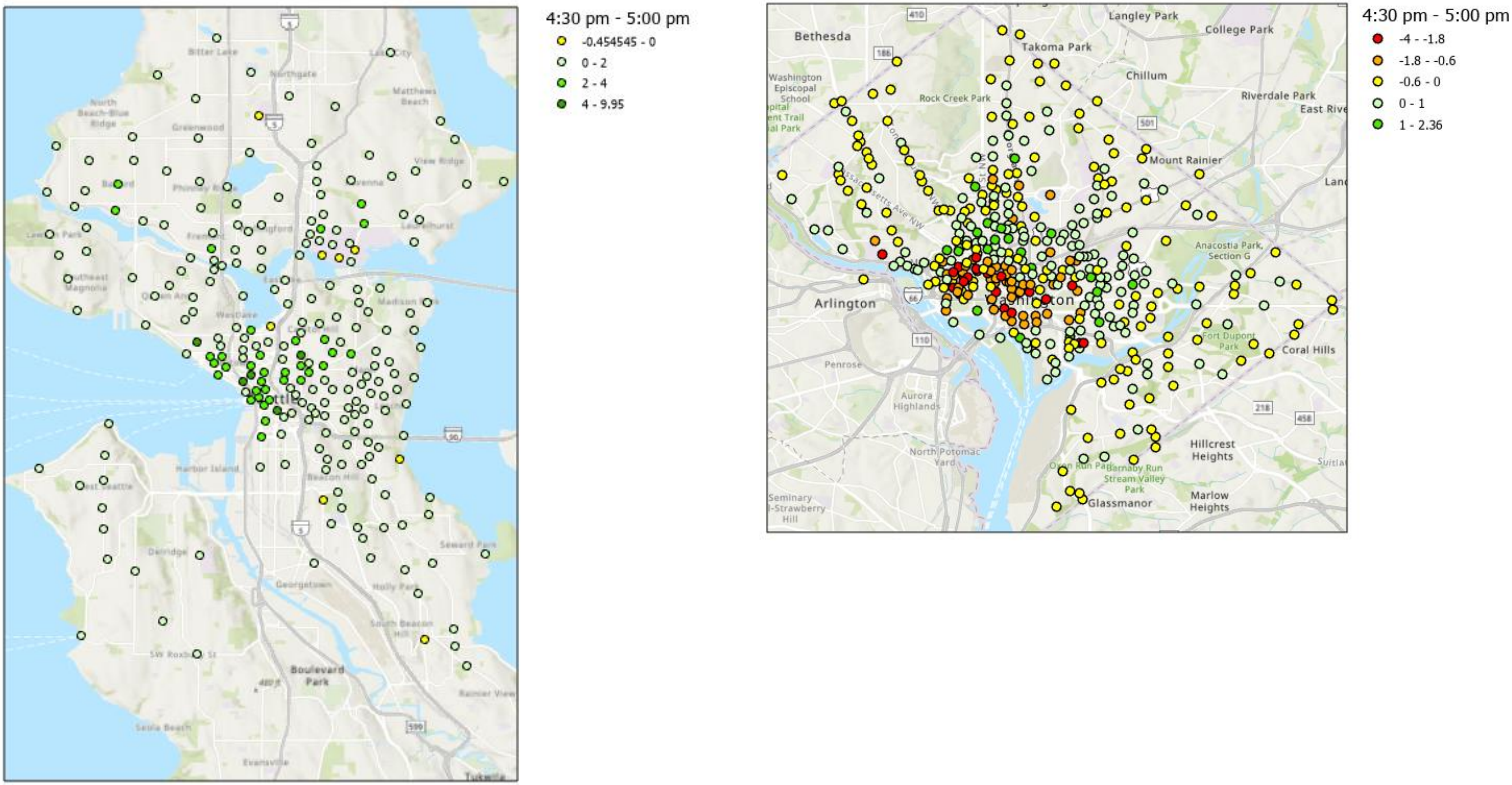


Figure 26: Lime (Seattle) and Capital Bikeshare average weekday flows from 4:30 pm – 5:00 pm

Pearson Correlation Tables, Selected Results

As described in the previous chapter, I chose to include selected results from the Pearson Correlation tests. Within each time frame, a variable was included if it was found to be statistically significant in either of the two systems. While occasionally variables were significant for both Lime and Capital Bikeshare, this was often not the case. If a variable was significant for one system, the results for the equivalent system were included as well for comparison.

Table 7: Pearson Correlation Test Results Table

	Capital Bikeshare		**Lime**	
8:00 am - 8:30 am	**P Value**	**Coefficient**	**P Value**	**Coefficient**
Distance from CBD	1.31E-05	-0.2271678	0.9249	-0.00612887
Population Density	2.20E-16	-0.5110144	0.182	-0.08662547
High Density Residential	0.01237	-0.131543	0.1861	-0.08581199
Low Density Residential	0.005008	-0.1474159	0.6627	0.02835879
High Density Commercial/Mixed Use	0.003556	-0.1530508	0.774	0.01866749
Transit Station	5.59E-12	0.3521592	0.8732	0.01042071

	Capital Bikeshare		**Lime**	
8:30 am - 9:00 am	**P Value**	**Coefficient**	**P Value**	**Coefficient**
Distance from CBD	3.91E-07	-0.2632	0.2019	-0.08284091
Population Density	2.20E-16	-0.4792222	0.9407	0.004837229
High Density Residential	0.02678	-0.1165727	0.1271	0.0989704
Low Density Residential	0.009443	-0.1364441	0.1579	-0.09163614
High Density Commercial/Mixed Use	5.01E-05	-0.2117312	0.05004	-0.1269112
Low Density Commercial/Mixed Use	0.0214	-0.1210739	0.06147	0.1211561
Downtown	2.20E-16	0.5646886	0.08466	0.1117709
Universities	0.001286	-0.1687895	0.02957	0.1407765
Transit Station	2.08E-06	0.2467393	0.9833	-0.00136826

4:00 pm - 4:30 pm	**Capital Bikeshare**		**Lime**	
Distance from CBD	0.002031	0.1618928	0.05915	0.1222491
Population Density	2.46E-15	0.4004292	0.1921	-0.08466491
Low Density Residential	0.07279	0.09454345	0.02839	0.1418037
High Density Commercial/Mixed Use	9.35E-05	0.204166	0.4883	0.04504255
Low Density Commercial/Mixed Use	0.07927	0.09248685	0.01932	-0.1512338
Industrial	0.05059	0.1029737	0.4205	0.05234505
Transit Station	4.69E-07	-0.2614783	0.3701	0.05848383

	Capital Bikeshare		**Lime**	
4:30 pm to 5:00 pm	**P Value**	**Coefficient**	**P Value**	**Coefficient**
Distance from CBD	2.01E-05	-0.2223589	0.5666	-0.03725262
Population Density	5.62E-11	-0.3360056	0.8199	-0.01480483

Spatial Autocorrelation and Moran’s Global I

A key consideration when conducting analysis with a spatial component is whether the dependent variable, in this case bikeshare flows, is correlated with factors related to the spatial arrangement of its data rather than any of the variables under consideration. One of the most common ways to account for spatial autocorrelation is to compute Moran’s Global Index, a statistical method that tests for autocorrelation. After testing the Pearson Correlation of each variable, I computed Moran’s Global I for Capital Bikeshare and Lime across all four time periods in ArcGIS Pro.

Table 8: Moran’s Global Index

8:00 am – 8:30 am

Measurement	**Lime**	**Capital Bikeshare**
Moran's Index	0.024475	0.453040
Expected Index	-0.004049	-0.002488
Variance	0.000678	0.000568
z-score	1.095647	19.116860
p-value	0.273233	0.000000

8:30 am – 9:00 am

Measurement	**Lime**	**Capital Bikeshare**
Moran's Index	0.118397	0.446463
Expected Index	-0.004049	-0.002488
Variance	0.000650	0.000564
z-score	4.801444	18.903216
p-value	0.000002	0.000000

4:00 pm – 4:30 pm

Measurement	**Lime**	**Capital Bikeshare**
Moran's Index	0.459949	0.269902
Expected Index	-0.004049	-0.002488
Variance	0.000681	0.000568
z-score	17.775328	11.429083
p-value	0.000000	0.000000

4:30 pm – 5:00 pm

Measurement	**Lime**	**Capital Bikeshare**
Moran's Index	0.386941	0.301201
Expected Index	-0.004049	-0.002488
Variance	0.000667	0.000566
z-score	15.141461	12.763514
p-value	0.000000	0.000000

Chapter 7: Discussion

Both on a visual and statistical level, Lime's net flows, aggregated at the station level, do not resemble those of Capital Bikeshare, sharing none of the spatiotemporal characteristics or relationships with built environment and demographic features. In this chapter, I explore these results further, and detail the specific ways in which the two systems differ, as well as why they might do so.

Capital Bikeshare: Net Flows at Station Level

Mapping Capital Bikeshare's net flows presents clear spatiotemporal patterns. From 8:00 am to 9:00 am, net flows are negative in the areas immediately surrounding the Central Business District, while net flows within the CBD and adjacent federal agency buildings are positive. The pattern holds through noon. Between noon and 4:00 pm, the flows reverse, becoming negative inside the CBD and its surroundings and positive in commercial and residential areas. From the visual comparison of flows alone, it is clear that Lime and Capital Bikeshare exhibit significantly different spatiotemporal patterns. The results of the Pearson Correlation tests confirm that these differences extend to each system's respective relationship with built environment and demographic variables. While Capital Bikeshare exhibits clear relationships with variables such as population density and the presence of transit stations, Lime's relationships are both less frequent and less consistent across time frames. The most significant finding, perhaps, is that when Capital Bikeshare displays spatiotemporal patterns, such the positive bikeshare flow into downtown during peak morning commute, those patterns are broadly visible systemwide. In the ring roughly 1.5 miles outside of Washington's CBD, *all* stations exhibit a negative flow during peak morning commute, and *all* exhibit a positive flow during peak afternoon commute. In Seattle, on the other hand, Lime exhibits a mix of positive and negative flows both within the CBD and in its surroundings, indicating a lack of systemwide effects that are clearly present in Capital Bikeshare. One explanation for this could be that docked systems are inherently part of a larger network–flows are in part determined by the availability of docking spaces to end a trip, whereas dockless bikeshare does not face the same limitation. With that in mind, I would propose that Lime Bike is not necessarily a transportation *system* but a transportation option, something that individuals may use if they choose, but not an active part of the larger urban transportation ecosystem. A summary table of each time frame and the associated spatiotemporal patterns seen in each system is included below.

Table 9: Summary of Bikeshare Flow Patterns

Time	Capital Bikeshare	Lime
8:00 am - 8:30 am	Strong positive flow into downtown, strong negative flow out of neighborhoods within 1 mile to 2 miles away from the CBD. Moderately negative flows out of neighborhoods further out.	Mixed flows, with the CBD exhibiting both strong negative and positive flows. Moderately negative flows in residential neighborhoods close to downtown such as Capitol Hill and the Central District. Geographically isolated neighborhoods like West Seattle and Magnolia are slightly positive.

8:30 am - 9:00 am	Strong positive flow into the CBD, followed by a strong negative flow in surrounding neighborhoods, and moderately negative flows further out. Clear distance thresholds between positive/negative/moderately negative.	Strong positive flow into downtown with a handful of stations still expressing net loss. Positive flows in commercial and residential areas within two miles from the CBD. Strong positive flow at the University of Washington. Slightly positive flow along arterials 2+ miles away from CBD. Mixed flows in more isolated neighborhoods. No clear distance thresholds.
4:00 pm - 4:30 pm	Dramatic geographic shift with positive flows pushing outwards roughly 1 mile north of CBD, and CBD turning moderately to strongly negative. Beyond 2 miles away from CBD, mix of slightly positive and slightly negative with no clear spatial pattern.	All but a handful of stations express slightly to moderately negative flows, indicative of demand surge across the city.
4:30 pm - 5:00 pm	Continuation of previous trend, with positive flows being pushed slightly further out. Outside of 2 miles away from the CBD, nearly all flows turn slightly negative.	Few strong negative flows are almost evenly distributed throughout the city. In CBD and ~ 1 mile surrounding, moderate to strong positive flows. From 1 mile - 2 miles away, the majority of flows are a mix of slight negative and slight positive.

From the spatial analysis, we can obtain three distinct results, detailed below.

1. Capital Bikeshare exhibits strong and geographically consistent AM and PM characteristics, with trip origins in residential and commercial areas outside of the CBD and trip destinations within the CBD. These patterns create a clear flow, analogous to tides, that can easily be seen in spatial data. From 8:00 am - 9:00 am, all stations within the CBD have positive flows, meaning that they receive more trip ends than trip starts. Within the same time frame, nearly all stations outside of the CBD experience negative flows, with the magnitude of flows decreasing roughly two miles away from the CBD. Lime expresses similar flows, but does *not* exhibit the same geographic consistency, with the CBD experiencing both negative and positive flows during peak commute. Geographically isolated neighborhoods such as Magnolia and West Seattle remain slightly positive during this time, a dynamic that can also be seen at the stations farthest from the CBD in Washington D.C. From 4:00 pm - 4:30 pm, Capital Bikeshare reverses its morning flows almost completely, with negative flows turning positive and vice versa, a trend that continues until 5:00 pm. In contrast, nearly every Lime flow across the city turns negative from 4:00 pm - 4:30 pm, which would be unprecedented in a docked bikeshare network.
2. Within the Central Business District specifically, Capital Bikeshare exhibits consistent behavior, either entirely negative or entirely positive, while Lime's dynamics are much more varied, with stations hundreds of feet away from each other exhibiting strong negative and strong positive flows within the same window. From 8:00 am to 9:00 am in Seattle there is some degree of a spatial pattern to these flows, with the southern portion of the CBD being negative and South Lake Union and Belltown majority positive, but there is no obvious explanation for the negative flows. The following page includes an inset of the Seattle CBD vs D.C. CBD from 8:00 am to 9:00 am.

3. Both cities' Central Business Districts appear to have a roughly two mile area of influence, with stations in that area experiencing the most significant positive/negative fluctuations. For Capital Bikeshare, the spatiotemporal consistency of activity within that radius makes it clear that commuting is the cause, however the less consistent nature of activity in Seattle's downtown area of influence could be attributed to other factors, such as the concentration of commercial activity in Capitol Hill, Belltown, and South Lake Union. Outside of that two mile radius, however, flows appear to be largely unaffected by commuting flows, and while stations flip from negative to positive and back again, the magnitude of flows

remains low. This could be explained by low demand with lower population density, as well as low demand for bikeshare trips longer than a certain distance.

Pearson Correlation Tests and Regression Modelling

There are very few variables shared between Capital Bikeshare and Lime that both exhibit significance, the same magnitude of correlation, and the same directionality. Capital Bikeshare returns robust correlation across a majority of variables across all but one time frame. The one exception is 4:30 pm - 5:00 pm, for which it returns only two significant relationships, population density and distance from the CBD. There are certain expectations associated with this study's time windows—8:00 am to 9:00 am, and 4:00 pm to 5:00 pm—that help us calibrate our expectations. Both times represent peak commuting, with the AM peak representing inflows into the Central Business District and the PM peak representing outflows. As such, in the morning we would broadly expect positive correlations with variables associated with the urban core (Population Density, Downtown land use), and negative correlation with the Distance from CBD, as the further distance commuters would have to travel, the lower mode share of active transportation we would expect to see. In the evening, we would expect the signs of correlation coefficients flip as commuters leave downtown, reversing the trend from the morning commute. The relationships that appear to be present broadly align with existing literature on docked bikeshare systems, with population density and distance from the CBD returning negative coefficients in the morning and positive coefficients in the evening representing commute patterns. Many land use variables achieve significance across the tests, but generally have weaker relationships with flows as demonstrated by their coefficients. This may point to my use of zoning as a land use proxy being a misstep, as the connection between land use and bikeshare demand has been well established by several authors (Faghih-Imani & Eluru, 2014, 2015; Tran et al, 2014; Wang et al, 2015; Noland et al, 2016). In contrast, very few variables appear to correlate with Lime's flows. Distance from the CBD is significant from 4:00 pm - 4:30 pm, however outside of that window it never reappears as a correlate. Lime does seem to have a correlation with several land use variables, including Low Density Residential and Low Density Commercial, however these relationships are the opposite of what one would expect, with LDR returning a positive coefficient from 4:00 pm - 4:30 pm and LDC generating a negative coefficient. In the (early) after work window, one would certainly expect positive flows to residential areas, but negative flows at low density residential during that time frame does not track with expectations. Capital Bikeshare flows appear to have a far greater relationship to the built environment than Lime does in Seattle. Distance from CBD and Population Density are significant across every peak commute time frame. Their respective coefficients are negative in the morning, which is what we would expect to see from flows that primarily represent commuting into the downtown core—as distance to the CBD decreases, flows increase. Following that, we would expect signs to flip during afternoon peak commute, representing flows out of the CBD and into commercial and residential neighborhoods, which they do between 4:00 pm and 4:30 pm. After 4:30 pm, however, flows return to a negative sign, which is somewhat unexpected.

Looking specifically at shared correlations, between 8:30 am and 9:00 am, Capital Bikeshare and Lime both exhibit correlation between High Density Commercial/Mixed Use and Universities. The former exhibits similar correlation and has the same sign across systems, but Universities is flipped, exhibiting a negative relationship in

Washington D.C. and a positive relationship in Seattle. From 4:00 pm to 4:30 pm, both systems exhibit positive correlation between Distance from CBD and flows. Unlike Capital Bikeshare, Lime demonstrates correlation with Low Density Residential and Low Density Mixed Use/Commercial, however the former is positive and the latter negative. A positive sign on residential areas after 4:00 pm tracks with expectations, as commuters begin to return home, though a negative sign associated with Low Density Mixed Use/Commercial is odd. This may be explained by there just being low representation of that land use in the dataset, or just noise in the data.

The results of the Pearson Correlation tests must be considered within the context of the Moran's Global Index results. The Index relies on the hypothesis that spatial data points are randomly distributed, and do not demonstrate spatial correlation. If Moran's Global Index is used on a dataset and returns a p value < 0.05, we reject the null hypothesis and conclude that the data is spatially correlated. Across both Capital Bikeshare and Lime, all but one set of flows (8:00 am - 8:30 am, Lime) returned p values < 0.05, leading me to reject the null and find that bikeshare flows are spatially correlated. This result does not necessarily impact my ability to draw conclusions from the Pearson Correlation tests, however, as we might expect a docked bikeshare system with a proven record of clear spatial patterns to demonstrate spatial autocorrelation. That Lime had almost the same results, however, is interesting, considering how few spatial patterns Lime appears to demonstrate on the maps of its flows. One possible explanation could be Lime's apparent tendency to manifest patterns systemwide, such as nearly every station level flow turning positive from 4:30 pm to 5:00 pm, although this does not explain the Moran's Index results for the previous windows of time.

Based on the spatial variation of flows and the respective systems' relationships with built environment and demographic variables, it is apparent that Lime does not behave similarly to Capital Bikeshare, exhibiting none of the same AM peak or PM peak inflows or outflows that characterize Capital Bikeshare's weekday flows. At the beginning of my research, I hypothesized that despite its status as the dominant bikeshare service in Seattle, Lime Bike flows would *not* exhibit similar spatiotemporal characteristics as Capital Bikeshare, which has been validated by the results and interpretation presented in the two previous chapters. The second part of my hypothesis was that the two systems may share similar relationships with the built environment, especially during the afternoon demand peak. My theory regarding the afternoon peak was related to the similarities in PM demand visible in the average weekday demand profiles of Lime and Capital Bikeshare (Figure 16). I can now reject this part of my hypothesis, and we can conclude based on spatial analysis and Pearson Correlation results that the two systems do not share similar relationships with the built environment or demographic variables. This analysis is somewhat complicated by the fact that neither dataset is normally distributed, however these findings are supported visually by the near complete lack of patterns visible in the spatial distribution of Lime's flows. That the two systems differ significantly does make sense–Lime does not share Capital Bikeshare's defining characteristic, the docking station, and as such it is reasonable to assume that it would exhibit different system dynamics as a result. Whether the difference between the two systems is significant from an operational, planning, or policy perspective, however, is a different question.

Chapter 8: Conclusion

Dockless bikeshare is a recent innovation, no more than eight years old, and much remains unknown about its characteristics, potential, and even long term feasibility. Given its differences from preexisting docked bikeshare systems, researchers have demonstrated significant interest in studying dockless systems in comparison to docked bikeshare, writing on its equity implications (Lazarus, 2020), geospatial patterns (McKenzie, 2018), and competition with docked bikeshare (Feng, 2020). I would argue, however, that much of this scholarship (while valuable) has been lacking. Comparisons between docked and dockless systems in the same city analyze systems at different scales that are simultaneously competing with each other for ridership. Comparisons across cities are analyzing systems under different spatial, socioeconomic, and regulatory conditions. While both of these approaches can generate valuable insights, they are insufficient for analyzing the true character of dockless bikeshare. To do so, one would need to study a dockless bikeshare system in a vacuum, and find a way to compare it to a docked bikeshare system without the two being in competition or operating under radically different locational conditions.

In this thesis, I have attempted to do just that. I began by establishing that clear typologies of bikeshare systems exist, and that different ways of building and organizing systems have clear implications for user behavior and trip demand. Because of the demonstrable similarities between systems of a certain size, it is appropriate to use a single system to represent "docked bikeshare" in general. It is also reasonable to expect dockless bikeshare systems, if operating with sufficient bikes in a large enough service area, to exhibit some of the same characteristics as docked systems. I demonstrated that while Lime does have stronger concentrations of vehicles than most docked bikeshare systems, it *does* provide citywide service comparable to a docked bikeshare system. Using the spatial organization of Capital Bikeshare, I created a theoretical network of docking stations in Seattle, aggregated Lime Bikes to stations, and calculated flows across set time frames, allowing for a direct comparison between Capital Bikeshare and Lime on their merits as a docked and dockless system. In doing so, I found significant departures from what one would expect from a docked bikeshare system. While Capital Bikeshare, and similar bikeshare systems, exhibit a tide-like flow into and out of downtown aligning with peak AM and PM commute, Lime exhibits a fractured pattern in which "stations" hundreds of feet apart may exhibit strong positive and strong negative flows at the same time. In terms of statistical analysis, Capital Bikeshare flows have a clear, consistent, and significant relationship to built environment factors including the distance of stations to downtown, the population density surrounding stations, certain land use categories, the presence of universities nearby, and the presence of transit stations nearby. In contrast, Lime has few statistically significant relationships, and the ones it does exhibit are not consistent across time frames.

Dockless systems present an appealing opportunity to cities, especially now that Lime has emerged as the dominant force in the market. A city seeking to cut costs could sell off its underperforming docked bikeshare assets, or bring in Lime in lieu of funding an expensive system expansion to less dense parts of the city. They would not have to pay for infrastructure, and instead would generate revenue off of annual permitting and per vehicle fees, as SDOT has (SDOT, 2023). From a financial perspective the choice is clear, but there are clear tradeoffs in terms of accessibility and policymaking that must be weighed. Dockless vehicles, even when properly managed, add sidewalk clutter that reduces physical accessibility. Without direct control of the bikeshare system, as they would in a publicly operated system, program managers cannot expand docking stations to accommodate demand or add docks to underserved areas to increase access to low cost transportation. Without a proper accounting of all aspects and impacts of dockless bikeshare, governments cannot make informed decisions when deciding between docked and dockless systems. This thesis, to an extent, contributes to that accounting. This remains a very salient concern–while Seattle replaced its docked system nine years ago, Minneapolis replaced NiceRide just last year (Felegy & Sepic, 2023). Lyft, the operator via Motivate of

Capital Bikeshare, CitiBike, BlueBikes, Divvy, and more, has expressed interest in exiting the bikeshare space, leaving the future operations of many successful systems in doubt (Griswold, 2023).

While "equity" is an overused and under-defined term in transportation, the differences between docked and dockless bikeshare *do* have important equity implications, particularly in terms of bike availability, bike quality/maintenance, and reliability of access. In a docked system, a planning agency can deploy a docking station to a neighborhood that requests increased service, guaranteeing at least *some* level of bike availability, however guaranteeing the same in a dockless system is more difficult. Agencies such as SDOT can and do mandate that vendors redeploy a certain share of vehicles in marginalized areas, but such areas are generously defined, and the vendors operate under a profit motive to put their bikes in areas where they are most likely to be rented (SDOT, 2023). Public agencies do not operate under the profit motive, and while it would be a best practice to place stations in a central location, they can also place them in lower demand areas to increase access, a goal Capital Bikeshare has been committed to for five years (DDOT, 2019).

One aspect of dockless bikeshare that I was only briefly able to touch on, but is directly related to my research question, is the extent to which policymakers can mold privately operated dockless bikeshare systems into something more closely resembling a docked system. While many bikeshare systems have experimented with hybrid systems in which bikes can be docked or left locked to public bike racks (Portland's Biketown and Capital Bikeshare, to name two), this arrangement still entails the infrastructure costs of purchasing docks and bikes. If SDOT could leverage its permit to get Lime to agree to exclusively leave bikes at set locations, at certain times of day, it would increase reliability and accessibility, potentially to the level that users of docked bikeshare systems experience. If the systematic differences between docked and dockless systems are due to the effect of bikeshare docking stations on concentrating bikes in a reliable location, then any action that would concentrate dockless bikeshare in certain known locations would be a policy victory. It appears that SDOT attempted to achieve this to some extent in 2019 with their deployment of on-street corrals, though this could equally be explained by pressure to better manage sidewalk clutter (SDOT, 2020). More broadly, the relationship between planning/regulatory bodies and private dockless bikeshare operators, and its effect on policy outcomes, is worth further research. As I argued in Chapter 6, Lime appears to operate less like a "system" and more like a set of unlinked individual vehicles. Whether adding or removing language from permit documents on a bi-annual basis is enough to shape a system like that, and leverage it to work towards policy objectives, is unknown. It is possible that this era of dockless bikeshare is just a blip in the development of a transportation technology that can be fully integrated in the urban transportation ecosystem. Given how quickly micromobility has evolved over the past eight years, it would not be entirely surprising. For the moment, however, Lime and its competitors exist in an in-between space in Seattle, not quite a transportation system on their own, but certainly more than a passing novelty. Whether that's sufficient, considering what docked bikeshare systems have accomplished across the world, is an entirely different question.

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