

Complement or Substitute? An Analysis of Bikeshare's Effect on Transit Ridership in Portland

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Abstract

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Free-floating bikeshare is a relatively new service in North America but offers significant mobility benefits and intriguing potential for first- and last-mile access to transit. This study of Portland's Biketown system will explore whether the introduction of bikeshare has a complementary effect for transit ridership, that is: does presence or usage of bikeshare lead to an increase in transit use? Additionally, because Biketown has both docked and free-floating bikes available, this study will examine whether the introduction of free-floating bikeshare leads to higher increases in transit ridership than traditional docked bikeshare. Because the system has gone through a variety of changes to its home area and operating rules, this study completes a longitudinal study of TriMet transit ridership in areas where service has expanded or docking rules have been changed. This study is unique; although many previous studies have explored the usage of bicycles or bikeshare for first- and last-mile transit access, few studies have considered free-floating bikeshare's relationship to transit.

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Introduction

Even a well-designed and well-operated transit system is only as effective as riders' access to the stops and stations that are served. Planners have long grappled with issues regarding stop and station access, the so-called "first- and last-mile problem." North American residential development patterns have traditionally lacked the density and grid connections that are conducive to transit service. In order to increase transit ridership and mobility for those who live in these areas, some solution must exist for a potential rider to get from their front door – which may not be located in an area with transit service – to the bus stop, where they can catch a bus that covers the majority of the journey. This is called the "first-mile problem" (although it refers to any sort of distance that hinders access) – how can this resident travel from their home to the bus stop when it is not comfortable, practical, or possible to walk it? Conversely, the "last-mile problem" views the issue from the destination end. If a rider's desired destination is not immediately adjacent to the closest transit stop, how can they get there when it is uncomfortable, impractical, or impossible to walk? Addressing the first- and last-mile problems can potentially lead to higher transit ridership and lower single-occupancy vehicle use as well as improving accessibility for those without drivers' licenses.

To say that bicycles can serve as a complement to public transit use is not groundbreaking. Some academic studies, detailed in the *Literature Review* section, have demonstrated the utility of bicycles for first- and last-mile access to transit stops. Traditionally, transit users wishing to ride their bike to a nearby transit stop would need to either park their privately-owned bicycle at a station or bring the bike aboard the vehicle. However, taking bikes on board transit is restricted by some transit agencies, either outright or at particular times of the day. If bicycles are indeed allowed, capacity is often limited, either by the number of bike rack spots available on a bus or by a transit agency's rule regarding a set number of bikes per train car. Many individuals do not feel comfortable simply locking their bike near the stop due to fear of theft or vandalism, and this practice does not allow for the bike to be used at the destination end. Finally, many individuals simply do not own a bicycle, and thus cannot utilize this method for station or stop access. Modern "bikeshare" systems have begun to create new possibilities for integrating bikes into a transit trip without needing to own a bike or to take one on board.

In the 21st century, North American bikeshare systems have opened the possibilities for a transit user to reach the station. The earliest iterations of these systems utilized "docks":

specially designed corrals that lock bicycles when not in use, where users must begin a trip by unlocking a bike or end a trip by locking a bike. In order to access transit, a user would be able to take a bicycle from a dock near the point of origin, leaving the bicycle at a dock near the stop, and then board transit. Users may also be able to find a shared bicycle at a dock near their destination stop and then ride to another dock closer to their final destination. By utilizing these shared bicycles, riders can effectively extend the “range” that they can travel both to and from transit stops, greatly increasing mobility on either end and extending the range of destinations and transit lines that can be reached. However, these types of bikeshare systems are limited because of their reliance on the docks to start or end a trip: if a user wishes to use a bikeshare to extend range of access, there must be a dock that readily serves their specific origin or destination. And while bikeshare docks may be readily available in urban cores and urban centers, docks are less likely to exist further from these cores.

Recently, “dockless” bikeshare systems have begun to operate in some North American cities. These systems do not rely on fixed dock locations, which force a user to start or end a trip at the dock. Instead, riders can end their trip directly at or closely adjacent to their destination. Riders typically start a trip by using a smartphone app to locate and unlock a bike. The rider can then travel as they wish within the bounds of the allowable service area, typically paying a fee for unlocking the bike plus a fee based on how many minutes they ride. Upon the end of a trip, users end the trip by placing the bike in an approved parking location and locking the wheels, thus leaving the bike available for the next user.

Some docked systems have begun taking on characteristics and features shared with dockless bikeshare systems. Portland’s Biketown system, for example, does not force a user to start or end a trip at a specified dock location. Instead, riders can end their trip directly at or closely adjacent to their destination by locking to a public bike rack and paying a \$2 fee. Riders can even pay an extra \$10 to end their trip outside of the system’s service area, offering additional flexibility. And in some so-called “super hub” areas, bikes can be locked to any rack for no charge. For the purposes of this study, I will refer to this feature as “free-floating” or dockless service, which can be considered distinct from the normal practice of starting and ending trips exclusively at docks.

For this study, I will examine how the presence of bikeshare may increase transit ridership, and whether free-floating bikeshare lead to an increase in transit ridership that differs

from docked bikeshare. Do usage patterns show that bikeshare users might be utilizing “free-floating” bikeshares for first- and last-mile connections? Does transit use rise when bikeshare is introduced to an area? This would suggest that the introduction of bikeshare is indeed providing first- and last-mile connections. Even more specifically, is the transit ridership increase higher in “super hub” areas where all bikes can go free-floating for no charge? This would suggest that free-floating bicycles provide greater transit access than do docked bikes.

It is important to examine the value of this free-floating service as it relates to transit first- and last-mile access. The implications of free-floating bikeshare on transit planning are varied. First, if the data can support that bikeshare supplements transit, transportation planners can begin to actively utilize and promote free-floating service as an additional tool to improve transit usage. For example, it is possible that free-floating service helps to address first- and last-mile access more effectively than docked bikeshare for some individuals. Second, decisionmakers can consider policies that formally integrate free-floating bikes into transit services. For example, the findings could support an exploration of allowing transit fares to transfer to bikeshare credit or vice versa. Third, if capacity issues begin to preclude bicyclists from taking their bikes on board transit (especially during peak hours), planners can use this information to explore incentivizing bikeshare as a substitute for personal bikes. Last, there may be insights regarding the spatial distribution of transit ridership changes which may demonstrate some of the ways in which bikeshare is being used differently in zones across the city.

Literature Review

Existing literature does explore the intersection between bikeshare and transit but is generally limited to docked bikeshare, or it focuses on cities outside of North America. Many studies do address first-mile and last-mile issues, which are a major focus for my research.

Bicycle-Transit Integration

In studying the nature of bikeshare’s relationship to transit, we first must explore the how personal bicycles are used to complement transit use, as this type of usage significantly predates the introduction of bikeshare to North America.

Singleton and Clifton (2014) studied synergy in bicycle and transit use, namely the flexibility that one mode can offer the other. The authors determined that transit and bicycling were short-term substitutes but long-term complements. That is, changing a commute pattern

from primarily transit to primarily bicycle may nominally remove the rider from the transit mode share, but make it more likely for the individual to use transit, rather than other modes, for future trips. A potential limitation was that this study relied heavily on user trip survey data, which could have introduced bias.

Wang and Liu (2013) discovered that rail transit does not attract a statistically significant higher rate of bicycle access/egress trips than bus transit. They also found that a clear concentration of bicycle-transit integrated trips did exist in dense urban areas, and that the share of bicycle-transit trips increases with the size of a metropolitan statistical area and the density of the census tract of the user. Additionally, the study emphasized that different socio-demographic groups (income, race, age, gender) do have statistically significant differences in their utilization of bicycles for transit first- and last-mile connections. Therefore, this informs the efforts to control for these socio-demographic factors when selecting treatment and control groups (see *Creating Control Group* section). The authors also emphasized a need for stronger integration between the two modes due to their complementary nature.

In 2011, Krizek and Stonebraker reported to speaking with focus groups to discuss built environment factors that influence the decision to integrate bike and transit use. These included factors such as rack or bike cage availability, ability to take a bicycle onboard transit, and availability of shared bicycles. The study found various cost-effective options for enticing bicycle-transit integration, such as bicycle racks on buses and more secure bike parking or storage.

Bikeshare-Transit Integration in North America

The majority of the literature on bikeshare-transit integration has focused on docked systems; the relative lack of studies investigating free-floating bikeshare underscores this as an emerging area of study.

Capital Bikeshare, a docked system in Washington, DC, is subject of many published pieces on bikeshare. These reports have not reached unanimous conclusions, especially with regard to transit integration. For example; Ma, Liu, and Erdoğan (2015) explored the effect of Capital Bikeshare on Metrorail ridership, concluding that Metrorail ridership rose 2.8% for each 10% increase in bikeshare ridership. This study analyzed bikeshare usage around Metrorail stations and compared this to ridership statistics for each station. On the other hand, the 2016 Capital Bikeshare Member Survey Report (LDA Consulting), based on user self-report, found

that nearly six in ten bikeshare users reported that their transit usage decreased after they began to use Capital Bikeshare. This same report also discovered that more than 25% of respondents used bikeshare to reach locations inaccessible by transit or at times of day when transit was inconvenient or unavailable.

A recent 2018 study by Xie and Wang completed a comprehensive analysis of Capital Bikeshare usage patterns. The authors identified seven important aspects of bikeshare systems: trip demand and flow, operating activities, use and idle times, trip purpose, origin-destination flows, mobility, and safety. The methods provide a useful framework for evaluating bikeshare systems. This study distinguished utilitarian trips from recreational trips by identifying those that began and ended at the same place as recreational trips and found that these trips had a much more uniform frequency distribution over the day than did utilitarian trips which peaked in the morning and evening commute times. With regards to transit integration, the study found that most of the highest-frequency O-D pairs in the bikeshare system suggested first- and last-mile connections between transportation hubs and residential neighborhoods. Such multimodal connections indicate a complementary relationship between bikeshare and transit.

Positive correlations have been identified between bikeshare usage and proximity of transit stops or stations (Rixey 2013). Rixey's work identified variables that showed a correlation with increased bikeshare usage in Washington, DC (Capital Bikeshare), Minneapolis, MN (Nice Ride MN), and Denver, CO (Denver B-Cycle), all docked systems. Notably, this study was focused on the effect of transit stops on bikeshare ridership, not the other way around, and made no conclusions about bikeshare's effect on transit ridership.

Bachand-Marleau (2011) studied the BIXI system of Montreal, QC, concluding that about one-third of survey respondents replaced a transit trip with bikeshare, but also that more than 40% used transit as part of their multimodal bikeshare trips. The author also asserted that "special multimodal offers, including access to shared bicycle systems ... would encourage individuals to adopt shared bicycles by making the integration into their current travel habits as seamless as possible," an assertion which suggests that transportation planners should consider allowing transit fares to transfer to bikeshare credit.

Ravensbergen et al. (2018) used surveys to study self-reported barriers to integrating cycling with regional rail transit in the Toronto, ON area. It was found that 34% of cyclists and 25% of non-cyclists reported bicycle parking at the station as being a barrier for them to utilize a

bike-to-transit trip. Additionally, 22% of cyclists and 15% of non-cyclists reported that limiting on-board bicycles to non-peak hours was another barrier for them to use bike to access transit. Both of these concerns could be alleviated by bikeshare, which typically has specific bikeshare parking areas and does not require a user to bring a bike on board.

Oates et al. (2017) focused on bikeshare usage patterns for different demographic groups. By comparing user ZIP data to demographic data from those ZIP codes, the researchers were able to extrapolate the likely attributes from users, then analyze trip patterns among users from different ZIPs. This aimed to compare socioeconomic disadvantage of different neighborhoods to bikeshare usage. The authors discovered that higher neighborhood socioeconomic disadvantage is associated with higher bikeshare use. Based on this finding, they stated that bikeshare may be an effective tool for planners to improve the mobility of underserved areas, particularly if it can increase access to transit.

Using self-reported surveys integrated with spatial data, Martin and Shaheen (2014) explored transit mode share for bikeshare users in Washington, DC and Minneapolis, MN. Their findings were especially interesting and could be applicable to other large cities; bikeshare users closer to the dense urban core were more likely to *substitute* bikeshare trips for transit trips, while those more on the periphery of the urban area were more likely to *complement* transit use with bikeshare. In other words, location of the user and the characteristics of the surrounding built environment were extremely important in determining whether the bikeshare was a first- and last-mile tool or completely replacing transit usage.

Campbell and Brakewood (2017) designed a natural experiment using the phased bikeshare implementation in New York, NY to investigate how bikeshare was related to bus ridership. Interestingly, this group discovered that bikeshare seemed to have a negative effect on bus ridership. Bus ridership in this case fell approximately 2% for every thousand bikeshares located along a route. The group also noted the potential importance of bike infrastructure improvements, which accompanied some of the new bikeshare locations.

The intersection between bicycle usage and transit ridership was explored by Flamm in 2013, but in this case, it is related to bicycles on board buses (BoBBs). Like in many North American cities, bus riders in Cleveland are able to load bicycles onto bike racks on the front of buses. Although this is not a bikeshare system, it does highlight some of the first mile/last mile issues that might be addressed with a bicycle. The study, which utilized data collected from

drivers reporting bike boardings in real-time, found that weather was a major factor in BoBBs: poor weather discouraged people from bringing bikes but did not significantly hurt transit ridership. The study also examined economic factors such as employment and gasoline prices to search for correlation to BoBBs, and it found a weak correlation between unemployment/high gas prices and BoBBs. Above all, it appears that transit service level was an influencing factor for BoBBs, suggesting that the bicycle was the primary mode for the traveler and that the bus served best as a facilitator for the trip.

Welch et al (2018) utilized travel diary data to study bikeshare, transit, and taxi trips in Washington, DC. The authors found that while many trips originated from and terminated at metro stations, a significant portion of them took place using other modes (bicycle and taxi). The group determined that Metro fare played a significant role in mode choice, and that travelers were five times more likely to use bikeshare for each dollar increase in WMATA fares. Not surprisingly, bikeshare appeared to have lower ridership during cold or rainy days. The group concluded that the surrounding built environment played a major role in mode choice, that travelers were more sensitive to price than previously expected, and that policymakers can modify policies to make public transit more attractive and increase ridership.

Noland et al (2016) created a set of models to predict bikeshare trip generation in New York, NY. These models were developed using CitiBike trip generation data, and were tailored for different times of year, different days of the week, and different user types. Subway stations were demonstrated to be major trip generation locations, although the model failed to accurately forecast trip generation at new or planned stations.

The transit/bikeshare relationship seems to be affected not just by mobility factors, but by economic ones as well. Kaviti et al. (2018) examined bikeshare and transit ridership in after cheaper bikeshare fees were implemented on the Washington DC Capital Bikeshare program. Their research demonstrated that the new fare program did not seem to affect ridership among heavy users of the system but did seem to attract more casual riders. This study was performed during a time of SafeTrack, a major Metrorail maintenance project that led to service delays, and a potential confounding factor in this study. This work underscores the importance of considering financial aspects of the user decision-making process, including study design or statistical control for changes to prices to transit and bikeshare rates.

Sener and Griffin (2016) discussed the planning implications of integrating bikeshare and transit and explored the relationship between transportation planning goals of bikeshare and transit. “Despite its promising role in providing alternative solutions to access transit stations and then to final destinations,” they wrote, “there have been relatively few studies quantifying bike sharing’s potential impact in facilitating transit trips.” Their study focused on docked bikeshare systems in Chicago, IL (Divvy) and Austin, TX (B-Cycle), and found that the highest volume bike share stations were not necessarily located near transit stations. The study also showed that Chicago’s Divvy system had an overall positive correlation between bikeshare trips and proximity to transit stations, but with a negative relationship for day-use bikeshare customers (who were more likely to be tourists). The authors concluded by suggesting a policy and planning framework for integrating bikeshare and transit planning, which they observed had not been sufficiently addressed previously.

Barber, Kopca, and Starrett (2017) investigated the links between bikeshare trips and light rail ridership in Minneapolis, MN. The group compared actual train arrival times to bicycle checkout times at docks immediately next to light rail stations. They noted a spike in bikeshare checkouts at these docks in the first four minutes after a train’s arrival, which dropped to the baseline after four minutes. These demand peak effects were not seen at control docks located away from train stations. Although they lacked individual-level data, the results strongly suggested that train riders will take advantage of rideshare if available near light rail stations.

Bikeshare-Transit Integration Worldwide

As previously noted, most of the research on bikeshare in North America focused on docked systems. However, there have been some studies conducted in locations outside of North America, which can provide examples of research on bikeshare-transit integration specifically focusing on dockless bikeshare. China was one of the earliest adopters of free-floating bikeshare.

Shaheen, Guzman, and Zhang’s 2010 work did not specifically focus on bikeshare usage patterns but does provide an excellent primer on the history of bikeshare as well as helping contextualize the difference among systems worldwide. They performed a qualitative study of a number of bikeshare systems in different international locations, including their attributes and characteristics. The paper also discusses some of the lessons learned, some of which are constraints that still bind bikeshare policy decisions. Their work demonstrates the evolution of the service and suggests what may be on the horizon for the technology.

Ma et al. (2018) focused on riders using dockless bikeshare to access transit in Nanjing, China. Because the bikeshare and transit payment systems in Nanjing are integrated into the same smart-card, the smart-card trip data can be used to clearly identify bikeshare-Metro “transfers.” This method was extremely effective at researching the relationship between the two modes because of the ability to study the fine-grain data of these smart-card transfers. It showed that bikeshare-transit transfers occurred more frequently in areas further away from the urban core, suggesting that the use of bikeshare for first- and last-mile access is more useful in areas where transit is not plentiful. Additionally, the study showed that most users only used bikeshare-transit transfers infrequently, suggesting that for most users it was an occasional behavior and not part of their regular routine. This behavior could speak to the flexibility that bikeshare offers – it is there when one needs it, but that is infrequent. Conversely, a very small number of riders were very frequent transfer users who had made bikeshare-transit transfers part of their regular travel routines. The authors suggested a type of loyalty program to reserve some bicycles for these high-frequency users at each dock, so as to ensure that their needs were met. Ultimately, the authors concluded that the demand for the bikeshare-transit transfers was not being met by the current amount of dock capacity adjacent to metro stations and recommended that additional docks be installed to meet this demand.

Ji et al. (2018) also focused on Nanjing and the geographical constraints on bikeshare usage and travel patterns. The research used regression analysis to determine which demographic and geographic factors might encourage bikeshare usage. The authors discovered that use of bikeshare to access transit was significantly lower in areas of higher income, but since these areas lacked sufficient bicycle infrastructure, they stated that an improvement of bike paths and lanes could increase this. Additionally, they discovered that density of bus stops surrounding metro stations was negatively correlated with bikeshare-transit transfers, suggesting that riders prefer to use bus transfers where they are available. Lastly, the authors noted that the length of time that bikeshare has been available in a neighborhood appears to affect the frequency of bikeshare-transit transfers, as they are more frequent in areas that had been in the bikeshare home area for longer. This suggests that time is an important factor on users’ behavior, and that travel patterns do not change very quickly.

In 2018, Yiyun Sun researched dockless bikeshare in Beijing. This paper used a survey of both bikeshare users and non-bikeshare users. The authors examined commuting and usage

patterns, safety, right-of-way blockage, negative externalities such as vandalism, and self-reported complementary transit and bikeshare usage. This study is notably quite recent and specific to dockless bikeshare; however, it did not examine North American bikeshare and used survey data rather than analysis of objectively measured usage and trip data.

Uniqueness of Bikeshare Patterns

In recent studies, bikeshare usage patterns have been shown to be different from personal bicycle usage patterns, particularly in how bikes are used for commuting or recreation.

Wergin and Buehler (2017) used Capital Bikeshare GPS data to explore bikeshare travel patterns of annual members vs. single day users. They found that day users' trips were more concentrated around tourist sites, and as expected, they rode more in parks and around attraction sites than did annual members. On the other hand, annual members' trips were more concentrated in the job-dense downtown area. These findings supported the authors' expectation that bikeshare serves very different needs for tourists as opposed to commuters. Therefore, we might expect to see different usage patterns for user groups with regard to using bikeshare to access transit.

Jain et al (2018) examined maturation of bikeshare systems. In their study of Melbourne's Bike Share, they noted that usage slowly dropped over time, and regular users have now been overshadowed by casual, or "sometimes" users. These casual users represent a very different usage pattern than regular users - their trips may be more spur-of-the-moment or driven by lack of immediate access to other modes or connections they need. This study has implications for bikeshare as we consider its lasting value as a transportation mode.

The difference between bikeshare users and regular cyclists plays a major role in trip patterns. Buck et al. (2013) studied these riders in the Washington, DC area. Particular attention was paid to socioeconomic factors such as race, age, and income. The researchers concluded that bikeshare users were more likely to be younger, female, and to cycle for utilitarian (rather than primarily recreational) purposes.

Portland-Specific Studies

McQueen (2018) studied Biketown out-of-dock trip end parking behavior. First, McQueen was able to track changes in parking behavior over time, identifying a lag in behavior change after a policy change. The data confirm that it took users a few months to become aware of their ability to travel to and park in different places. Therefore, any study of bikeshare's effect

on transit which uses data that is too recent after the policy changes may not detect any changes in transit ridership patterns. Second, McQueen identified that rider behavior was notably different between “casual” users who pay per-ride and subscribers who pay for unlimited rides during a subscription period.

Barber (2018) studied Biketown in Portland, focusing bike idle time or dwell time. He concluded that areas near streetcar lines had statistically significant lower dwell times per bike, meaning that bicycles were turned over more often in these areas. This may suggest that areas along streetcar lines are better-integrated with bikeshare, and that a possible complementary relationship between bikeshare and transit exists in these high-frequency transit areas. However, it should be noted that the areas with streetcar lines in Portland also happen to be the densest in the city, and this study did not control for density.

Barber, Guo, Hu, and Starrett (2018) explored this bikeshare-transit relationship even further in their later study of the Chicago area. They analyzed L station ridership to determine whether Divvy bikeshare presence and ridership was a significant factor to transit ridership at each L station. The team considered a lag effect for their model, including a variable for how old a Divvy dock is, as well as a transit quality score for the area and demographic characteristics. Three models were used: an OLS model, a fixed effects panel regression model, and a random effects panel regression model, which showed a statistically significant lag effect, supporting the aforementioned finding of McQueen (2018). Additionally, the team determined that the number of bikeshare trips ending near stations correlated with increased ridership, but that the count bikeshare trips starting near stations correlate with decreased ridership. This is either due to their methodology (L stations do not track “outgoing” riders, so no transit trip at the station would be associated with a bikeshare trip starting near the station), or due to some trip mode substitution occurring. The authors concluded that these conflicting results suggest that a complementary and substitutional relationship was likely between transit and bikeshare, although the methodology limitations may cast doubt onto the substitutional theory.

Finally, Meng, Khorasanian, Tay, and De Simone (2019) completed a study of transit ridership in Portland in parallel with the research done in this paper. The group focused on the route-stop level (where multiple routes can share a single stop but appear as unique lines in the dataset). Stops were stratified depending on their spatial relationship to the study areas, with the stops inside the 2018 expansion area considered the treatment group and stops inside the existing

2017 Biketown area as the control group. This study focused on the docked bikeshare expansion area only, and no specific distinction was made between all stops and those inside of the Super Hub areas. This previous work focused on 2018 as the treatment date rather than 2017, leaving an opportunity to study treatments in 2016 and 2017 in this paper. A group of stops was identified from the control area which had similar demographic and topographic characteristics as the treatment stops. Statistical analyses showed that there was no significant difference in transit ridership from fall 2017 to fall 2018 between the treatment areas and control areas. Additionally, the team found that bikeshare ridership volume was not an overall significant predictor of transit ridership. A fixed effects model was also utilized, measuring effects on a block group level. 93 block groups within the city of Portland were studied. 15 block groups showed statistical significance of bikeshare ridership being a predictor of transit ridership. Of these, only one block group was within the treatment area (the Hollywood neighborhood). Ultimately, the group concluded that expansion of the docked system appears to have not led to an increase in transit ridership at the route-stop level across most portions of the city.

Although much research has been devoted to the relationship between bikeshare and transit, to date, studies in North America have focused exclusively on *docked* bikeshare systems, whereas any studies focused on dockless bikeshare and transit have been aimed at researching Asian markets. The study of more-flexible free-floating bikeshare may provide new insights and lessons on fine-grain user patterns.

Methods

Description of Study Area and Biketown System

The study area for this research was Portland, OR, where the publicly owned Biketown bikeshare system has been operating since July 19th, 2016 (Njus, 2016). The system's title sponsor is Nike, and the aluminum-framed, bright orange bicycles are commonly seen throughout the city's Biketown service area.

Biketown offers a variety of subscription levels to cater to users' needs. The pricing levels have changed slightly over the life of the system, but has always included the following options: (Biketown 2019a)

- 1) "Pay-as-you-go": users pay a flat fee for a 30-minute ride, or pay by the minute

- 2) Month-to-month membership: users pay for an entire month of unlimited trips (90-minute max per trip, 8¢ per minute beyond 90 minutes)
- 3) Annual membership: users pay for an entire year of unlimited trips (90-minute max per trip, 8¢ per minute beyond 90 minutes)

Biketown originally launched as a mostly docked bikeshare system but had some flexibility to allow for dock-free operations. Users were required to begin and end all trips at designated docks within the network or be subject to an extra docking fee: \$2 inside the service area, or \$20 outside of it (Njus, 2016).

Due to popularity of the system, Biketown has undergone a series of home area expansions since its launch. The first of these expansions took place in summer of 2017, when Biketown expanded mostly northeast and southeast (Njus, 2017). As part of this expansion, Biketown first piloted the “super hub” zones: areas where bikes were not required to be docked and could be parked at any public rack for no additional charge. These super hubs were located in two districts: the area surrounding Portland State University, and the Central Eastside Industrial District. At the end of the pilot period, the super hubs were made permanent in September of 2017.

Another expansion took place in 2018. As part of this expansion, the service area was pushed even further north and east. Additionally, the entire service area effectively became dockless for annual members, who were no longer required to return the bike to a dock to avoid the \$2 out-of-dock fee (Maus, 2018).

All these expansions and service rule changes have resulted in instances where some specific areas can be compared in terms of differential increased bikeshare access, which forms the basis of the current study

Description of Tests

My research has employed quantitative analysis of TriMet transit ridership to determine whether Biketown expansion or rule changes have resulted in significantly different ridership numbers between areas that had increases in bikeshare versus those that did not. These rule changes provide the framework for a natural experiment to test for significant differences.

There were five distinct study areas, each of which saw a rule change occur at a distinct point in time that created experiment conditions. Operational rule changes were implemented in

three phases from 2016 to 2018, creating five distinct areas. The Biketown home area expanded in 2017 and 2018. These expansions created areas where new docks were installed, and users could bring the bikes without paying an “out of network area” fee of \$10. Additionally, in 2017 Biketown implemented two super hub areas where trips could be ended at any bike rack (free-floating) for no fee. Based on the application (or lack thereof) of rules, all transit stops within the city of Portland fell within one of five distinct study areas, as shown in Table 1.

Table 1: Study Area Categories

Study Area	Description
1	Stops that have never been part of Biketown
2	Stops that were added to the Biketown area in 2016 and do not feature free dock-free trips
3	Stops that were added to the Biketown area in the 2017 expansion and do not feature free dock-free trips
4	Stops that were part of the initial 2016 launch and were made into a “super hub” in 2017
5	Stops that were not part of the Biketown area in 2016 or 2017 but were included in the “traditional” docked service area as part of the 2018 expansion.

A map showing these study area categories can be seen in Figure 1, which shows that some of the areas within the same category were not spatially contiguous.

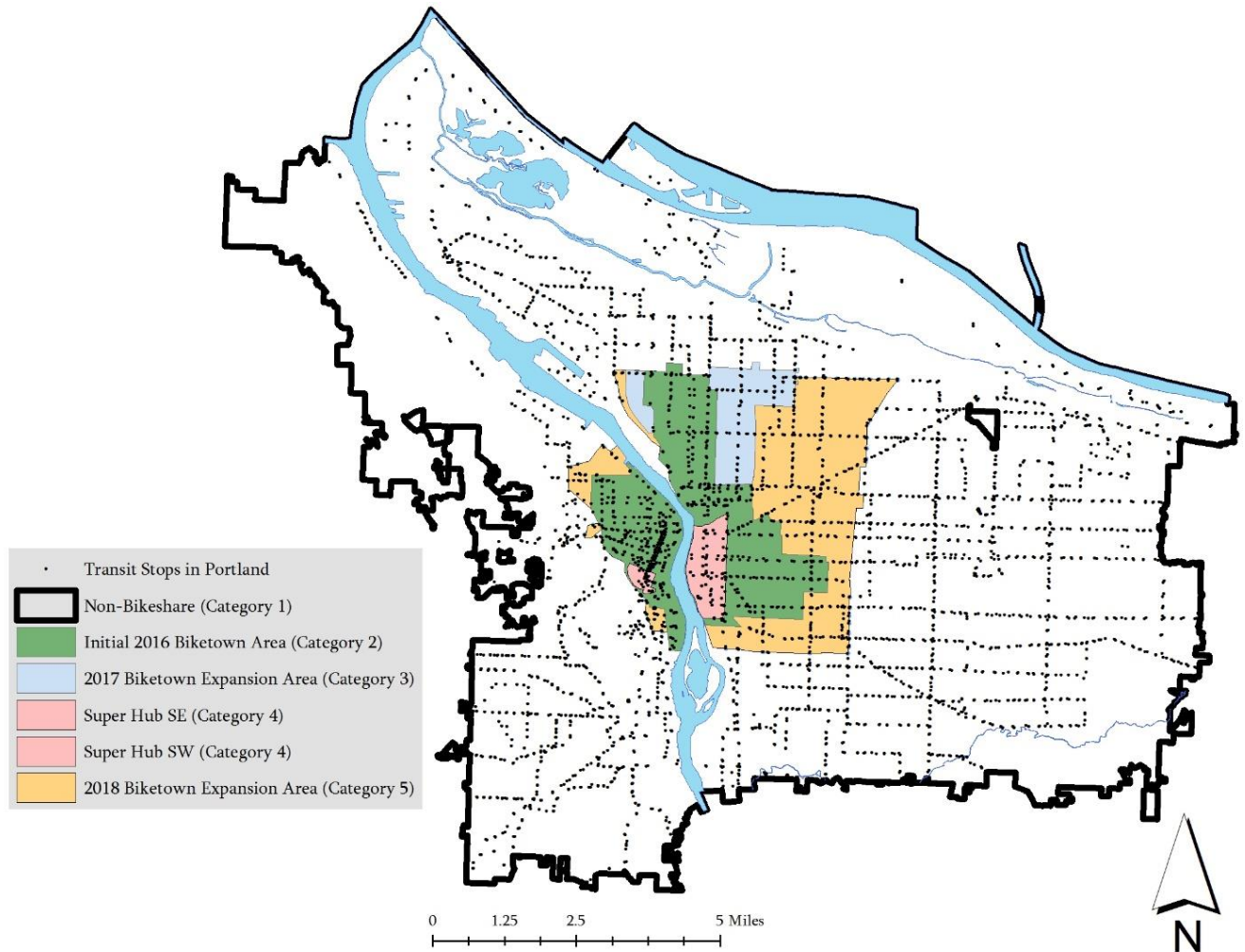


Figure 1: Study Transit Stops and Study Areas

Within these study areas, transit ridership data, including combined boardings and alightings per week for each route at each stop were used for the primary analysis. In addition to the stops within treatment areas, control stops were selected, matched for similar demographic, residential density, and job density.

Ridership information (total boardings, total alightings, overall “activity” per stop) was also aggregated at the census block group level, giving each block group a total number of combined boardings and alightings per week.

Treatment and control stops were analyzed for changes in ridership from before versus after the Biketown rule changes went into effect.

Data Sources, Constraints, and Study Timeframe

TriMet ridership data were obtained via public records request. Data were available aggregated by quarter: Fall 2016, Fall 2017, Spring 2018, and Fall 2018 (where Spring is defined as March 1 through May 31 and Fall is defined as September 1 through November 30). Three periods were analyzed: Fall 2016 (pre-expansion), Fall 2017 (after the first expansion and implementation of super hubs), and Fall 2018 (after the second expansion). These three time points provided a longitudinal study design (one and two years after treatment), and for the same time of year, establishing control for general seasonal weather patterns. Additionally, this allows for three months of rider behavior pattern change after rule changes (from June 2017 to September 2017, and from June 2018 to September 2018). This is salient, as McQueen (2018) previously demonstrated that it took riders multiple months to fully adapt to system rule changes.

Portland's Aerial Tram was omitted from this study due to its extremely unique situation. It links only two destinations (one of which, the main OHSU campus, is an area not within the bikeshare home area). Additionally, it is considered a major tourist attraction due to its excellent views and unique type of transportation mode. Therefore, while some people *may* have used bikeshare to access the lower aerial tram terminal, it is apparent that the aerial tram's ridership patterns would not be indicative or illustrative of the Portland transit system as a whole. The Portland Streetcar was also omitted from this study due to the unreliability of data available.

It was also necessary to control for changes in transit service levels, which could have had an independent effect on ridership levels. For example, a route that received an increase in service hours would logically expect an increase in ridership. Therefore, routes (and their corresponding route stops) that saw a major service change between 2017 and 2018 were omitted from the study (TriMet 2018). A summary of these routes is listed in Table 2. Additionally, any individual route stops that saw ridership increases of over 400% year-to-year or decreases of over 90% year-to-year because of the overwhelming likelihood that these stops had a major service change occur. In those cases, any changes would be unrelated to bikeshare, and therefore would cloud the findings of this study. After this filtering, 4134 stops were used for the study, and 1004 were omitted.

Table 2: Omitted Routes

Omitted Route	Rationale	Month of Change
2	Route split and service significantly increased	September 2018
4	Route split and service significantly increased	September 2018
20	Service span significantly increased	September 2018
73	Service span significantly increased	September 2018
74	New route	March 2018
87	Service span significantly increased	March 2018
96	Service span significantly increased	September 2018
272	New route	September 2018

The data were initially sorted into average boardings and alightings per stop by route run (for example, average boardings at the first stop for the first run of the day, average boardings at the second stop for the first run, etc.). These were aggregated to yield the mean count of riders boarding or alighting a route at a stop by weekday, Saturdays, and Sundays. These were then combined to average *weekly* boardings and alightings.

Although Biketown system area expansion and rule change information is available via their website, the system areas were not available in as GIS data sets, which required manual creation of shapefiles of the system areas based on the online maps. Polygons were initially digitized using Google Earth, and then exported into ArcGIS for further use. A polygon of the 2017 system map was overlaid with a polygon of the 2018 system map, and by using the Trim feature function I was able to create a new shapefile featuring the specific system expansion area. Additionally, I used the same method to create a polygon of the combined super hub areas.

Census block groups for the city of Portland were obtained from US Census Bureau TIGER/Line shapefile data. Each census block group was matched with relevant demographic and topographic data (see *Requirements or Creating Control Group*). Each block group was assigned to one of the five system expansion area categories, based on overlap between the block group centroid and the expansion areas.

Each stop within a block group was then assigned the demographic data for that entire block group for the purposes of matching and linear regression.

Creating the Control Group for t-test

In order to create a control group for student's t-test, I needed to first characterize my treatment group study stops by their growth rate, job density, and residential density. My goal was to identify control stops that were characteristically similar to ones within the study area.

Population at the block group level was taken from one-year 2017 American Community Survey (ACS) data, the most recent year available. U.S. Census Bureau's "On the Map" tool provided block group level employment data for 2015, the most recent year available.

Due to the lack of available census data for 2018, it was necessary to control for urban development with another variable. In this case, residential building permit data from the City of Portland has been used as control for residential development. A variable was created for each block group by aggregating the number of new construction residential units which were permitted in 2016, 2017, or 2018 and are now denoted by the city as complete. This development variable was stratified into 2016-17 completed permits and 2017-18 completed permits. Urban development was included as a control to help ensure that areas experiencing significant new recent development were matched with other areas experiencing similar scale of growth.

Bikeshare ridership was aggregated at this census block level using a spatial join function applied to both trip start points and trip end points. Counts of trip start and end points were aggregated for each census block group and for each period during the study timeframe.

With each prepared at the census block group level, the final GIS analytical step was assigning each transit stop with the characteristics of the census block group in which it was located using an ArcGIS Spatial Join.

A summary of these "stop characteristic" variables, including source and year of data, can be found in Table 12 in the Appendix.

Using R's "MatchIt" package, treatment stops were matched with control stops. These stops were matched on Fall 2016 (pre-expansion) transit ridership, residential density (total population/block group area), job density, residential demography (median household income and percentage of non-white population), recent residential development, topographic characteristics, and bikeshare ridership. The goal was to create pairs of control/treatment stops that were *functionally as similar as possible* prior to the bikeshare expansion and rule changes. The MatchIt package creates a control group that matches the treatment group on a one-to-one

basis (or a different ratio, if needed) with the goal of automatically selecting a control that is as similar as possible to the treatment group. The group is selected using a propensity score matching based on covariates which are selected by the user. The user is also able to select how to handle values that fall outside of the maximum matching limits.

There are a number of optimization methods and standards available for selecting a control group. For example, the two simplest selection methods are the “optimal” method and the “nearest” method – the difference between the two being that “nearest” will allow for control units to pair with multiple treatment rows simultaneously, while “optimal” will not. “Optimal” was used for this study so that single route-stops were not considered multiple times in the same analysis.

Additionally, the “caliper” option was utilized to limit matching to values that are within a pre-determined number of standard deviations away from each other and to target any unmatched values for removal. This study set the caliper to 0.01 SD. Effectively, this means that the values chosen for the post-treatment t-tests would be free of outliers and as effectively close to the same pre-treatment means as possible.

All observations that were targeted for removal were considered to be “unmatched” or “discarded” and not used for the t-tests. Again, note that “unmatchable” route-stops have characteristics that could not effectively be matched to a control. This issue is best illustrated by the example of route-stops in the downtown core of Portland. Due to the density and activity level in downtown, it is very difficult to match these stops to a non-downtown stop that has the same boarding and alighting activity. Therefore, MatchIt effectively excludes treatment stops for which a suitable control stop cannot be found, leaving only stops that have a closely matched pair for the final t-test analysis. While this does exclude some stops, it ensures that the two samples are *as similar as possible* prior to Biketown introduction, so that the study can better isolate the effects of Biketown.

T-test Analysis

Student’s t-tests were used to investigate statistical significance in ridership between treatment groups (study groups which received bikeshare changes) and control groups. These tests were performed on the weekly mean ridership per stop of the study groups. A p-value of 0.05 was used to determine statistical significance. Table 3 describes the t-tests which were run (see Table 1 for further details on the study area groups characteristics).

Table 3: Summary of T-Tests

#	Test Description	Treatment Group	Control Group	Transit Data Tested
1	Introduction of Super Hubs against an existing bikeshare area (Year 0*)	4 (Super Hubs)	2 (Original Area)	2017
2	Introduction of Super Hubs against an existing bikeshare area (Year 1*)	4 (Super Hubs)	2 (Original Area)	2018
3	Introduction of docked bikeshare against no introduction (Year 0*)	3 (2017 Expansion)	1 (Never Biketown)	2017
4	Introduction of docked bikeshare against no introduction (Year 1*)	3 (2017 Expansion)	1 (Never Biketown)	2018
5	Introduction of docked bikeshare against no introduction (Year 0*)	5 (2018 Expansion)	1 (Never Biketown)	2018
6	Introduction of docked bikeshare against no introduction (Year 1*)	2 (Original Area)	1 (Never Biketown)	2017
7	Introduction of docked bikeshare against no introduction (Year 2*)	2 (Original Area)	1 (Never Biketown)	2018
8	Introduction of Super Hubs against no introduction (Year 0*)	4 (Super Hubs)	1 (Never Biketown)	2017
9	Introduction of Super Hubs against no introduction (Year 1*)	4 (Super Hubs)	1 (Never Biketown)	2018

*Year “X” refers to the year of transit data tested in relation to the particular change. For example, if the data from Fall 2017 is being tested after a change that had been implemented previously in Summer 2017, that is denoted as a test of “Year 0.” Likewise, data from Fall 2018 being tested after a Summer 2017 change is denoted as “Year 1.”

Linear Regression Analysis

Linear regression models were also used to analyze significant factors in transit ridership growth. In this case, the difference in weekly transit ridership between Fall 2016 and Fall 2017 was the independent variable. The model was completed at both a granular route stop level (change in transit activity per week per route stop) and aggregated block group level (change in transit activity per week per block group). A p-value of 0.05 was used to determine statistical significance.

Dependent variables included demographic changes and growth factors by census block group between 2016 and 2017. These included population change, median income change, and change in number of non-white residents (diversity change). These were determined by the difference in 2016 and 2017 ACS data. This also included the number of new residential units in 2016 and 2017. This variable aggregated number of new construction residential units completed by census block group in 2016 or 2017, and it is intended to account for the nature of a neighborhood changing due to land development.

With regard to bikeshare, treatment status (expansion of bikeshare to the area in 2016 or 2017) was used as a dummy variable. Therefore, four separate linear models were completed.

Table 4: Linear Regression Model Descriptions

Linear Model	Analysis Level	Treatment Description
1	Route Stop	Introduction of <i>any</i> bikeshare in 2016 or 2017
2	Route Stop	Introduction of <i>super hub</i> in 2017
3	Block Group	Introduction of <i>any</i> bikeshare in 2016 or 2017
4	Block Group	Introduction of <i>super hub</i> in 2017

For each model, if a transit route stop or block group received the treatment, it was given a dummy variable value of 1. If it did not, it was given dummy variable value of 0.

It is important to note that because 2018 ACS data was not available, it was not possible to measure changes between 2017 and 2018 for the linear regression models. Therefore, the models are limited to bikeshare changes taking place between 2016 and 2017. Additionally, in these models it is not necessary to build a control and treatment group because two groups of stops are not being compared with each other in the same manner as the t-test.

In order to verify that the models adhere to OLS assumptions and therefore are suitable for interpretation, tests for collinearity (VIF test) and homoskedasticity (Breusch-Pagan test) will be performed. Additionally, QQ plots will be used to support the Bresch-Pagan test, to further determine the normality of residuals.

In short, the model attempts to identify statistically significant factors that are correlated with changes in transit ridership among all stops. If introduction of bikeshare (treatment dummy variable) or number of bikeshare rides is statistically significant, then we will know its status as a predictive factor on transit ridership changes and will also know the direction of the impact (either reducing or increasing transit ridership – substituting or complementing).

The model can be summarized as:

$$2016-17 \text{ Transit Ridership Difference} \sim \text{Treatment} + \text{Population Difference} + \text{Income Difference} + \text{New Residential Units} + \text{Diversity Difference}$$

~ “as predicted by”

+ additional predictor variables

Results

From 2016 to 2018, Biketown expanded spatially and also introduced super hubs. Table 5 shows how many transit stops fell within the various areas (no service, docked service, dock-free service) for each year. The number of transit stops within the Biketown docked areas increased from 907 in 2016 to 1166 in 2018. Additionally, 276 stops are located within the super hub areas introduced in 2017.

Table 5: Summary of Stops and Service Areas

Location	Year*		
	2016	2017	2018
Outside of Biketown service area	3332	3245	2854
Inside Biketown docked service area	907	1051	1166
Inside Biketown “Super Hub”	0	276	276

*Annual data were measured in September

Table 6: Overall Transit Ridership Trends

Study zone	Description of stops	Weekly Ridership [†] , Mean (SD)		
		2016*	2017*	2018*
n/a	citywide	529.6 (1424.5)	528.9 (1497.4)	529.1 (1486.9)
1	never part of Biketown	378.3 (1229.3)	379.7 (1327.5)	351.3 (1168.6)
2	added to the Biketown area in 2016 and without free dock-free trips	1535.9 (2842.2)	1505.5 (2698.7)	1497.5 (2713.6)
3	added to the Biketown area in the 2017 expansion and without free dock-free trips	743.5 (1235.0)	761.4 (1315.3)	753.8 (1289.4)
4	part of the initial 2016 launch and made into a “super hub” in 2017	453.1 (824.2)	449.3 (825.3)	438.8 (807.5)
5	not part of the Biketown area in 2016 or 2017 but included in the “traditional” docked service area in the 2018 expansion.	381.0 (419.6)	367.5 (399.9)	361.2 (383.1)

[†]Weekly Ridership consists of combined boardings and alightings

*Annual data were measured in September

Within all t-tests performed, none of the tests demonstrated statistical significance for bikeshare rule changes having influenced mean weekly transit ridership. Table 7 shows the t-test results. We do see some differences in treatment and control means. These differences fluctuate between the control group having a higher mean and the treatment group having a higher mean. However, it is important to note that the lack of statistical significance means that we do not have confidence that the population means are different.

Table 7: Summary of T-Test Results (Transit Ridership Mean Change)

Test #	P-value	Weekly Ridership [†] , Mean (SD)	
		treatment	control
1	0.564	706.8 (1188.1)	795.3 (1420.0)
2	0.578	692.6 (1163.4)	776.9 (1412.8)
3	0.465	405.5 (567.3)	492.4 (777.2)
4	0.523	403.9 (566.4)	478.2 (751.3)
5	0.827	329.9 (343.9)	316.7 (343.9)
6	0.998	734.3 (1482.7)	734.6 (1581.0)
7	0.603	730.8 (1489.1)	684.2 (1440.2)
8	0.864	327.9 (450.3)	321.9 (472.6)
9	0.804	317.0 (437.3)	308.5 (451.6)

[†]Weekly Ridership consists of combined boardings and alightings

For the linear regression models, data generally adhered to OLS assumptions. Each of the four models' residuals demonstrated homoskedasticity, verified by each model's Breusch-Pagan values being greater than $p = 0.05$. Variables were shown to not suffer from collinearity: VIF values did not exceed 2.5 in any of the models. QQ plots demonstrated that models generally adhered to normal distribution of residuals, although in some circumstances revealed outliers that were later discovered to be incorrect TriMet data (later fixed, before regression).

Linear Model 1 suggests that introduction of bikeshare is statistically significant, as is new residential development. The results here suggest that introduction of bikeshare may be associated with a ridership drop of approximately 16 weekly boardings and alightings for a transit stop. Additionally, new residential development is associated with an increase in transit ridership of 0.14 additional boardings and alightings per week per stop for every new residential unit located in its block group. Differences in diversity and median income are not statistically significant, and population difference is not statistically significant at the pre-determined $p = 0.05$ level. The R-squared of this model is relatively low, suggesting that the model may not be a very accurate predictor of transit ridership change.

Table 8: Linear Model 1 (Transit ridership change at route stop level, 2017)

	Estimate	StdError	t-value	Pr(> t)	
(Intercept)	-11.23	3.22	-3.48	0.001	***
Treatment (Introduction of all bikeshare)	-16.03	5.70	-2.81	0.005	**
2016-17 Population Difference	0.05	0.03	1.76	0.078	.
2016-17 Diversity Difference	0.00	0.00	1.51	0.130	
2016-17 Median Income Difference	0.00	0.03	0.14	0.887	
2016-17 New Residential Units	0.14	0.03	4.60	0.000	***

*** Significant at <.01

** Significant at .01

* Significant at .05

. Significant at .1

Breusch-Pagan: 0.08

Adj R² = .008

In Model 2, super hub treatment does not have statistical significance as it did in the first model, suggesting that free-floating bikeshare itself does not have an effect on transit ridership change. New residential units are significant at a level of $p = 0.01$, suggesting 0.12 additional boardings and alightings per week per stop for every new residential unit located in its block group. The magnitude of the change is also identical to the first model: an additional 0.05 boardings per week per stop for every new resident in the area. As in the first model, changes in diversity and median income are not significant predictors of transit ridership change, and changes in population are not significant at $p = 0.05$. R-squared of 0.0005 suggests a low predictive power of the model.

Table 9: Linear Model 2 (Transit ridership change at route stop level, 2017)

	Estimate	StdError	t-value	Pr(> t)	
(Intercept)	-15.62	2.99	-5.22	0.000	***
Treatment (Introduction of super hub)	4.23	8.80	0.48	0.631	
2016-17 Population Difference	0.05	0.03	1.81	0.070	.
2016-17 Diversity Difference	0.00	0.00	1.41	0.160	
2016-17 Median Income Difference	0.01	0.03	0.37	0.709	
2016-17 New Residential Units	0.12	0.03	3.98	0.000	***

*** Significant at $<.01$

** Significant at $.01$

* Significant at $.05$

. Significant at $.1$

Breusch-Pagan: 0.18

Adj $R^2 = .0005$

Model 3 is similar to Model 1 but is analyzed at the block group level instead of individual route step level. In this model, treatment does not have statistical significance, suggesting that treatment is not a significant predictor of transit ridership at the block group level. Once again, the number of new residential units are significant for predicting transit ridership change, suggesting 0.07 additional boardings and alightings per week per block group for every new residential unit located in its block group. Population difference, changes in diversity, and median income changes are not significant predictors of transit ridership change. R-squared of 0.013 is the highest of the four models, but still does not indicate a strong predictive power of this model.

Table 10: Linear Model 3 (Transit ridership change at block group level, 2017)

	Estimate	StdError	t value	Pr(> t)	
(Intercept)	-7.22	2.50	-2.89	0.004	**
Treatment (Introduction of all bikeshare)	-3.87	4.68	-0.83	0.409	
2016-17 Population Difference	0.01	0.02	0.72	0.472	
2016-17 Diversity Difference	-0.01	0.02	-0.41	0.684	
2016-17 Median Income Difference	0.00	0.00	1.39	0.167	
2016-17 New Residential Units	0.07	0.03	2.49	0.013	*

*** Significant at <.01

** Significant at .01

* Significant at .05

. Significant at .1

Breusch-Pagan: 0.55

Adj R² = .013

Model 4's results are somewhat similar to Model 3. This model suggests that introduction of the free-floating bikeshare of super hubs is not a significant predictor of transit ridership. New residential units in a block group are, however, a significant predictor of transit ridership change, with 0.06 additional boardings and alightings per week in a block group for every new residential unit. Population, demographic, and median income changes are not significant predictors of transit ridership changes in this model. R-squared is slightly lower than in Model 3, but higher than the first two models, meaning that it is not a very strong predictor of ridership.

Table 11: Linear Model 4 (Transit ridership change at block group level, 2017)

	Estimate	StdError	t value	Pr(> t)	
(Intercept)	-8.28	2.38	-3.48	0.001	***
Treatment (Introduction of super hub)	1.24	6.61	0.19	0.852	
2016-17 Population Difference	0.01	0.02	0.74	0.461	
2016-17 Diversity Difference	-0.01	0.02	-0.36	0.722	
2016-17 Median Income Difference	0.00	0.00	1.33	0.185	
2016-17 New Residential Units	0.06	0.03	2.35	0.019	*

*** Significant at <.01

** Significant at .01

* Significant at .05

. Significant at .1

Breusch-Pagan: 0.82

Adj R² = .011

Discussion

The results shown above suggest that there is some support for a statistically significant relationship between bikeshare introduction and transit ridership, but that further study is needed to support such a relationship. Additionally, there does not appear to be evidence to support a relationship between the introduction of dockless or free-floating bikeshare and transit ridership in Portland. The added flexibility of the free-floating bikeshare was originally hypothesized to have a tangible effect on transit ridership. However, the data do not support this hypothesis.

The t-tests do not show significance of change of means between the treatment and control groups. The results of these relatively simple tests do not offer support for a bikeshare-transit relationship, neither substitutionary nor complementary.

The first linear model offers some support that bikeshare may have a substitutionary effect with transit: the addition of bikeshare in a block group area leads to a decrease of weekly transit ridership of approximately 16 combined boardings and alightings.

Additionally, all linear models suggest that new residential development is a contributing factor to increased transit ridership, while population change itself is only sometimes a contributing factor, and only at $p = 0.1$ level significance. Differences in population and median income do not seem to be significant predictors of transit ridership according to these model.

However, the very low R-squared for all four linear models suggests that the predictive power of the model is not very high. . Therefore, the findings in this paper may merit additional study with different methodology regarding the effect of bikeshare on transit ridership in Portland. While bikeshare treatment does show statistical significance for having a substitutionary transit effect in one model, the model's strength of prediction suggests that further research with other methods may be warranted in order to further clarify and potentially strengthen this finding.

One finding that does seem to be clear is new residential development's positive effect on transit ridership changes. This variable had significance across all four models, including the two models with the highest R-squared values. It is notable that new residential units had such an effect which changes in population did not. New residential units are an indicator for a change in a neighborhood's character in a way that simple population change (birth, death, relocation) is not. In other words, it may not simply be the absolute change in demographics or population

density which matters for transit ridership change but rather the change in the built form that makes transit a more suitable or appealing mode.

One major takeaway from the results of the linear models is that changes in transit ridership in Portland from 2016 to 2017 are not always associated with factors that might be expected on a neighborhood level. These expected predictive factors include changes in population, changes in income, changes in demographics, or a bikeshare treatment. With this in mind, one may conclude that transit ridership may be subject to even larger urban and economic forces that this study is unable to account for, transit service level changes that this study was not able to control for, or simply commuters' flexibility in terms of which stops they board at during their daily routine.

Conclusion

The findings in this study show some support for bikeshare having a substitutionary effect on transit ridership as riders replace transit trips with bikeshare trips. As shown in linear model 1, introduction of bikeshare in an area is associated with an expected drop of approximately 16 transit boardings and alightings per week at a stop. This suggests that transit riders more commonly substitute transit trips for bikeshare than they use bikeshare to increase their frequency of using transit. This finding can aid transportation planners as they weigh the effects of bikeshare introduction in their own municipalities.

The findings of this study also suggest that new residential development – the change in built form – is more of a contributor to increased transit ridership than in increased population itself. This has implications beyond the scope of this bikeshare-focused study, and it gives planners an area for further study when considering the effects of new development on mode choice.

Some study limitations may have affected the ability for this study to statistically discern a relationship. One major weakness of this study is the omission of Portland Streetcar data for study. Although the Portland Streetcar carries approximately 14,000 riders across its two lines on an average weekday (Portland Bureau of Transportation 2019), complete and accurate ridership data were not available for this study. Inclusion of these data may have altered study results substantially.

Available TriMet data were somewhat of a limitation in this research. The agency was only able to provide data at the quarterly average level as part of a public records request. Ideally, the individual monthly or weekly level as might be preferable, as this would allow a closer examination of ridership trends.

Seasonality may also have played a larger role than expected. The analyses were performed on fall quarter data, from September 1 to November 30 of the respective years. In the Pacific Northwest, September and October are transitional months but still typically offer enough warm and dry weather to support a relatively pleasant bicycling experience. However, two possibilities exist. First, it is possible that Biketown trips tail off notably after the most pleasant bicycling months of June, July, and August; 2018 data show that trips decreased notably in late August (Biketown *System Data* 2019). Second, it is possible that aggregation to quarters masks actual effects that may exist in September and early October. However, this study was constrained by the data made available by TriMet through public records requests; use of monthly data may show patterns that did not appear with the quarterly data.

While efforts were made to create balanced control group for the t-tests, the attempts to include too many factors in the matching process severely impacted the ability to find a control group that matched the treatment group on 2016 transit activity, the most important factor. Because of this, many of the demographic data were omitted for the matching process. However, it is possible that these omissions affected the matching between treatment and control stops to the point that it hid changes that *did* occur in reality.

Another potentially confounding factor for the t-tests was the introduction of e-scooter sharing in Portland in 2018. Bird, Lime, and Skip (three private companies) provided e-scooter service in Portland from July 2018 to November 2018 as part of a 120-day pilot program (Portland Bureau of Transportation 2018). While the presence of scooters did not affect the rollout of Biketown changes in 2018 that were studied in this paper, it is possible that their introduction complicated the hypothesized bikeshare-transit relationship by diverting riders who would have otherwise used bikeshare. For example, the scooters were not required to be limited to a home service area like Biketown is – instead, they were allowed to operate anywhere within Portland city limits, allowing greater flexibility for travelers. This could have affected mode choice, especially on the edges of Biketown service areas. Additionally, the scooters are all electric and can travel at a max speed of about 15 to 18 miles per hour, which can be competitive

with effective bus speeds in urban areas. In comparison with the all-manual bikes used in the bikeshare available at the time of this study, e-scooters may be more attractive because they can be used without requiring physical exertion. Finally, a sort of “novelty” factor might have boosted choices of e-scooters during this period. This study may have benefited from inclusion of data on e-scooter ridership; however, data were not available. Furthermore, future studies on the scooter-transit relationship may be difficult for researchers as the private scooter companies are known to be extremely protective of their data, likely making them unavailable for study.

Future studies of this nature could take various forms that might be more focused or more accurate predictors of the effects of bikeshare. First, some of the suggestions mentioned in this section could be applied in a similar study: inclusion of (accurate and verified) Portland Streetcar data, different matching methods, finer-grain monthly ridership data instead of quarterly ridership data, or a study in Fall of 2019 to further give opportunity for rider behavior to change.

Second, one might consider a model that links bikeshare rides more directly to transit. For example, the model of the Twin Cities study completed by Barber, Kopca, and Starrett (2018) could easily be applied to the Portland region. This was the model which applied a negative binomial model to study nearby bikeshare starts in the time period immediately following the arrival of a light rail train. While this model may be limited because of its difficulty in applying to TriMet buses (buses typically take on and discharge fewer passengers per stop than a light rail train does, and therefore impacts may be harder to measure), it could certainly be applied the TriMet’s MAX system or the Portland Streetcar.

Third, it may be simpler (and more fruitful) to gain insights into rider behavior using a travel survey method rather than taking an approach that relies heavily on large volumes of transit ridership data. Conversely, a survey could be used alongside a quantitative study to supplement the findings. Surveys are prone to their own sorts of shortcomings but might give a good picture of rider trends. It is very possible that many Portlanders *are* supplementing their transit use with bikeshare, but due to the large volume of transit ridership data from which to draw conclusions, it is simply too difficult to make statistically-significant conclusions. For example, it is possible that some individuals substitute transit trips for bikeshare on some days, and complement transit with bikeshare on others. This would result in ridership data that cannot bear out a definitive conclusion about the nature of the bikeshare-transit relationship. Conversely, survey responses could give more insight about why the statistics do not bear out the

hypothesis about a measurable bikeshare-transit relationship by having respondents identify how often they complement or substitute transit trips on a weekly basis.

Fourth, it may be feasible to incorporate an investigation of scootershare into future studies similar to this one. Although there is no “home area” for scooters in Portland and it may be difficult to obtain the scooter origin-destination data due to the private companies’ unwillingness to share data, it may be possible to create a variable for scooter ride density and include this in a predictive model of transit ridership. This could isolate the effects of the new scootershare and keep it separate from bikeshare so as not to muddle the bikeshare-transit relationship.

If it does stand as true that the data support the concept that bikeshare takes away from transit ridership instead of adding to it, it might come as some disappointment to transportation planners who had touted the potential first-mile and last-mile benefits of such a relationship. However, the mere presence of bikeshare and transit together is valuable, and many bikeshare benefits are not captured in the methodology employed by this study. Even if Portlanders do not change their transportation habits when bikeshare is introduced, the *flexibility* offered by the system may be considered most valuable.

Bikeshare allows for some trips to be made that would be difficult, time-consuming, or impossible with transit. Bikeshare also allows individuals to travel on their own schedule, not requiring them to wait until the next bus or train arrives. It may be utilized on an *ad-hoc* basis that allows people to use the bikes when it is convenient for them, even if this is not frequent or widespread enough to be discernable in the transit data. Bikeshare might encourage some residents to switch to a car-free lifestyle, with the knowledge that bikeshare can transport them when transit is sparse or unavailable. Because this study did not address the effects of bikeshare on automobile mode choice, it is difficult to speculate on this beyond the fact that bikeshare offers another feasible alternative mode beyond automobile travel.

Bikeshare may also greatly increase mobility for low-income residents, and Biketown’s reduced-fare memberships may help support this. Furthermore, bikeshare may boost tourism and recreational cycling in the city, providing potential economic benefits that are beyond the scope of this study.

Ultimately, the overall impact of bikeshare is not limited to its effects on transit but can be considered in the context of overall mobility, additional non-automobile travel options for

residents, potential economic benefits, and health of citizens. For these reasons, transportation planners should continue examining the micromobility-transit relationship for further evidence of benefits for residents and businesses.

Appendix

Table 12: Description of Variables

Variable	Source	Description	Date Range	Units	Notes
Population	American Community Survey	Total population within each CBG	2016-2017	# of persons	
Land Area	TIGER/LINE (US Census Bureau)	Area of each CBG	CBGs for 2010-2020	Square Meters	
Population Density	“Population” and “Land Area” variables	Residential density	Mixed, see above	Persons per sq m	“Population” divided by “Land Area”
Median Income	American Community Survey	Median income of residents in each CBG	2016-2017	\$ (USD)	
Diversity	American Community Survey	Percentage of residents in each CBG who are non-white	2016-2017	%	Self-identified white population minus total pop, divided by total pop
Employment	U.S. Census Bureau “On the Map” / LEHD	Number workers based in a CBG	2015	# of workers	
Development	City of Portland Open Data	Number of “completed” residential building permits per CBG	2016-17 and 2017-18	New residential units/sq m	Attempts to control for development-caused changes
Bikeshare Ridership	Biketown	Number of bikeshare trips originating or ending in a CBG	2016-2018	Total # of rides	
Bus/MAX Boardings	TriMet	Average passengers boarding a route at a stop during a day	Sept 1 – Nov 30 for 2016, 2017, 2018	Average by weekday, Saturday, Sunday	Via Public Records Request
Bus/MAX Alightings	TriMet	Average passengers disembarking a route at a stop during a day	Sept 1 – Nov 30 for 2016, 2017, 2018	Average by weekday, Saturday, Sunday	Via Public Records Request

CBG: Census Block Group

Notes

The Portland Streetcar, which is operated by the Portland Bureau of Transportation instead of TriMet, was not included in this study. A public records request was made to PBOT to acquire these records for study. Unfortunately, the dataset was in poor shape: it lacked large portions of stop-level data, missed entire dates and large chunks of certain days, did not balance in terms of boardings and alightings, and did not aggregate to the total weekly ridership that PBOT public shares. For example, the dataset entirely lacked data for “A” (clockwise) loop stops on the “AB” Central Loop Line. Because of these problems, it was determined that the dataset was unfortunately not practically feasible for this research, and streetcar ridership was omitted from the final analysis.

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