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Bluebikes at the Blue Line: Bikesharing Facilities and Subway Station Ridership Throughout the COVID-19 Pandemic in Boston

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Summary

As transport planners around the world attempt to bridge the first-mile/last-mile gap and improve accessibility to public transport systems, many, including those in Boston, have turned to micromobility modes, such as bikesharing, as a solution. While bikesharing systems have the potential to facilitate connections to public transport, they may also be used as a replacement mode altogether. This is especially of concern in the context of the COVID-19 pandemic, when fears of infection have disincentivized public transport travel. The full effects of bikesharing systems on public transport ridership, especially during pandemics, therefore remains unclear. In order to inform the planning of bikesharing systems in Boston and similar cities, this research studies the association between the presence of bikesharing facilities and ridership at subway stations in Boston, both under normal conditions and throughout the COVID-19 pandemic. To do so, it conducts a statistical analysis of subway ridership data from January 2019 through October 2021. Through a series of ordinary least squares regressions, this research tests hypotheses from other cities on this association, the moderating effect of station area density, and the moderating effect of the pandemic, in the context of Boston. This research finds that the presence of bikesharing facilities is positively associated with ridership at subway stations in Boston, but this association is negatively moderated by the employment density of the area surrounding the station. Thus, locating bikesharing facilities at subway stations is associated with higher ridership for stations with few jobs in the area, but this association diminishes as the number of jobs in the station area increases. In addition, the COVID-19 pandemic in Boston caused the association between bikesharing facilities and subway station ridership, as well as the moderating effect of employment density, to temporarily disappear, before gradually returning in late 2020. In addition to informing the academic debate on this topic, this research recommends that planners in Boston and similar cities invest in and expand their bikesharing systems to improve subway station accessibility and boost subway ridership. These efforts, however, should be focused in peripheral stations where employment density is low for the greatest benefits. Finally, this research advises planners that, during future crises that reduce the public's willingness to travel on public transport, the accessibility benefits of bikesharing systems likely will not be enough to keep riders on public transport, so other solutions are necessary.

Keywords

Mobility; Bikesharing; Public Transport; COVID-19; Multimodality

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Abbreviations

BTD	Boston Transportation Department
FMLM	First-Mile/Last-Mile
IHS	Institute for Housing and Urban Development Studies
MassDOT	Massachusetts Department of Transportation
MBTA	Massachusetts Bay Transportation Authority
OLS	Ordinary Least Squares
OVB	Omitted Variable Bias
PBC	Perceived Behavioral Control
TPB	Theory of Planned Behavior

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1: Introduction

1.1 Problem statement and background information

A major challenge for public transportation agencies across the globe is improving the accessibility of their systems through first-mile/last-mile connectivity, or "connecting origin and destination points to stations or stops on the transit network" (Kanuri et al., 2019, p. 657). Due to the fixed nature of public transport routes, there may be significant distance between an individual's origin or destination and the transport network. The size of this distance may dissuade travelers from using public transport, or may prevent this mode from even being considered as an option (Kanuri et al., 2019).

To solve this challenge, many transportation planners, especially in North America, have begun to look to the opportunity of innovative micromobility modes. Micromobility includes a range of low-carbon lightweight vehicles that are often shared (Abduljabbar et al., 2021). One popular form of micromobility is bikesharing, in which members of the public can rent a bike on a short-term basis, often using a mobile app or digital kiosk (Shaheen et al., 2013b). In most systems, the bikes can be rented from one of many docking stations across the city, ridden for a short period, and returned to any dock in the system (Shaheen et al., 2013b). The popularity of bikesharing has grown significantly in recent years, reaching over 2,000 systems operating in cities across the globe in 2020 (Meddin Bike-sharing World Map, 2021). In one such city, Boston, the Bluebikes program has been steadily growing since its introduction. Bluebikes saw 140,000 rides in 2011 when it first launched (Shaheen et al., 2013b) and 2.5 million trips in 2019 (Bluebikes, n.d.-b). Much of this growth in ridership has been driven by an expansion in the number of stations, which approximately doubled from 2018 to 2020 (City of Cambridge, 2020). Municipalities in metro-Boston continue to expand the system, such as in Cambridge where 20 additional stations were planned to be implemented in 2021 to meet the City's goal of every resident having a station within a 5-minute walk of their home or office (City of Cambridge, 2020).

Supporters of bikesharing systems argue that this mode can facilitate first-mile/last-mile connections to public transport, as individuals can rent a bike from a docking station at or near a public transport stop and return it to a docking station near their destination, or vice versa (Shaheen et al., 2013b). Evidence of bikesharing systems being used in this way has been found in a number of cities, including Boston (Romm, 2022; Tarpin-Pitre & Morency, 2020; Shaheen et al., 2013a; Ma et al., 2015). However, while bikesharing systems have the potential to significantly benefit the accessibility of public transport systems, the novel nature of these systems implies that their full impacts are not yet understood. There is growing concern that bikesharing systems may actually draw riders away from existing public transport systems by offering a more attractive alternative mode. Studies in several cities have found evidence of travelers replacing public transport trips with bikeshare trips, and of ridership at bus routes and subway stations decreasing with the introduction of bikeshare facilities at these locations (Campbell & Brakewood, 2017; Chen et al. 2022; Fishman et al., 2015). Research in Washington D.C. has also found that while bikesharing systems may increase public transport ridership in areas of low density, it may have the opposite impact in areas of high density (Martin & Shaheen, 2014; Ma and Knapp, 2019). While it is often also the goal of transport planners to encourage greater travel on active modes, such as walking and cycling, these trips should ideally come at the expense of automobile travel, not public transport, in order to maximize environmental benefits.

Uncertainty surrounding the impacts of bikesharing systems on public transport ridership have only grown in the context of the COVID-19 pandemic. The COVID-19 pandemic has disrupted every transportation mode through a drastic reduction in the need and ability to travel (Ciufini et al., 2021). On top of this, the pandemic has made public transport a less desirable mode in particular due to fears of infection in enclosed public spaces (Gkiotsalitis & Cats, 2021). Many of the remaining travelers in cities have therefore shifted away from public transport to more socially-distanced modes (Habib & Anik, 2021). As a result, while ridership on all modes has suffered, public transport ridership has fallen the most and has taken the longest to recover (Ciufini et al., 2021). As a socially-distanced mode, on the other hand, bikesharing in many cities rebounded rapidly after an initial drop in ridership (Wang & Noland, 2021). In Boston, Bluebikes rentals fell significantly at the end of March 2020, but quickly increased during the summer months (Boston Transportation Division [BTD], 2021). Rentals in 2020 were overall only 18% lower than 2019, representing a much smaller ridership loss than other modes in the city (BTD, 2021). Rapid transit ridership on the public transport system, the MBTA, fell from 700,000 daily riders in Fall 2019 to below 50,000 riders per day during the initial onset of the pandemic (Massachusetts Bay Transportation Authority [MBTA], n.d.-c). By the second half of 2021, daily ridership reached levels between 200,000 and 250,000 riders, representing a slight rebound, despite still being far below that seen in 2019 (MBTA, n.d.-c). It is therefore possible that travelers are replacing public transport trips with bikeshare trips more frequently during the pandemic than they had prior. Given these changing travel patterns, any existing understandings of the relationship between bikesharing systems and public transport ridership are called into question and must be revisited.

As transport planners in Boston and similar cities expand bikesharing systems and continue to locate bikesharing facilities at public transport stations, they must be fully informed of the consequences for existing public transport systems. Without greater information on how these planning decisions impact public transport ridership, especially under the changing conditions of the COVID-19 pandemic, planners face the risk of actually harming the very systems they seek to benefit.

1.2 Research objectives

The main objective of this research is to understand the extent to which the presence of bikeshare facilities is related to ridership at subway stations in Boston, prior to and during the COVID-19 pandemic. Based on the existing literature, to fully understand the association between these variables, it is also necessary to test the moderating influence of station area density. Thus, the specific objectives of this research are:

- Test the extent to which the presence of Bluebikes docks is associated with subway ridership at MBTA stations prior to the pandemic;
- Test the extent to which this association differs based on the density of the MBTA station area;
- Test how this association and the influence of station area density changed throughout the pandemic.

1.3 Main research question and research sub-questions

In pursuit of these objectives, this research seeks to answer the following question:

To what extent is the presence of Bluebikes facilities associated with subway ridership at MBTA stations, prior to and during the COVID-19 pandemic?

To do so, it will answer the following sub-questions:

- To what extent is the presence of Bluebikes facilities associated with subway ridership at MBTA stations prior to the pandemic?
- To what extent does the density of the station area moderate this association?

- To what extent has each phase of the pandemic moderated this association and the influence of station area density?

1.4 Relevance of the research

This research will add to existing literature on the association between the presence of bikeshare facilities and subway station ridership by examining it in a new case city, Boston. Utilizing a novel case allows this research to test the findings from other cities and contribute new evidence to the debate of whether bikesharing facilities positively or negatively influence subway station ridership. This research also tests the initial findings that the density of the surrounding station area moderates this association in the case of Boston. Finally, this research expands academia’s understanding of the association between bikeshare facilities and subway station ridership by considering it under abnormal conditions. Studying this association during the COVID-19 pandemic illuminates how external disruptions to the transport system may also serve as a moderating factor. This element of the study also has some implications for academia’s understanding of how the pandemic has changed travel patterns on bikeshare and public transport systems, as well as the longevity of such impacts.

In addition to contributing to an academic gap, this research has important implications for mobility planning and policy in Boston and similar cities. Primarily, the results of this research can improve the planning of bikesharing systems by illuminating the possible ramifications of locating bikeshare facilities at subway stations, and how such ramifications may differ based on the density of the surrounding area. Planners can then be more fully informed when deciding whether to locate such facilities at subway stations, and at which stations doing so may have the biggest accessibility benefits. Furthermore, conducting this research during the COVID-19 pandemic allows planners to make such decisions with the most recent data, rather than relying on outdated travel patterns. Beyond the current pandemic, the findings from this research can also be used to anticipate the effects of future crises similar to the COVID-19 pandemic. This can further aid the planning of bikeshare systems by allowing planners to consider the ramifications of their decisions in multiple scenarios, rather than just under normal conditions.

2: Literature review

2.1 Introduction

This chapter discusses the theoretical underpinnings of transportation mode choice and how these theories explain the current understanding of how bikesharing influences public transport ridership. Existing studies of the association between bikesharing facilities and subway station ridership, as well as those that account for density and external disruptions are reviewed. It then considers various conceptualizations of the COVID-19 pandemic and reviews existing literature on the impacts of the pandemic on bikeshare systems, subway systems, and the relationship between these modes. It concludes with a discussion of gaps in this literature that must be revisited to inform the planning of bikesharing systems.

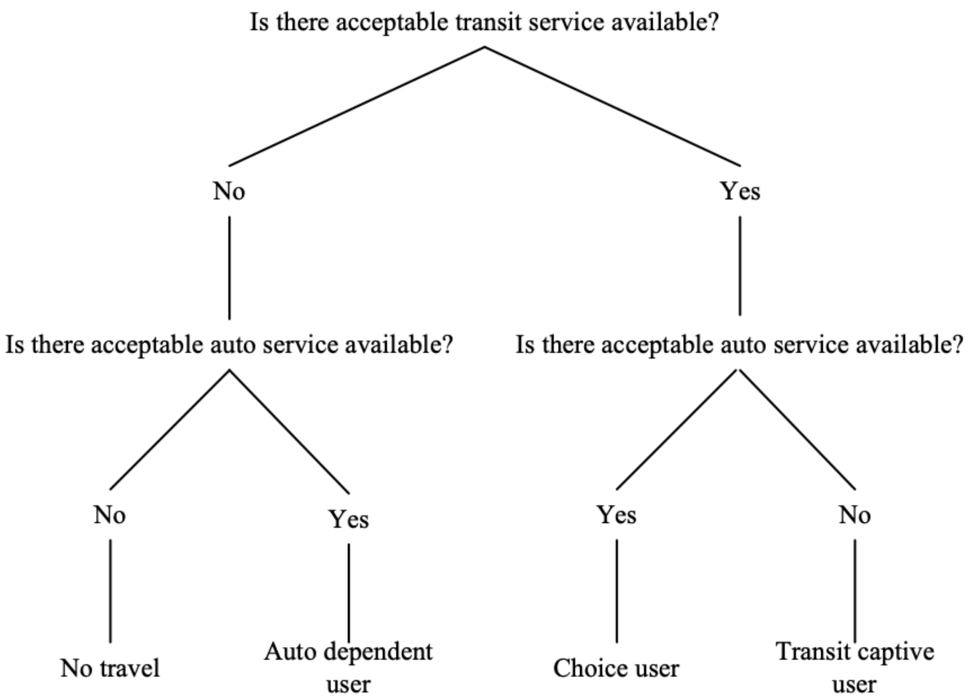
2.2 Transportation mode choice

A central concern within mobility literature is understanding and predicting travelers' choice of transportation mode. Mode choice can be understood as two distinct decisions: first, a consideration of which modes are available, and then a decision of which mode is preferable (Beimborn et al., 2003).

2.2.1 Mode availability

The availability of a mode requires accessibility, connectivity, safety, knowledge, and usability (Beimborn et al., 2003). For many people, these conditions are only met for a single mode, making them captive users, meaning they do not have the ability to choose another mode (Beimborn et al., 2003). This situation is visualized in Beimborn et al. (2003)'s decision tree in Figure 1. While these authors only consider auto travel and transit service, this figure illustrates how the unavailability of a particular mode can restrict the mode choice of certain travelers. For choice users, however, these conditions are met on multiple modes, and they can consider the preferability of each to make their mode choice (Beimborn et al., 2003).

Figure 1: Mode Availability Decision Tree



Source: Beimborn et al. (2003)

2.2.2 Mode preference

Research has identified a plethora of factors that influence mode preference, such as the travel time, cost, accessibility, safety, and social norms of the mode, as well as the socioeconomic status of the traveler (Sekhar, 2014). Borrowing from the fields of psychology and economics, many authors have put forward theories and models in an attempt to explain how individuals consider these various factors in choosing their preferred mode. Two major schools of thought in explaining mode choice are Utility Theory and the Theory of Planned Behavior (TPB). Utility Theory is rooted in utilitarianism and posits that individuals choose a mode from a set of finite options based on which one will maximize their utility (Sekhar, 2014). Utility in this sense is defined as "an attraction associated to by an individual for a specific trip" (Sekhar, 2014, p. 277). This theory assumes that individuals are rational actors with perfect information, thus their mode choice can be determined from a cost-benefit analysis of their options (Sekhar, 2014; Ettema et al., 2016). TPB, on the other hand, contends that an individual's decision is a combined outcome of their intention and perceived behavioral control (PBC), or the individual's perception of their ability to carry out a certain behavior (Ajzen, 1991). In the context of mode choice, PBC entails the individual's evaluation of the various factors that either facilitate or hinder using a particular mode (Ahmed et al., 2021). According to TPB, an individual's intended mode choice is also based on their attitude towards the mode, social and personal norms, and habit (Ahmed et al., 2021). TPB therefore accounts for the fact that individuals do not always act rationally or have perfect information, but are influenced by social factors and their own perceptions. These two theories can therefore be used to understand how travelers choose a mode, and how various intrinsic and external factors can change this decision.

2.3 Influence of bikesharing on public transport as a mode choice

Significant empirical research has been dedicated to understanding how bikesharing systems can change individuals' decisions to use public transport as a travel mode. Such literature is largely divided between those that have found a complementary influence of bikesharing on public transport and those that have found a competitive influence. Studies into how these influences manifest in changes to public transport ridership at a local level are similarly divided, but the moderating effect of density may clarify this dispute. Finally, there is initial evidence that the influence of bikesharing on public transport as a mode choice may change during disruptions, but further research is necessary.

2.3.1 Bikesharing as a complement to public transport

Theory suggests that bikesharing systems can complement public transport as a mode choice by facilitating FMLM connections. FMLM connectivity determines the accessibility and convenience of public transport (Krygsman, 2004). By easing station access and egress, bikesharing therefore increases the number of people who can consider public transport as an available option and the preferability of public transport over other modes, in terms of both actual and perceived utility.

The use of bikesharing as a FMLM connection is evident from empirical research in a number of cities, including Boston (Romm et al., 2022). Tarpin-Pitre and Morency (2020) not only find evidence of public transport passengers using the bikeshare system in Montreal to complete the first and last kilometer of their trips, but also that these types of trips make up a greater percentage of bikeshare trips as the system expands. Fan et al. (2019) find that bikesharing actually replaces walking as the preferred FMLM mode after this mode is introduced in Beijing. Evidence of this resulting in ridership benefits for public transport is found by Shaheen et al. (2013a) in Minneapolis, where more bikeshare users reported increasing their rail transport usage after beginning to use bikeshare than reported decreasing their rail transport usage. The authors hypothesize this is due to the fact that Minneapolis is not a very dense city and lacks an extensive rail system, so bikesharing plays a crucial role in connecting people to the rail system in this city. By improving the accessibility of public transport systems, bikesharing systems therefore appear to bolster the choice of public transport as a travel mode.

2.3.2 Bikesharing as an alternative to public transport

At the same time, theory suggests that bikesharing can be a competitor with public transport systems as an alternative mode. Research has found that the adoption of bikesharing as a mode choice is influenced by factors such as infrastructure, weather, topography, and trip distance (Ye et al., 2020; Fishman et al., 2012; El-Assisi et al., 2017). Utility Theory would argue that these are all factors that influence the utility of bikesharing and travelers will switch to this mode for a trip in instances where its utility outweighs that of public transport. Wang et al. (2018) finds that the adoption of bikesharing is also positively influenced by positive personal attitudes towards bikesharing and "greenness". This can be explained by the influence of personal values and attitude on an individual's intention within TPB. Thus, under TPB, individuals are motivated to switch from public transport to bikesharing not just based on utility, but also based on the perceived social and environmental value of this mode.

Bikeshare users in numerous cities have reported using bikesharing to complete trips they previously would have made on public transport (Shaheen et al., 2011; O'neill & Caulfield, 2012; Bachand-Marleau, 2011). Chen et al. (2022) and Fishman et al. (2015) find in Beijing, Melbourne, and Brisbane that bikeshare users replace public transport trips more than they replace trips of any other mode. Contrary to their findings in Minneapolis, Shaheen et al. (2013a) find in Washington D.C., Montreal, and Toronto that a higher percentage of bikeshare users report decreasing their rail transport usage after beginning to use bikesharing than report increasing their rail transport usage. The authors hypothesize that this is due to the fact that, unlike Minneapolis, these are denser cities with more congested rail networks, so bikesharing may be used more often as an efficient alternative than an access mode. Bikesharing therefore can both positively and negatively influence the choice of public transport as a travel mode, but the strength of each influence may depend on the context.

2.3.3 Local-level influence of bikesharing on public transport ridership

These system-wide influences of bikesharing have ramifications for public transport ridership at a local level. Recent studies have endeavored to understand how the co-location of bikeshare and public transport facilities impacts transport ridership at such facilities. For instance, Campbell and Brakewood (2017) find in New York City that for every 1,000 bikeshare docks added along a bus route, ridership on that route decreases by 2.42%, suggesting that co-location has a competitive effect in this context. Regarding subway stations, Ma et al. (2015) study metro stations in Washington D.C. with bikeshare stations within walking distance. These authors find that a 10% increase in ridership at the bikeshare stations leads to a 2.8% increase in subway ridership at the corresponding metro station. They therefore identify a complementary station-level association between bikeshare facilities and subway ridership, but this association is based on the ridership of the bikeshare facilities. It is therefore unclear whether the presence of these facilities alone have an impact in this context. Despite the limited research on the topic and the inability to prove more than correlation, these studies provide initial evidence that co-locating bikesharing and public transport facilities may impact public transport ridership at a local level. Whether this impact is positive or negative, however, remains disputed.

2.3.4 Moderating effect of urban density

As noted earlier, Shaheen et al. (2013a) find that the influence of bikesharing on public transport use differs across urban contexts, and they hypothesize this is due to differences in the density of each city. This influence may also be moderated by different levels of density within a city itself. A study from Boston previously found that bikesharing is more often used as an access mode to public transport in the urban core and as an egress mode in the periphery (Romm et al., 2022). Differences in density can therefore change the utility of bikesharing in relation to public transport, thus changing how bikesharing influences mode choice. Martin and Shaheen (2014) find in Washington D.C. that, while most bikeshare users overall reported decreasing their rail transport usage after beginning to use bikeshare, those who reported increasing their rail transport usage are located in greater percentages in the periphery. Similarly, Ma and Knapp (2019), find that the presence of bikeshare facilities at D.C. metro stations is associated with higher subway ridership in the periphery but lower subway ridership in the urban core. Specifically, the presence of bikeshare docks would reduce morning peak exits at core stations by 4,738 passengers per month, but would increase the same measure at periphery stations by 1,175 passengers per month (Ma & Knapp, 2019). These findings indicate that bikesharing has a positive influence on public transport ridership in less dense parts of the city, and a negative influence in more dense parts of the city. Bikesharing therefore may increase the utility of public transport in less dense areas where individuals have to travel further distances to reach stations, and have greater utility than public transport in denser areas where trip distances are shorter. While the findings of these two studies are limited to Washington D.C., they demonstrate that it may be necessary to account for density in order to properly understand the association between bikesharing facilities and public transport ridership in other cities as well.

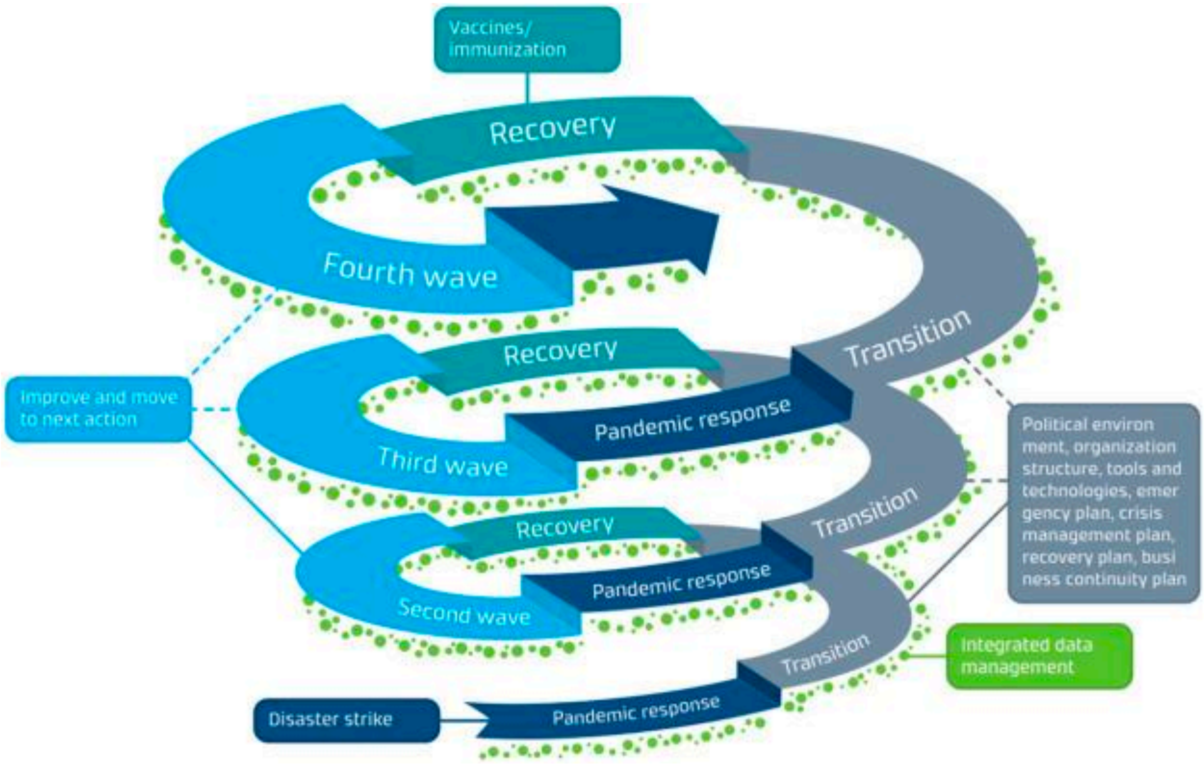
2.3.5 Influence of bikesharing during disruptions to public transport

Disruptions to a particular mode, from minor service changes to major closures, can alter the availability and preferability of the mode, and thus result in individuals changing their mode choice. Under Utility Theory, individuals will shift modes when a disruption renders the mode in question less utile than its alternatives. Looking through the lens of TPB, however, it is also important to consider how a disruption changes an individual's perception of the utility of the mode, even if the actual utility is not changed. This approach is supported by findings from a terrorist attack on the London underground, where a shift to alternative modes endured longer than the actual disruption to the subway system, due to the lasting public perception of risk (Cox et al., 2011). Bikesharing's influence on public transport as a mode choice therefore may also change during disruptions to the transport system. Saberi et al. (2018) and Fuller et al. (2019) both identify increases in bikeshare ridership during public transport strikes in London and Philidelphia, respectively, suggesting that transport riders shifted to bikesharing during the strike. In these cases, however, the disruption removed public transport from being an available mode in the first place, rather than merely lowering its utility. To the author's best knowledge, shifts to bikesharing during disruptions that significantly lower the utility of transport, without completely removing the option, have not yet been explored in the literature.

2.4 Conceptualizing the COVID-19 pandemic

Since the outbreak of the COVID-19 pandemic, significant research has been conducted to understand its impacts. There is much diversity, however, in how such research conceptualizes the pandemic. Many conceptualize the pandemic purely as a public health phenomenon and thus measure it through health indicators such as case counts (Teixiera & Lopes, 2020). Other research conceptualizes the pandemic in political terms by focusing on the impact of governmental restrictions implemented to reduce contact between members of the public (Nivette et al., 2021). Such an approach focuses narrowly on one specific aspect of the pandemic. Other researchers have attempted to capture the full breadth of the pandemic's impacts on society by conceptualizing it as an event, similar to literature on natural disasters. Such literature often analyzes the impacts temporally, looking at conditions before and after the outbreak of the pandemic, or studying the recovery from the outbreak (Wang & Noland, 2021; Kim, 2021). Other authors dispute this approach, however, as it reduces the pandemic to a one-off event. Fahkruddin et al. (2020) explain how, unlike one-off emergencies such as natural disasters, pandemics evolve in waves and thus have inherently nonlinear response and recovery phases. These authors therefore conceptualize the recovery from a pandemic as a spiral composed of distinct phases, as visualized in Figure 6. This conceptualization views the pandemic not just as a public health or political event, but as a time period marked by a set of changes to multiple aspects of society. In mobility research, Park et al. (2022) utilize phases in their evaluation of the pandemic's impacts on the relationship between the built environment and pedestrian behavior. This allows them to understand the full breadth of the pandemic's impacts on mobility and the nuanced differences between the impacts in each phase as the pandemic ebbs and flows.

Figure 2: Phased, Spiral Model of Pandemic Recovery



Source: Fahkruddin et al. (2020)

2.5 Impacts of the COVID-19 pandemic on bikesharing and subway systems

While research on the COVID-19 pandemic is still evolving due to the recent nature of the event, a considerate amount of focus in the field of mobility has been dedicated to studying the impacts of the pandemic on subway and bikesharing systems since its outbreak. These impacts have altered the availability and preferability of each system, and thus changed individuals' choice of either as a travel mode.

2.5.1 Impacts on subway systems

The COVID-19 pandemic has drastically disrupted subway systems across the globe. Specifically, literature has identified two major changes to these systems as a result of the onset of the pandemic: a significant loss of ridership due to reduced out-of-home activities and aversion to public spaces, and subsequent cuts to service due to the loss of ridership and financial woes (Abreu & Conway, 2021). More in-depth studies of the changes to subway ridership patterns reveal that the pandemic has led to a reduction in peak ridership, longer average trip distances, and a geographic shift in tripmaking away from central business districts (Halvorsen et al., 2021). In terms of which populations are still using the subway, research from New York City finds that a higher percentage of healthcare workers, essential workers, black residents, and hispanic residents, as well as a higher poverty rate in a neighborhood are all associated with greater subway ridership retention (Halvorsen et al., 2021). This suggests that public transport is still used by essential workers and marginalized communities who are likely to be captive users without other mode options. Therefore, while most of the changes to subway ridership during the pandemic are driven by the loss of commute trips, these systems remain vital to many.

2.5.2 Impacts on bikesharing systems

Existing research on the impacts of the COVID-19 pandemic on bikesharing systems has explored a variety of ways in which trip making on these systems have changed. In general, bikesharing ridership in most cities dropped at the start of the pandemic but recovered in later phases (Wang & Noland, 2021; Kubaľák et al., 2021). Furthermore, Song et al. (2022) find in Singapore that the initial easing of the lockdown in Singapore led to a boom in bikeshare ridership. Park et al. (2020) and Kim (2021) find that social distancing measures implemented at the start of the pandemic in Seoul had a positive impact on bikeshare ridership overall. Thus, the pandemic may have actually added to the ridership of many bikesharing systems in 2020. In terms of what has driven this ridership boost, Teixiera et al. (2021) find in Lisbon that avoiding public transport and social distancing have become major motivations for using bikesharing. Research on how the use of bikesharing has changed has found an increase in trip durations (Wang & Nolan, 2021; Teixiera & Lopes, 2020) and trips being made near recreation areas (Kim, 2021), suggesting greater recreational trip making. The pandemic therefore appears to have made bikesharing a more appealing option for commuters and increased the recreational use of this mode.

2.5.3 Impacts on the relationship between bikesharing and public transport systems

Due to the changing relative utility of bikesharing and public transport, some research has already begun to study the changing relationship between these modes during the COVID-19 pandemic. Much of this research has considered how this changing relationship has affected bikeshare ridership in particular. Kim (2021) finds in Seoul that being located near subway stations and bus stops is positively associated with ridership for bikeshare stations in both 2019 and 2020, but the magnitude of this association decreases in 2020. Similarly, Hu et al. (2021) find in Chicago that “regions with higher transit ridership generate more bike-sharing trips during regular periods” (p. 12), but this relationship disappears during the pandemic. These findings suggest that public transport complements bikeshare ridership under normal conditions, but the pandemic has weakened this influence. Furthermore, Li et al. (2021) find that bikeshare stations near rail stations in London lost more ridership during the initial pandemic lockdown than the general trend. In each of these cases, it appears as though the loss of commuters who would previously connect bikesharing and public transport trips has reduced the complementary relationship between these modes. However, Hu et al. (2021) find that bikeshare stations in areas with traditionally high transit ridership actually retain more bikeshare ridership during the initial onset of the pandemic. The authors attribute this to public transport passengers shifting to bikesharing as a more socially distanced mode. Therefore, while this research remains limited and contains some disagreement, it has thus far identified two main ways in which the pandemic has impacted the relationship between bikesharing and public transport systems. First, the overall loss of commute trips has reduced the number of trips connecting bikeshare and public transport. The accessibility benefits of bikesharing therefore may be of less importance in the context of the pandemic. Secondly, the higher fear of infection on public transport has increased the number of substitutive trips being made on bikeshare.

These existing studies have explored how the COVID-19 pandemic has moderated the influence of the presence of public transport on bikeshare ridership. Less explored in the literature is how the pandemic has moderated the influence of the presence of bikesharing on public transport ridership. To the author's best knowledge, Teixiera & Lopes (2020) is the closest study of this kind. These authors calculate the ratio of subway ridership to bikeshare ridership in New York City and find that an increase in COVID cases is associated with a decrease in the ridership ratio, indicating greater loss of subway ridership than bikeshare ridership. More interestingly, the authors also find a stronger negative association between COVID cases and the ridership ratio when only considering bikeshare stations within subway station catchment areas. While these findings only demonstrate that COVID-19 has impacted subway ridership relatively more than bikeshare ridership, the fact that this impact is stronger in station areas suggests that the pandemic may have led to a more negative association between the presence of bikeshare facilities and subway station ridership. Further research is therefore necessary to study this association directly and assess if this hypothesis is valid. In addition, this study only considers the initial impacts of the pandemic, so it is necessary to update this research with data from later phases of the pandemic to understand the longevity of these effects.

2.6 Conclusion

According to the relevant literature, an individual's mode choice is dependent first on the availability of modes, and secondly on the preferability of the available modes. By locating bikesharing facilities at public transport stations, planners increase the accessibility of such stations, thus allowing more individuals to consider public transport as an available mode. However, they also make bikesharing a more available mode for public transport riders to consider as an alternative. Whether the presence of bikesharing facilities positively or negatively influences public transport station ridership is therefore disputed in the literature and existing studies have found competing results. Some clarity has been found by accounting for differences in density within urban contexts, as bikesharing appears to have a more positive influence in peripheral areas and a more negative influence in urban areas. Such findings have not yet been tested in other cities, however, so further research is necessary to inform planners on the validity of such effects.

Initial research during the COVID-19 pandemic suggests that the accessibility benefits of bikesharing to public transport systems may be of less importance in this context, and that travelers may be replacing more public transport trips with bikesharing trips than they had prior to the outbreak. Based on these findings, it may be the case that the presence of bikesharing at public transport stations has a more negative influence on transport ridership during the pandemic. However, such a hypothesis has yet to be fully tested in the literature thus far. In addition, studies on the relationship between bikesharing and public transport systems during the COVID-19 pandemic are largely focused on the pandemic's outbreak. Further research that considers this relationship throughout the multiple phases of the pandemic is therefore necessary to understand the full breadth and longevity of the pandemic's impacts on these systems.

3: Research design and methodology

3.1 Introduction

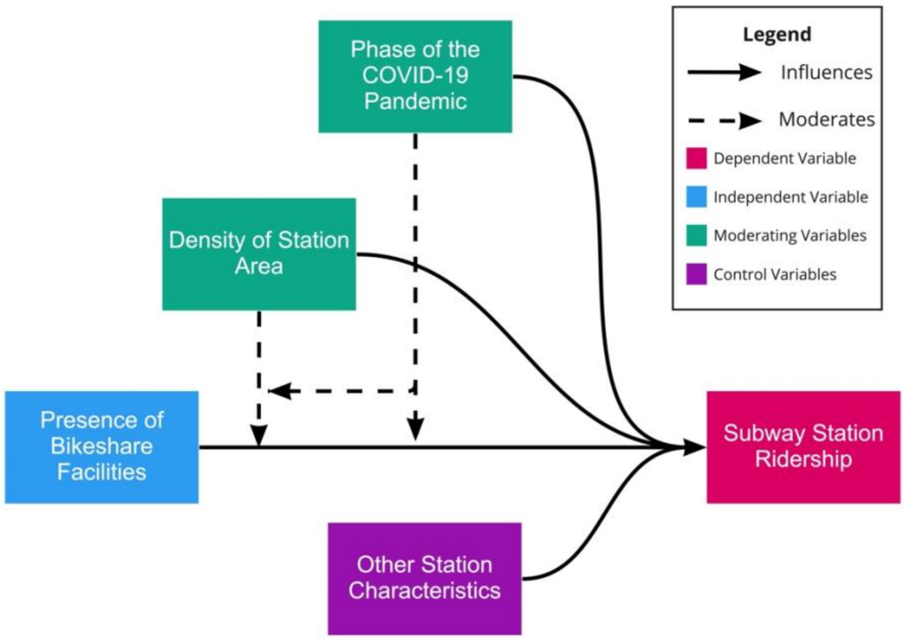
This chapter explains and justifies the chosen design and methodology for this research. It begins with a conceptual framework which links the various concepts of this research and guides the research design. Based on the literature review and conceptual framework, a set of hypotheses are formed to be tested in answering the research questions. The following sections describe the chosen research approach, the analysis methods, and the operationalization of the concepts from the conceptual framework. The chapter concludes with expected challenges and limitations within this research design.

3.2 Conceptual framework

Figure 3 depicts the conceptual framework for this research. Based on the literature review conducted in Chapter 2, this framework illustrates the expected relationships between the relevant concepts in this research. It is established in the literature that the presence of bikeshare facilities is associated with subway station ridership. In addition to influencing station ridership, it is hypothesized that the density of the station area moderates the association between the presence of bikeshare facilities and subway station ridership. Finally, while it is well established that the phase of the COVID-19 pandemic influences subway ridership, it is also hypothesized that the phase of the pandemic moderates the association between the bikesharing and station ridership, as well as the moderating effect of density.

This research is particularly interested in the magnitude and polarity of the relationship between the presence of bikesharing facilities and subway station ridership, as well the magnitude and polarity of the moderating effects of the station area density and the pandemic phase. The subway ridership at a station is also influenced by a number of other station characteristics outside of the ones studied in this research (Ma et al., 2019). While the particular influence of these characteristics on station ridership is not of interest in this research, they are considered here as factors for which this research must control in order to isolate the relationships of interest.

Figure 3: Conceptual framework



3.3 Hypotheses

Based on the relevant literature, this research tests the following hypotheses:

1. Prior to the pandemic, the presence of bikeshare facilities is positively associated with subway ridership at MBTA stations;
2. Prior to the pandemic, the association between bikeshare facilities and subway ridership at MBTA stations is negatively moderated by the density of the station area;
3. During the pandemic, the association between bikeshare facilities and subway ridership at MBTA stations becomes negative, but the magnitude of this negative association decreases during phases when pandemic restrictions are eased;
4. During the pandemic, the moderating effect of station area density disappears but returns to a lesser extent during phases when pandemic restrictions are eased.

Hypotheses 1 and 3 are based on the findings of Hu et al. (2021), who, as discussed in the previous chapter, studied the relationship between bikesharing and subway ridership during the pandemic in the similar case city of Chicago. Hypothesis 3 is also informed by the loss of commute trips and fear of infection identified in the literature, both of which likely cause a negative association between bikesharing and subway ridership. However, it is assumed that during phases when pandemic restrictions are eased, some commute trips return and the public's fear of infection is lowered, reducing the magnitude of the negative association. Hypothesis 2 is based on the findings of Ma and Knapp (2019) and Martin and Shaheen (2014). Finally, Hypothesis 4 is based on the loss of trips to central business districts identified in the literature, and the assumption that such trips return to an extent during phases of reduced restrictions.

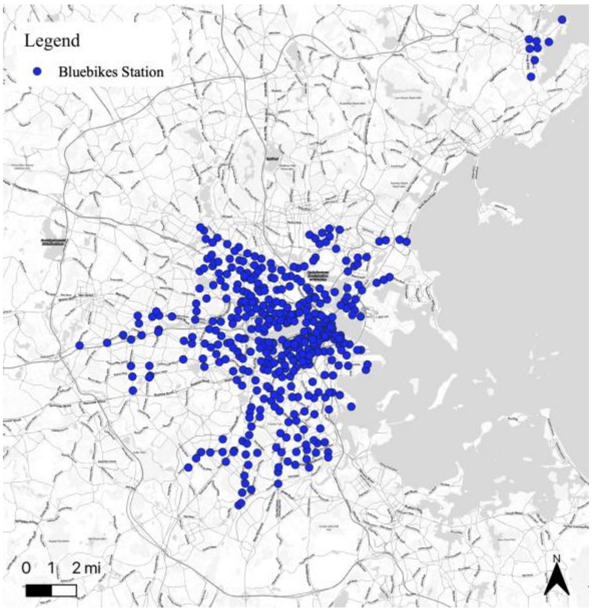
3.4 Description of the research design and methods

This research is conducted through the analysis of a case study. While a cross-city comparison may yield more generalizable results, the different timelines of the impacts of and responses to the pandemic in each city hinder such comparisons. Boston is selected as the case, as it is a city that has been gradually expanding its bikesharing network and thus could use the results of this research to inform the planning of such expansions. In addition, despite having robust bikesharing and public transport systems, Boston has not yet been studied in the existing literature on the relationship between bikesharing facilities and public transport ridership. Thus, it is also a prime case to test the generalizability of findings of other similar cities in North America. Therefore, while the findings of this study primarily inform planning in the Boston context, they also progress the larger body of knowledge on this topic and can thus support planning efforts in similar cities.

3.4.1 Case study background

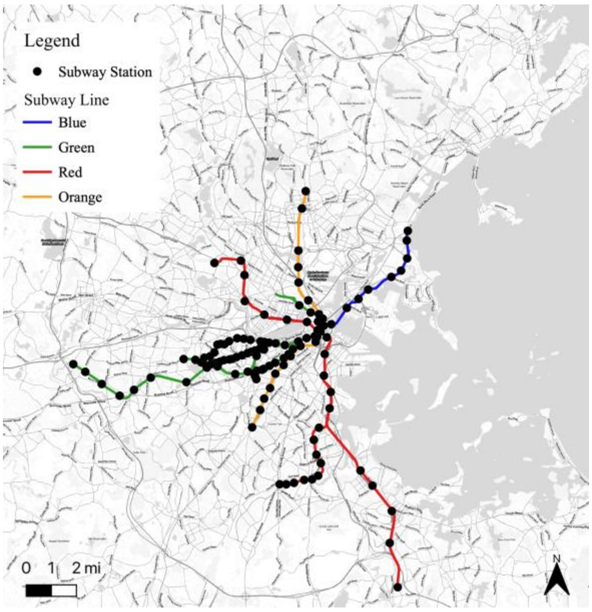
The capital and largest city of Massachusetts, Boston has a population of over 675,000, as of 2020 (U.S. Census Bureau, n.d.). Boston's bikeshare program is known as "Bluebikes" and provides over 4,000 bikes at over 400 docking stations across metro Boston (Bluebikes, n.d.-a). Figure 1 displays the distribution of Bluebikes docking stations throughout greater Boston, as of May 2022. These stations are often located at major points of interest in the city, including at many subway stations. Boston's public transport system is known as the Massachusetts Bay Transportation Authority (MBTA) and provides subway, bus, commuter rail, ferry, and paratransit service to eastern Massachusetts and parts of Rhode Island (Massachusetts Bay Transportation Authority [MBTA], n.d.-d). The MBTA's subway service includes 128 stations connected by 3 heavy rail lines (Red, Orange, Blue) and 1 light rail line (Green) (MBTA, n.d.-a). It served more than 700,000 subway trips on an average weekday in Fall 2019 (MBTA, n.d.-c). Figure 2 depicts the locations of MBTA subway lines & stations prior to the extension of the Green Line in March 2022.

Figure 4: Bluebikes Stations as of May 2022



Source: Author, data from Bluebikes (n.d.-c)

Figure 5: MBTA Subway Lines and Stations as of February 2022



Source: Author, data from MBTA (n.d.-b)

3.4.2 Case study analysis methods

This case is analyzed through a statistical analysis of secondary datasets. This method was chosen due to the wealth of available data at a granular level over an extended period of time, allowing for the study of subway ridership at a station level through the entirety of the study period. Using surveys or interviews may provide more information on the reasoning behind individuals' bikesharing and public transport mode choices, which may be used to establish causality between the variables. However, such approaches would rely on self-reported travel behavior or intentions, which is less accurate as individual's intentions do not always match their behavior (Sekhar, 2014), and respondents may suffer from recall bias (Brassley & Mahtani, 2017). Recall bias is an especially significant concern in this study, since it requires information on travel behavior prior to and throughout the pandemic, which is a significant span of time. A quantitative analysis of existing datasets, on the other hand, allows for directly measuring the association of the independent variables with a more accurate measure of subway ridership.

3.4.2.1 Pre-Pandemic Association

This research specifically utilizes a series of ordinary least squares (OLS) regression models. To answer the first research sub-question, the first OLS model is conducted based on a pre-pandemic time period and models station ridership using the number of bikeshare docks as the explanatory variable. The coefficient for the presence of bikeshare facilities in this model can then be interpreted as the association between this variable and subway ridership at an average station. This method is based on that of Ma and Knapp (2019), Ma et al. (2015), and Campbell and Brakewood (2017). To account for possible omitted variable bias (OVB), several station area characteristics are tested as other possible influences of station ridership that may be correlated with the number of bikeshare docks. The variables that are correlated with the number of Bluebikes docks and have a statistically significant relationship with the dependent variable are added to the model. As many variables are added to the model as are necessary to account for OVB without diminishing the accuracy of the model. This model can be understood as Equation 1, where $E_0(Y)$ is a station's expected pre-pandemic subway ridership; β_1 is the expected change in ridership for a one unit change in the number of bikeshare docks; X_1 is the number of bikeshare docks at the station; and β_0 is the constant, or the expected ridership if all of the explanatory variables in the model are equal to 0. In this case, X_2 represents a relevant station area variable and β_2 represents the slope for that variable. The equation is not finite as multiple station area variables may be added, depending on their relevance.

Equation 1: Basic Expected Station Ridership Model

$$E_0(Y) = \beta_0 + \beta_1*X_1 + \beta_2*X_2 + \ldots$$

3.4.2.2 Moderating Effect of Station Area Density

To answer the second research sub-question, this research runs another OLS model using the number of bikeshare docks, station area density, and an interaction term between the two as explanatory variables for pre-pandemic subway ridership. Similar to the methods of Park et al. (2022), the significance, direction, and magnitude of the interaction term is then evaluated to understand the moderating effect of station area density. This model can be understood with Equation 2, where X_2 is now the station area density and β_3 is the interaction term between the number of bikeshare docks and station area density.

Equation 2: Expected Station Ridership Model Based on the Interaction of Station Area Density

$$E_0(Y) = \beta_0 + \beta_1*X_1 + \beta_2*X_2 + \beta_3*X_1*X_2$$

To again account for possible OVB, other station characteristic variables are tested and those that are found to compete with the model for the explanation of station ridership are added. This is represented in Equation 3, where X_4 is a relevant station characteristic and β_4 is its appropriate slope. The resulting fitted model should provide the most accurate measures of β_1 and β_3, or the predicted influence of bikesharing and the predicted moderating effect of station area density, respectively.

Equation 3: Expected Station Ridership Model Based on the Interaction of Station Area Density, Fitted

$$E_0(Y) = \beta_0 + \beta_1*X_1 + \beta_2*X_2 + \beta_3*X_1*X_2 + \beta_4*X_4 + \ldots$$

3.4.2.3 Moderating Effect of Pandemic Phases

To answer the third research sub-question, the model in Equation 3 is repeated using data for each phase of the pandemic. The extent to which β_1 and β_3 change in each phase illuminates how the pandemic has moderated the influence of bikesharing and the interaction between station area density and bikeshare facilities. These models can be understood through Equation 4, in which n is equal to the phase of the pandemic.

Equation 4: Fitted Expected Station Ridership Model, Based on n Phase of the Pandemic

$$E_n(Y) = \beta_0 + \beta_1*X_1 + \beta_2*X_2 + \beta_3*X_1*X_2 + \beta_4*X_4 + \ldots$$

3.5 Operationalization

In order to study the concepts of this research within the context of Boston, these concepts are operationalized into a set of variables with relevant indicators. These variables and indicators, along with the secondary data source from which the indicator is collected, are detailed in Table 1. The following sections detail why the particular variables and indicators were chosen for each concept, and how they are calculated using their relevant data source.

Table 1: Operationalization of Variables

Concept	Variable(s)	Indicator	Data Source
Subway Ridership	Station-level subway ridership	Average weekday entries at gated subway stations	MBTA Open Data Portal
Bikeshare Facilities	Presence of bikeshare facilities at subway stations	Number of Bluebike docks within ¼ mile of each station	Bluebikes Station Data
Station Area Density	Population Density	Population within ½ mile of station	American Community Survey
	Employment Density	Number of jobs within ½ mile of station	Longitudinal Employer Household Dynamics Survey
COVID-19 Pandemic	Phase of COVID-19 Pandemic	Phase of the COVID-19 pandemic in Boston	MassDOT Mobility Dashboard
Station Area Characteristics	Presence of Medical Jobs	Number of medical jobs within ½ mile of station	Longitudinal Employer Household Dynamics Survey
	Presence of Educational Jobs	Number of educational jobs within ½ mile of station	Longitudinal Employer Household Dynamics Survey
	Transit Criticality	Sum of % of population within ½ mile of station that is low-income, % that is people of color, and % that is from limited- vehicle households	American Community Survey
	Availability of Bus Routes	Number of bus routes within ¼ mile of station	MBTA Open Data Portal

3.5.1 Subway Ridership

Station-level subway ridership is measured through the average weekday entries at gated subway stations. “Entries” is the number of passengers who tap into a station at a fare gate. This metric therefore does not include passengers who evade paying the fare or instances where fare gates are left open, but these phenomena are infrequent enough that ridership can still be adequately measured without accounting for them. Entries can only be measured at stations with fare gates, meaning such data is unavailable at stations where riders tap on the vehicle itself, such as most Green Line stops. Such stations are therefore excluded from this analysis. This research uses station entries for an average weekday as this is a standard ridership measure in public transport research (Ma et al., 2019).

Gated station entries are posted publicly on the MBTA open data portal and is currently available through October 2021(MBTA, n.d.-b). This data is provided for every half hour on every service date, dating back to 2014. Using R, this research first filters the data to weekdays in the study period (January 2019 to October 2021) and aggregates to total daily entries at each station. Dates are then assigned to the appropriate phase of the pandemic or the baseline period, and weekday entries are averaged across the phase for each station. This results in the average weekday entries at each station for each phase of the pandemic. Two stations, Courthouse and World Trade Center, are removed from the data, as these are stations for the MBTA's bus rapid transit system, rather than the subway system. The stations of Lechmere and Science Park were closed from May 24, 2020 onwards due to construction of the Green Line Extension (*Lechmere Viaduct and Charles River Dam Road*, n.d.), so there is no entry data for these stations beginning in Phase 3. These stations are therefore excluded from the analyses in these phases.

3.5.2 Bikeshare Facilities

The presence of bikeshare facilities is measured through the number of Bluebike docks within ¼ mile of the subway station. This is based on the measure of Campbell and Brakewood (2017) who quantify the presence of bikeshare facilities along a bus route as the number of bikeshare docks within a ¼ mile catchment area of the route. ¼ mile is generally regarded within mobility research as the distance passengers are willing to walk to reach public transport (Campbell and Brakewood, 2017; Ma et al., 2019; Ma & Knapp, 2019). The number of bikeshare docks is chosen as a measure over a binary measure of whether or not a bikeshare station is present, such as that used by Ma and Knapp (2019), in order to account for subway stations with multiple bikeshare stations in their catchment area, as well as the diversity of bikeshare station sizes. Since Bluebikes stations were added throughout the study period, this measure may differ over time and thus must be calculated for each phase of the pandemic. However, the available data only contains the year of deployment, thus this measure cannot be calculated at a more granular time period than per year. For the number of docks in each phase, this research therefore uses the number of docks present at the conclusion of the prior year. For example, when analyzing a phase of the pandemic in 2020, only the Bluebikes stations implemented prior to and including 2019 are considered. This results in a slight underestimate in the number of docks in instances where more stations were deployed between the conclusion on the prior year and the phase being considered. However, this is favored to an overestimate caused by the inclusion of stations that have not yet been deployed.

The location of each Bluebikes station, as well the number of docks and year of deployment of each station is publicly available in a data file on their website (Bluebikes, n.d.-b). The location of each MBTA subway station is also available in a shapefile on the Open Data Portal (MBTA, n.d.-b). To identify the number of Bluebikes docks within the catchment area of each subway station in each year, a GIS analysis is conducted. First, Bluebikes stations are filtered to only those deployed prior to, and including, 2018. Subway stations are then buffered by ¼ mile to create the catchment area. Finally, the count points function, weighted by the number of docks at each Bluebikes station, provides the sum of Bluebikes docks within the catchment area of each MBTA station in 2018. This process is then repeated for 2019 and 2020.

3.5.3 Station Area Density

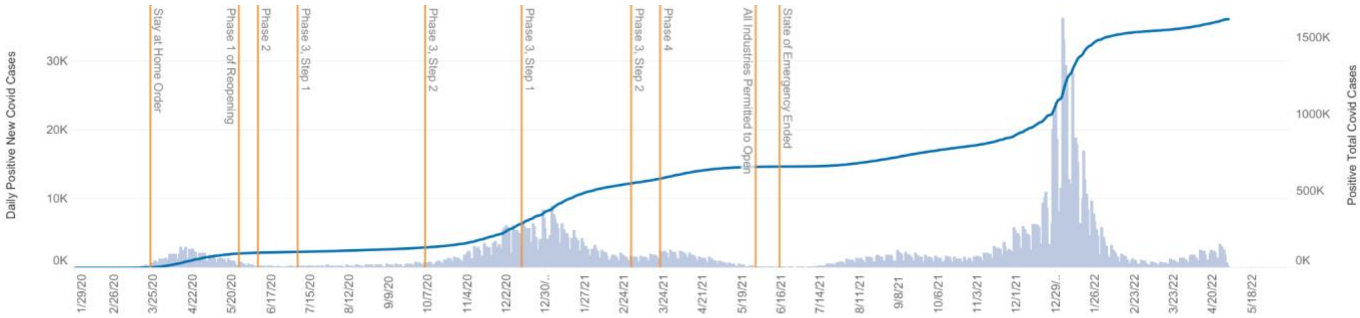
Station area density is evaluated through two variables: population density and employment density. The station area is defined as the area covered by a half-mile radius around the station. Population density is therefore calculated as the total population living within this half-mile radius. Employment density is calculated as the total number of jobs within the half-mile radius. The data for these measures is sourced from the Longitudinal Employer-Household Dynamics (LEHD) database and American Community Survey (ACS), both provided by the United States Census Bureau. While this data is publicly available, the calculated measures for each station was provided to this research by the MBTA.

3.5.4 COVID-19 Pandemic

This research operationalizes the COVID-19 Pandemic as a set of phases marked by changing government policies. The impact of the pandemic is therefore measured by evaluating the changes that occur during each of these phases. This is similar to the operationalization of Park et al. (2022) who argue that delineating the pandemic in this way is "intended to measure the effects of government policies and travel restrictions as well as the public's perceptions of and reactions to rising COVID-19 case counts, test positivity rates, hospitalizations, death counts, and so forth" (Park et al., 2022, p. 5). This operationalization therefore allows for measuring the impact of the pandemic as a wide set of changes in society, rather than just as the presence of disease or government restrictions. In addition, using multiple phases over time allows for understanding the changing impacts of the pandemic over time, rather than just the impacts of the initial outbreak.

The COVID-19 pandemic began to impact Massachusetts in mid-March 2020. As seen in Figure 6, an outbreak of cases led the state government to issue a Stay at Home Order on March 23rd. Throughout 2020 and 2021, the state eased restrictions in phases based on the perceived risk level of the pandemic, except for on the 13th of December, when it temporarily reinstated restrictions due to rising case numbers.

Figure 6: Daily New and Total Positive COVID-19 Cases and Restriction Changes in Massachusetts



Source: MassDOT (n.d.)

Based on milestone changes to pandemic-related restrictions set by the state government, this research uses the following phases of the pandemic in Boston:

Phase 1 ("State of Emergency"): 10 March 2020 - 23 March 2020
Phase 2 ("Lockdown"): 23 March 2020 – 25 May 2020
Phase 3 ("Initial Easing"): 25 May 2020 – 6 July 2020
Phase 4 ("First Summer"): 6 July 2020 – 5 October 2020
Phase 5 ("Fall Surge"): 5 October 2020 – 13 December 2020
Phase 6 ("Reversal of Easing"): 13 December 2020 – 22 March 2021
Phase 7 ("New Normal"): 22 March 2021 – 29 May 2021
Phase 8 ("End of Restrictions"): 29 May 2021 – 31 October 2021

Phases 1-4 encapsulate the first rise and fall of case counts, or the first peak, and Phases 5-8 encapsulate the second.

3.5.5 Station Area Characteristics

To control for other influences of subway ridership at MBTA stations which may be correlated with the presence of bikeshare facilities, a set of station area characteristics are included in this research. These characteristics were chosen based on the relevant station characteristic variables used in a similar methodology by Ma et al. (2019), as well as the significant factors identified in an analysis done by the MBTA to understand which station characteristics best predict pandemic-era ridership (Meakin, 2021). While this analysis is not peer-reviewed, there is currently no peer-reviewed study of subway ridership during the pandemic in Boston.

The selected characteristics are: the number of educational jobs, number of medical jobs, transit criticality, and number of bus routes. The station area is again defined as half a mile, as with the station area density measures. The exception to this is the number of bus routes measure, which only considers those within a quarter mile, as the goal of this measure is to identify bus routes in close proximity with the station, not just within the area. Transit criticality, as defined by Meakin (2021), is measured as a sum of the percentage of the station area population that is low-income, the percent that is people of color, and the percent that is from households with limited vehicle access. The scale of this index is therefore 0 to 3, with 3 representing 100% of the population being low-income, 100% being people of color, and 100% being from limited-vehicle households. These demographics are the most likely to be transit captive users, and combining these measures into a single index allows for measuring their impact while avoiding the statistical complications from their high correlation. The data for these measures is sourced from the LEHD and ACS databases, but were calculated for each station by the MBTA and provided to this research.

3.6 Expected challenges and limitations

The largest limitation to this research is the inability to identify causality. While every effort is made to control for outside factors and isolate the influence of bikeshare facilities, this research can only identify associations between bikeshare facilities and subway ridership. A major reason for this is the likely presence of endogeneity between the variables. Just as the number of bikeshare docks influences the subway ridership at a station, the subway ridership at a station may influence the decision of how many bikeshare docks to place at the station. The conclusions of this research therefore are limited to the association between the presence of bikesharing facilities and subway station ridership, rather than the influence of the former on the latter. As mentioned earlier, the chosen research design also limits the possible conclusions of this research. By using a case study, findings are limited to the context of Boston. In addition, by only using ridership data and not surveys, this research can only identify travel trends, not the motives behind those trends.

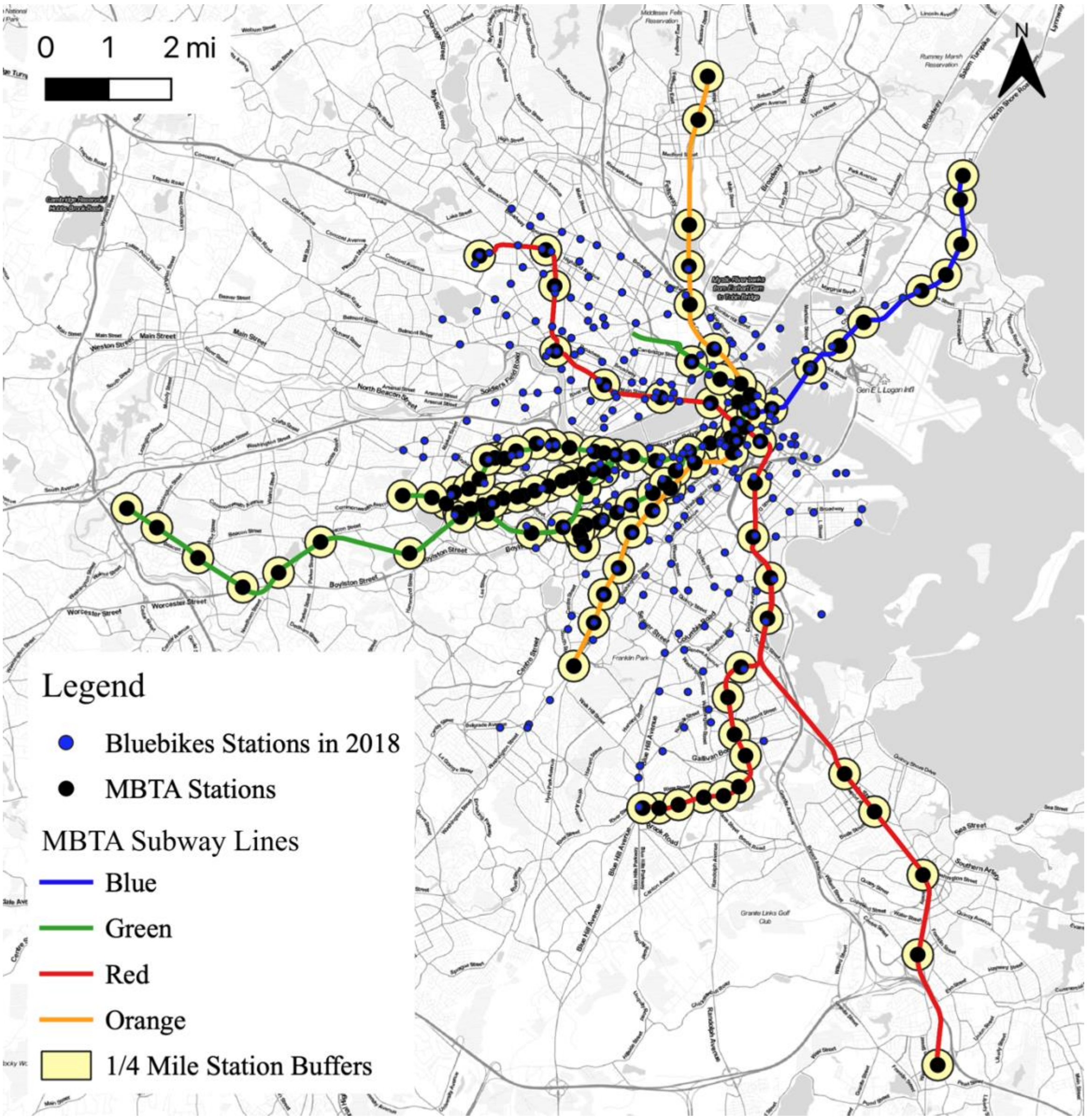
4: Results, analysis, and discussion

4.1 Descriptive Statistics

4.1.1 Number of Bluebikes Docks

The overlay of Bluebikes stations as of 2018 and MBTA station catchment areas is visualized in Figure 7. Of the 62 gated MBTA stations, 44 had at least one Bluebikes station within ¼ mile at the end of 2018. By the end of 2019, this number had gone up to 47 and remained constant through 2020. The number of docks at many stations increased throughout these three years, as seen in the descriptive statistics in Table 2.

Figure 7: MBTA subway station catchment areas and Bluebikes stations as of 2018



Source: Author, data from Bluebikes (n.d.-c) and MBTA (n.d.-b)

Table 2: Descriptive Statistics of Number of Bluebikes Docks

Variable	Mean	Std. Dev.	Minimum	Maximum
Number of Bluebikes Docks (2018)	33.35	32.50	0	118
Number of Bluebikes Docks (2019)	38.98	35.70	0	122
Number of Bluebikes Docks (2020)	41.85	40.37	0	191

Note: Number of observations is 62

4.1.2 Station Area Characteristics

The population, total jobs, education jobs, and medical jobs indicators were all calculated in thousands in order to make the numbers a reasonable scale. The population and employment densities of MBTA station areas are significantly spread, meaning there is sufficient variety to test for different effects at stations with different levels of surrounding density. Of note in the control variables is that the maximum transit criticality score for a station is 1.89, meaning no station scored a 2 or higher in this measure, where the highest possible rating is 3.

Table 3: Descriptive Statistics of Station Area Characteristics

Variable	Mean	Std. Dev.	Minimum	Maximum
Population (in thousands)	15.18	7.67	1.51	34.51
Total Jobs (in thousands)	38.14	46.63	0.72	147.78
Education Jobs (in thousands)	2.17	3.44	0.00	17.62
Medical Jobs (in thousands)	4.48	7.31	0.05	29.92
Number of Bus Routes	6.82	4.53	0	19
Transit Criticality Index	1.25	0.29	0.56	1.89

Note: Number of observations is 62

The correlation between the independent variables is found in Table 5. The number of Bluebikes docks at each station in 2018 is moderately correlated with the number of education jobs and medical jobs, as well as the population, in the station area. The number of docks is also heavily correlated with the total jobs in the station area. This analysis therefore must be cognizant of the influence of these variables obscuring that of the number of Bluebikes docks.

Table 4: Correlation of Independent Variables

	Bluebikes Docks (2018)	Total Jobs	Education Jobs	Medical Jobs	Population	Bus Routes	Transit Criticality
Bluebikes Docks (2018)	1.0000						
Total Jobs	0.7012	1.0000					
Education Jobs	0.3102	0.3106	1.0000				
Medical Jobs	0.4430	0.5806	0.1210	1.0000			
Population	0.4561	0.5096	0.4156	0.3175	1.0000		
Bus Routes	0.1261	0.3016	0.3675	0.0978	0.1385	1.0000	
Transit Criticality	-0.1361	-0.1096	0.3089	-0.1407	0.2499	0.1065	1.0000

4.1.3 Average Weekday Subway Station Ridership

Table 4 shows how average weekday subway ridership at MBTA stations changed greatly throughout the phases of the COVID-19 pandemic. Prior to the pandemic, the average MBTA station saw almost 7,500 subway passengers on a typical weekday. The deviation among stations is also quite large in this period, as the standard deviation is 5,118. As the effects of the pandemic began to set in during Phase 1, the mean of average weekday ridership across stations already began to drop, before hitting its lowest point in Phase 2 ("Lockdown") at only 674 passengers. In this phase, the station with the least average ridership saw only 41 passengers on an average weekday. Also of note, the deviation of ridership across stations also shrank in this time period. In Phases 3 through 8, average weekday subway station ridership slowly increased, along with the deviation across stations, but neither came close to returning to pre-pandemic levels.

Table 5: Descriptive Statistics of Average Weekday Subway Station Ridership in Each Phase of the COVID-19 Pandemic

Variable	Observations	Mean	Std. Dev.	Minimum	Maximum
Pre-Pandemic (Baseline)	62	7,496.73	5,118.31	674.01	23,621.96
Phase 1	62	3,448.27	2,095.08	202.11	10,094.00
Phase 2	62	674.23	415.89	41.18	1,823.04
Phase 3	60	1,128.77	682.08	92.03	2,755.53
Phase 4	60	1,820.63	1,053.19	234.38	4,784.46
Phase 5	60	1,902.00	1,110.13	283.74	5,087.76
Phase 6	60	2,237.86	1,304.99	304.40	6,144.77
Phase 7	60	2,293.77	1,329.84	262.86	6,135.86
Phase 8	60	3,889.02	2,242.84	314.05	9,730.90

Note: The number of observations falls in Phase 3 due to the closure of Lechmere and Science Park stations.

4.2 Pre-Pandemic Association

This research first endeavors to test the extent to which the presence of bikeshare facilities is associated with subway ridership at MBTA stations prior to the pandemic. Table 4 displays the results of a simple regression between these variables in the pre-pandemic period. These results indicate that, in the baseline period, for each additional Bluebikes dock at an MBTA station, the average weekday ridership at that station is expected to increase by about 64 riders. This relationship is also statistically significant at the 99% confidence level, so we can reject the null hypothesis that there is no association between these variables. However, the R-squared of this model is only 0.16, indicating that only 16% of the variation in average weekday ridership across stations can be attributed to differences in the number of Bluebikes docks. Thus, this is not a very strong relationship.

Table 6: Simple Regression, Baseline Period

	Coefficient	Std. Error	P>t
Number of Bluebikes Docks	**63.71**	**18.59**	**0.001**
Constant	5,371.73	862.50	0.000

Note: R-squared= 0.16, significant variables are bolded

After a series of test models, the total jobs and number of bus routes variables are the only other variables in this study found to have a statistically significant relationship with pre-pandemic station ridership. The extent to which these variables compete with the number of Bluebikes docks for the explanation of station ridership is then tested to account for possible OVB in this model.

Table 7 depicts the results of including total jobs in the model. The inclusion of total jobs reduces the coefficient for Bluebikes docks by almost half, suggesting that most of the variation attributed to the number of docks in the model in Table 6 is actually attributable to total jobs. However, the inclusion of total jobs causes both of the variables to become insignificant at all confidence levels. This is likely due to the high correlation between these two variables, causing imperfect multicollinearity and disturbing the estimation of these coefficients. The minimal increase in the R-squared value from the previous model to this one also demonstrates how the same variation in station ridership is being attributed to both of these variables. Thus, further analysis is necessary to disentangle the effects of these two variables.

Table 7: Regression Including Number of Bluebikes Docks and Total Jobs in Station Area, Baseline Period

	Coefficient	Std. Error	P>t
Number of Bluebikes Docks	34.36	25.73	0.187
Total Jobs (in thousands)	29.18	17.93	0.109
Constant	5,238.05	854.87	0.000

Note: Adjusted R-squared = 0.17, significant variables are bolded

Table 8 depicts the results of adding the number of bus routes to the model. First, the substantial increase in the R-squared value suggests that the number of bus routes at a station accounts for a large portion of the variation in ridership across stations. Interestingly, despite only being moderately correlated with total jobs (R=0.30), including bus routes in this model greatly diminishes the coefficient and significance of the total jobs variable. This suggests that much of the variation in station ridership that had been previously attributed to total jobs is actually attributable to the number of bus routes. The coefficient for the number of Bluebikes docks, on the other hand, actually increases and becomes significant at the 90% confidence level, though still insignificant at the 95% confidence level. Accounting for the number of bus routes at a station is therefore able to disentangle some of the overlapping effects of the number of Bluebikes docks and the total jobs in the station area. However, the coefficient for the number of Bluebikes docks is still slightly lower than that in the simple regression in Table 6, indicating that some of the variation in station ridership attributed to Bluebikes docks in that model is actually attributable to the number of bus routes. Based on this model, it is still not possible to reject the null hypothesis that there is no relationship between the number of Bluebikes docks and subway station ridership in the pre-pandemic period.

Table 8: Regression Including Number of Bluebikes Docks, Total Jobs, and Number of Bus Routes, Baseline Period

	Coefficient	Std. Error	P>t
Number of Bluebikes Docks	46.10	23.10	0.051
Total Jobs (in thousands)	8.75	16.76	0.604
Number of Bus Routes	**501.62**	**124.09**	**0.000**
Constant	2,202.96	1,069.44	0.044

Note: Adjusted R-squared = 0.34, significant variables are bolded

4.3 Moderating Effect of Station Area Density

The second objective of this research is to test the extent to which station area density moderates the association between the presence of bikesharing facilities and subway station ridership. This research tests the moderating effect of both population and employment density.

4.3.1 Population Density

Table 9 shows the results of including an interaction term for the number of docks and station area population in a regression of pre-pandemic station ridership. The coefficient for station area population, as well as the interaction term between these variables, are not statistically significant at any confidence level. Thus, we cannot reject the null hypothesis that population density does not moderate the relationship between Bluebikes docks and subway ridership.

Table 9: Regression Including Interaction Term for Bluebikes Docks and Station Area Population, Baseline Period

	Coefficient	Std. Error	P>t
Number of Bluebikes Docks	**127.47**	**54.93**	**0.024**
Population (in thousands)	100.91	124.58	0.421
Number of Docks * Population	-4.09	3.30	0.220
Constant	4,111.38	958.74	0.000

Note: Adjusted R-squared = 0.14, significant variables are bolded

4.3.2 Employment Density

Table 10 shows the results of including an interaction term for the number of docks and total station area jobs in a regression of pre-pandemic station ridership. Noticeably, all of the coefficients in this model are statistically significant at least at the 95% confidence level. We can therefore reject the null hypothesis that employment density does not have a moderating effect on the association between Bluebikes facilities and subway ridership. The coefficients in this model indicate that for each additional Bluebikes dock at an MBTA station, the predicted pre-pandemic average weekday subway ridership at that station increases by about 81 passengers, holding all other factors constant. However, the negative interaction term indicates that as the total jobs in the station area increases, this positive association between Bluebikes docks and subway ridership diminishes.

Table 10: Regression Including Interaction Term for Bluebikes Docks and Total Jobs in Station Area, Baseline Period

	Coefficient	Std. Error	P>t
Number of Bluebikes Docks	**80.97**	**32.01**	**0.014**
Total Jobs (in thousands)	**91.89**	**32.22**	**0.006**
Number of Docks * Total Jobs	**-1.22**	**0.53**	**0.025**
Constant	4,111.38	958.74	0.000

Note: Adjusted R-squared = 0.21, significant variables are bolded

The significance of this model also suggests that including an interaction term is able to disentangle some of the overlapping effects of these variables from the model in Table 7. In addition, the much larger coefficients for both variables in this model suggest that excluding the interaction term resulted in an underestimate of the association between these variables and subway station ridership. Finally, the higher adjusted R-squared in this model confirms that adding an interaction term results in a better fitting model.

The interaction effect can be better understood by examining how the association between the number of docks and subway ridership differs at different levels of employment density. Table 11 depicts the coefficient for the number of Bluebikes docks when the total station area jobs are equal to 720, 38,140, and 84,760, representing the minimum, mean, and one standard deviation above the mean. The minimum was used instead of one standard deviation below the mean, as one standard deviation below the mean is lower than the minimum and thus is not a practical benchmark. This first demonstrates how the number of Bluebikes docks has a positive relationship with subway ridership at stations with low numbers of jobs in the surrounding area. Secondly, as the number of jobs in the station area increases, this association between Bluebikes docks and subway ridership actually becomes negative and insignificant.

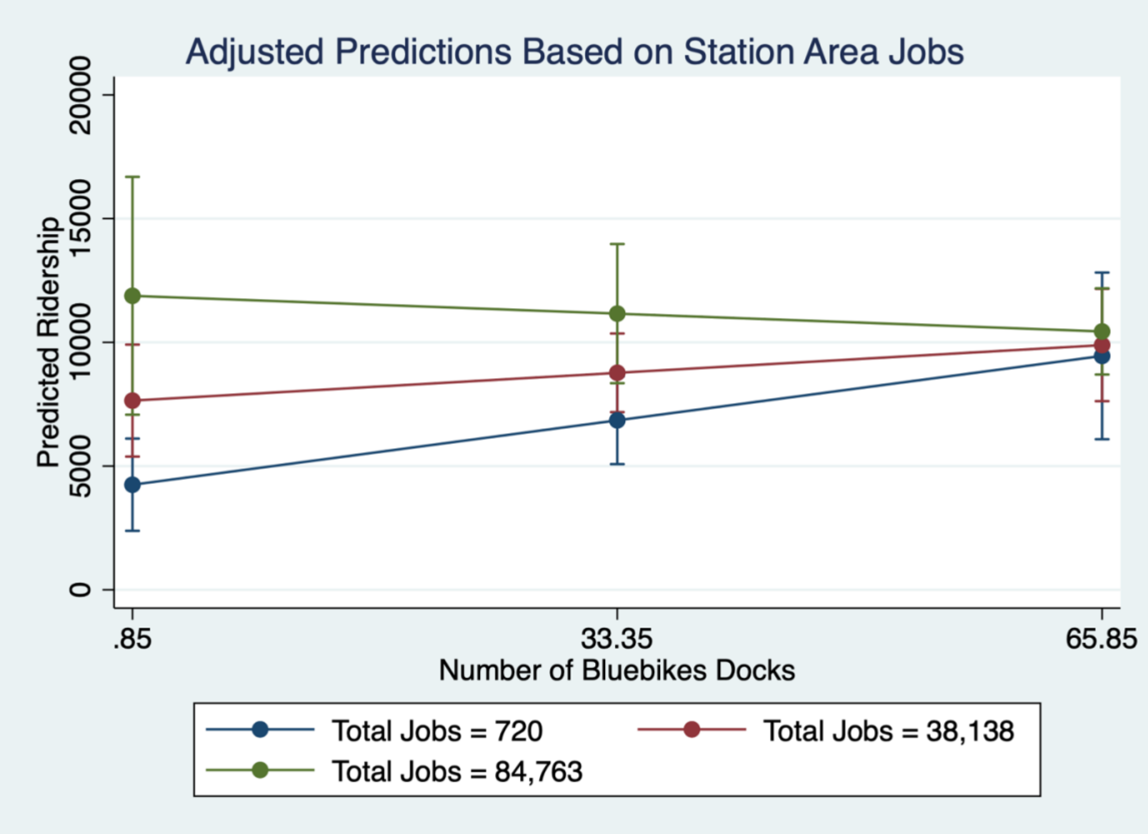
Table 11: Coefficients for Number of Bluebikes Docks at Different Levels of Station Area Jobs, Baseline Period

	Coefficient	Std. Error	P>t
Total Jobs = 720	**80.10**	**31.77**	**0.014**
Total Jobs = 38,140	34.56	24.83	0.169
Total Jobs = 84,760	-22.17	34.88	0.527

Note: Significant associations are bolded

This moderating effect of station area jobs is also visualized in Graph 1, which graphs the predicted subway ridership for MBTA stations with different levels of Bluebikes docks (representing one standard deviation above and below the mean) and different levels of station area jobs. This figure demonstrates how the association between Bluebikes docks and subway ridership becomes more negative as the number of jobs in the station area increases.

Graph 1: Station Ridership Predictions Based on Number of Bluebikes Docks, at Different Employment Densities, Baseline Period



4.3.3 Fitted Model

After finding the importance of including the number of bus routes in the models in section 4.2, this variable was added to the model from Table 10 to test for possible OVB. The results of such a model is displayed in Table 12. By including the bus routes variable, the significance of all of the variables in this model were improved, suggesting that the previous model was in fact affected by the omission of this variable. The coefficient for the number of Bluebikes docks increased, while the coefficient for total jobs decreased, again demonstrating the ability of this variable to disentangle the overlapping effects of these two variables. Finally, the substantial increase in the adjusted R-squared value shows how including this variable improves the predictive power of this model. This fitted model therefore provides the most accurate estimation of the association between the number of Bluebikes docks and subway station ridership in the pre-pandemic period. Based on this model, it is estimated that for each additional Bluebikes dock at an MBTA station, the average weekday subway ridership is predicted to increase by an average of about 105 passengers, holding all other factors constant. However, this association is diminished as the total jobs in the station area increases.

Table 12: Fitted Employment Density Interaction Model, Baseline Period

	Coefficient	Std. Error	P>t
Number of Bluebikes Docks	**104.77**	**27.75**	**0.000**
Total Jobs (in thousands)	**84.06**	**27.52**	**0.003**
Number of Docks * Total Jobs	**-1.50**	**0.45**	**0.002**
Number of Bus Routes	**551.82**	**115.64**	**0.000**
Constant	509.73	1,112.66	0.649

Note: Adjusted R-squared = 0.44, significant variables are bolded

Based on these findings, we can reject the null hypothesis that the number of Bluebikes docks at an MBTA station has no relationship with the subway ridership at that station prior to the pandemic. Rather, the number of Bluebikes docks at an MBTA station has a positive association with the average weekday subway ridership at that station, in general. However, based on these findings we can also reject the null hypothesis that the number of jobs around a station does not moderate the relationship between the number of Bluebikes docks and subway ridership. As the employment density of the station area increases, the association between Bluebikes docks and subway ridership becomes slightly negative and statistically insignificant. Population density, on the other hand, is not found to significantly moderate this association. Finally, these findings indicate that omitting the number of bus routes from ridership models using the number of Bluebikes docks and total jobs as explanatory variables results in biased results. The association between Bluebikes docks and subway station ridership, as well as the moderating effect of employment density, therefore can only be accurately understood when accounting for the number of bus routes at the station.

4.4 Moderating Effect of Pandemic Phases

With an understanding of the baseline association between the presence of bikeshare facilities and subway ridership at MBTA stations, as well as the interaction of station area density, the final objective of this research is to test the extent to which the pandemic has moderated this association and the interaction of employment density.

Table 13 displays the coefficients of the fitted model from Table 12 in each phase of the pandemic, as well as the adjusted R^2 of each model, with Phase 0 representing the pre-pandemic baseline. The coefficient for the number of Bluebikes docks falls dramatically in Phase 1, when the state of emergency is declared in Boston, and reaches its lowest point in Phase 2, during the initial lockdown. This means that the positive association between Bluebikes docks and subway ridership diminishes during these phases. The coefficient also falls below the 95% confidence level starting in Phase 2, meaning the association also becomes statistically insignificant. Starting in Phase 3, during the initial easing period, the coefficient begins to increase and becomes statistically significant from Phase 4 onwards. By Phase 8, when all restrictions are lifted, each additional Bluebikes dock at an MBTA station is associated with an average of about 42 more weekday passengers, when holding all other factors constant.

Table 13: Fitted Model in each Phase of the Pandemic

	Pandemic Phase								
	0	1	2	3	4	5	6	7	8
Number of Bluebikes Docks	**104.77**	**24.15**	2.64	6.25	**12.36**	**15.79**	**19.22**	**22.64**	**42.16**
Total Jobs	**84.06**	21.47	1.18	5.08	11.07	**12.20**	**16.67**	**18.89**	**30.04**
Docks * Total Jobs	**-1.50**	**-0.34**	-0.05	-0.11	**-0.21**	**-0.23**	**-0.31**	**-0.35**	**-0.54**
Number of Bus Routes	**551.82**	**262.48**	**62.89**	**95.75**	**130.25**	**134.94**	**162.33**	**163.26**	**246.79**
Constant	509.73	787.66	220.33	311.38	554.47	500.12	532.44	465.14	779.02
Adjusted R^2	0.44	0.41	0.41	0.40	0.36	0.39	0.42	0.46	0.48
N	62	62	62	60	60	60	60	60	60

Note: Bolded coefficients are significant at a 95% confidence level

The interaction term for the number of Bluebikes docks and total jobs follows a similar pattern as the coefficient for the number of docks. It falls dramatically in magnitude and loses significance by Phase 2, then slowly increases in magnitude and regains significance in Phase 4. Thus, the moderating effect of employment density also diminishes at the start of the pandemic before slowly returning. Interestingly, despite decreasing in Phases 1 and 2, the coefficient for the number of bus routes remains significant throughout all phases. This indicates that the number of bus routes at an MBTA station remained an important predictor of subway ridership throughout the pandemic.

Overall, the changes to this model throughout the pandemic indicate that the association between Bluebikes docks and subway ridership, as well as the moderating effect of employment density, disappear at the start of the pandemic, before slowly returning. While the coefficient in Phase 8 is still much lower than it was prior to the pandemic, this is likely due to the fact that ridership as a whole is much lower. Furthermore, the adjusted R^2 for the model in Phase 8 is higher than that of Phase 0, indicating that, despite there being less variation among stations in Phase 8, the model actually better explains this variation in station ridership than it did prior to the pandemic. Thus, these variables may be more important to subway ridership now than they were prior to the pandemic.

4.5 Summary of Results

In summary, this analysis finds that prior to the COVID-19 pandemic, the number of Bluebikes docks at an MBTA station is overall positively associated with the average weekday subway ridership at that station. This association is negatively moderated by the employment density in the station area, meaning as the number of jobs in the station area increases, the association between Bluebikes docks and subway ridership diminishes and becomes insignificant. Furthermore, this research finds that this association actually cannot be properly understood without accounting for these differences in employment density, and that the number of bus routes at a station also interferes with estimating these influences. Population density, however, does not significantly moderate this association. The best model for estimating the influence of Bluebikes docks on subway ridership is therefore one that also includes an interaction term with the number of jobs in the station area and the number of bus routes at the station. Finally, this research finds that the association between the number of Bluebikes docks and subway ridership at MBTA stations, as well as the moderating influence of employment density, disappeared at the start of the COVID-19 pandemic before steadily returning in each subsequent phase of the pandemic. While the magnitude of this association is lower than it was prior to the pandemic, this is reflective of lower ridership across the system as a whole. The model using Bluebikes docks, an interaction term with station area jobs, and bus routes actually explains more variation in station ridership than it did prior to the pandemic, suggesting these variables are more important to station ridership now than they were prior.

5: Conclusions

5.1 Answering the research questions

The first question of this research asked to what extent the presence of Bluebikes facilities is associated with subway ridership at MBTA stations prior to the pandemic. Based on the relevant literature, this research specifically tested the hypothesis that the presence of Bluebikes facilities is positively associated with subway ridership at MBTA stations during this period. The findings of this research support this hypothesis. Based on the fitted model created in this analysis, it is estimated that for each additional Bluebikes dock at an MBTA station, the average weekday subway ridership is predicted to increase by an average of about 105 passengers, holding all other factors constant. However, this association can only be properly understood when accounting for the employment density of the station area and the number of bus routes at each station.

The second question of this research asked to what extent the density of the area surrounding an MBTA station moderates the association between Bluebikes docks and subway ridership at that station prior to the pandemic. This research specifically tested the hypothesis that the density of the station area negatively moderates the association between Bluebikes facilities and subway ridership at MBTA stations. Based on the findings of this research, the employment density of the area around an MBTA station negatively moderates this association, but the population density does not. Thus, while the presence of Bluebikes facilities has a positive association with subway ridership at stations with low employment densities, this association diminishes at stations with higher employment densities.

Finally, this research investigated how each phase of the pandemic moderates the association between Bluebikes docks and subway ridership at MBTA stations, as well as the influence of station area density. This research hypothesized that, during the pandemic, the association between Bluebikes facilities and subway ridership at MBTA stations becomes negative, but the magnitude of this negative association decreases during phases when pandemic restrictions are eased. Based on the findings of this research, this association did not become negative during the pandemic, but rather disappeared entirely. The association did become more positive over time as pandemic restrictions were eased, however, it did not reverse course in Phase 6 when some restrictions were re-implemented, therefore the second portion of the hypothesis also cannot be proven. This research also hypothesized that during the pandemic, the moderating effect of station area density would disappear but return to a lesser extent during phases when pandemic restrictions are eased. This is true in general for employment density, but again does not reverse course in Phase 6 as expected, so this hypothesis cannot be fully proven. The linear fashion in which the association between bikeshare facilities and subway ridership, as well as the moderating effect of station area jobs, recover after from the end of the lockdown period onwards suggests that time, rather than the specific conditions of a pandemic phase, is more influential on these relationships.

5.2 Academic implications

This research contributes to the debate on the association between bikesharing facilities and subway station ridership by finding that, in the case of Boston, this association is generally positive. The findings of this research also support those of Martin and Shaheen (2014), as well as Ma and Knapp (2019), that the relationship between bikesharing and subway ridership is dependent on the density of the station area. Specifically, this research corroborates the findings of these authors that this relationship is more positive in areas of lower density. However, while these authors find that this relationship becomes negative in areas of higher density, this research finds that this relationship actually becomes insignificant in such areas. Thus, while these findings support the theory that bikesharing benefits public transport ridership at stations in low density areas by providing FMLM accessibility, they do not find evidence that bikesharing detracts from public transport ridership in high density areas by providing a more efficient alternative. It may be the case that many other factors influence the choice of whether or not to use public transport in these areas, so the presence of bikesharing facilities is less influential. It is also important to note that this research only identified a moderating effect for employment density and not population density, so it appears as though the type of density may be an important factor.

Using a different method and case, this research also supports the findings of Kim (2021) and Hu et al. (2021) that the complementary relationship between bikesharing and subway systems disappears during the COVID-19 pandemic. This therefore adds to the initial research on mobility trends during the pandemic that have found evidence of a possible decrease in trip chaining between bikesharing and public transport. However, this research did not find evidence of the relationship between bikesharing and subway systems becoming negative during the pandemic. Therefore, this research cannot support the theory that individuals are switching from public transport to bikesharing to complete their trips during the pandemic, as posited by Hu et al. (2021) and Teixiera and Lopes (2020). While this phenomenon may still be occurring, it may be obscured in the data by the many other factors that influence subway station ridership in the context of the pandemic. This research therefore contributes to the existing research on the association between bikesharing facilities and public transport ridership by finding that, at least in this particular case, such an association disappears during a shock to the transportation system.

This research also extends the initial research into the relationship between bikesharing and public transport systems during the pandemic by examining the relationship throughout the many phases of the first year and a half of the pandemic. Doing so allows this research to conclude that, while the pandemic's impacts on the ridership of public transport systems has largely endured, the pandemic's impacts on bikesharing's association with station ridership has not. The complementary relationship between these systems has returned as time has gone on, and appears unfettered by returning waves of case counts or government restrictions. This may indicate that, as time has gone on, the public's fear of infection on public transport has diminished, despite the actual risk ebbing and flowing. This would be reflective of Cox et al. (2011)'s finding that the public's perception of risk during disruptions to public transport does not always match reality. This then supports the use of TPB when analyzing mode choices during disruptions.

Future research should evaluate these trends in other cities in order to understand the generalizability of these findings beyond the context of Boston. Further research on this topic should also consider other variables that may be competing with the presence of bikeshare facilities for the explanation of the variation in subway ridership across stations, as the fitted model in this research still accounted for less than half of this variation. It is therefore possible that the omission of other variables still plagues these results. In addition, the relevance of the number of bus routes at each station should be explored further in future studies, as this variable may also moderate the association between bikesharing facilities and subway station ridership. Finally, future research should survey bikeshare users in Boston and other cities on how their ridership behavior changed during the pandemic, specifically in regards to using bikesharing as either a connection to, or replacement of, public transport. By using statistically analyses, this research was limited to only drawing conclusions of correlation, but not causality. Surveying can provide more information on the exact mode choices being made and the motives behind them, allowing for conclusions on how the presence of bikesharing facilities at public transport stations actually influences an individual's mode choice, especially during the pandemic.

5.3 Policy and planning implications

In addition to its academic implications, the findings of this research have significant policy and planning implications. Based on this research, planners in Boston hoping to increase the FMLM accessibility of MBTA stations should locate or expand Bluebikes facilities at these stations. Specific focus should be dedicated to peripheral stations, as this is where Bluebikes facilities can provide the greatest benefit. However, planners should be aware that the benefits to ridership at these stations may disappear during crises that decrease the attractiveness of public transport as a mode. Other investments therefore may need to be made to keep riders on public transport during such events. While these results are limited to the context of Boston, similar findings have been identified in Washington D.C. (Ma & Knapp, 2019) and Chicago (Hu et al., 2021). Thus, it is possible that these planning recommendations may apply to other similarly-sized American cities. However, greater research is necessary to validate the transferability of these findings. Finally, these results demonstrate the importance of viewing bikesharing and public transport not as two separate systems, but as pieces of the larger urban transportation system. The planning of bikesharing systems should not occur in a vacuum, as such decisions have important ramifications for public transport ridership. Greater consideration of multimodality in urban transportation planning therefore has the potential to improve public transport accessibility and boost the ridership of these systems.

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Appendix 1: Data

Included below is the compiled data utilized in this research.

stop_name	P0	P1	P2	P3	P4	P5	P6	P7	P8	NUMDOCKS1	NUMDOCKS1	NUMDOCKS2	totjobs	edujobs	medjobs	pop	bus	TransCrit
Airport	7367.86129	4471	986.767442	1932.88	2768.83077	2743.76	3171.65714	3375.32	5594.87273	13	13	13	5.44420603	0.00448452	1.37830478	18.3488696	5	1.7249991
Alewife	11177.271	4030.88889	647.777778	996.266667	1615.95385	1715.36	2136.2	2314.98	4435.83636	67	67	67	5.75527177	0.46969975	0.3499192	10.9093622	4	1.19076241
Andrew	5333.1	3468.44444	1108.02222	1281.13333	2103.73846	2236.96	2693.27143	2576.82	3626.42727	0	0	0	9.35548323	0.17894913	0.45934591	11.2937519	9	1.35185715
Aquarium	4836.98387	2105.66667	330.977778	783.533333	1456.87692	1220.38	1243.91429	1623.54	3300.66364	57	57	72	103.981415	2.19142943	2.53703277	13.2007364	5	1.02895414
Arlington	6604.23226	2334.11111	303.177778	547.5	935.753846	1070.2	1281.11429	1452.36	2591.39091	68	106	106	77.4894045	4.72366803	6.39473649	22.5053328	6	1.07599527
Ashmont	8341.77742	5255.11111	1557.13333	2119.16667	2832.03077	3012.18	3641.28571	3509.92	4960.19091	0	15	15	2.18050911	0.1577092	1.27029511	13.2768126	12	1.53469176
Assembly	4023.04516	1670.55556	272.688889	631.366667	988.369231	986.12	1008.71429	826.06	1869.39091	15	15	15	10.4554472	0.36423211	0.9172451	5.62324026	1	0.95778378
Back Bay	15228.7226	5922.77778	925.511111	1561.36667	2783.58462	3029.76	3247.65714	3269.24	6012.29091	69	107	107	87.4277352	1.65349012	2.43076866	27.9739066	7	1.10145237
Beachmont	3209.64516	2037.44444	527.425	990.64	1425	1396.68	1631.48571	1636.72	2379.02727	0	0	0	1.01924881	0.02903263	0.0657182	7.52043362	1	1.4497189
Bowdoin	2184.22903	1467.66667	344.133333	518.857143	879.030769	903.06	1098.34286	1060.86	1497.61818	61	61	61	118.015607	1.8280654	28.7154425	23.6813812	7	1.05986993
Boylston	5122.32903	2254.11111	331.488889	523.7	1012.75385	1193.94	1523.3	1593.82	2927.36364	102	102	102	111.881643	5.71132125	8.23418463	21.6350965	9	1.24332586
Braintree	4286.69355	2096.88889	438.288889	417.7	993.553846	927.18	1111.91429	1124.3	2036.71818	0	0	0	2.48414973	0.2483237	0.41019697	1.50944516	5	0.56764609
Broadway	5786.16452	2880.11111	582.844444	826.4	1472.06154	1605.98	1724.05714	1928.82	3211	34	34	34	37.76232	1.00827406	2.20498786	11.9385397	4	1.42805081
Central	14742.5936	6404.22222	1307.51111	1923.6	3118.29231	3204.78	4137.3	4239.44	7568.80909	50	50	50	18.9604059	0.48896524	1.54352046	21.6402371	6	1.15032732
Charles/MGH	10099.8774	5458	1458.31111	2226.66667	3692.03077	3993.74	4767.52857	4365.62	6572.66364	19	34	34	52.9599156	0.86636536	27.8451827	16.3397616	0	1.02767252
Chinatown	5500.45484	2375.22222	499.222222	745.733333	1242.89231	1478.98	1783.85714	1581.98	2703.98182	90	90	90	127.108952	5.79232752	8.54908995	19.2498064	9	1.36138233
Community C	3951.93871	1702.44444	297.644444	460.1	698.2	767.54	838.614286	889.34	1577.06364	45	45	45	15.186203	0.87205049	3.43756527	12.3192113	1	0.9012544
Copley	11520.9871	4435.66667	481.933333	1114.33333	2348.52308	2815.24	2865.98571	3331.18	6270.58182	103	122	122	84.2752866	1.80393776	1.74514121	23.2051993	7	0.96938809
Davis	11225.8452	4436.33333	592.266667	1053.86667	1845.15385	1974.5	2340.27143	2688.92	5067.63636	40	40	40	5.92439315	0.13944402	0.7059845	17.6069359	6	0.62643695
Downtown C	23129.8677	10094	1369.28889	2755.53333	4784.46154	5087.76	6144.77143	6135.86	9730.9	34	34	34	147.775288	5.00311585	8.4900858	18.601314	13	1.28334271
Fields Corner	4725.93548	3081.77778	860.355556	1273.23333	1904.27692	1913.4	2204.14286	2215.56	3145.77273	15	15	15	4.47771535	0.06447493	0.97198848	16.1962297	8	1.73357908
Forest Hills	12270.2097	6996.77778	1823.04444	2560.73333	3683.92308	3818.4	4472.54286	4219.74	6677.98182	0	40	40	2.3734237	0.12867435	1.11676254	8.85720493	19	1.10734956
Government	7405.65484	3089.88889	621.311111	1094.73333	1298.98462	1314.74	1529.42857	1701.6	3328.89091	86	86	86	139.608646	2.45006124	15.0219452	21.4006855	12	1.08240066
Green Street	2985.95807	1411.66667	234.422222	356.533333	530.2	550.74	652	755.5	1359.79091	23	23	23	3.66086804	0.27583494	1.35639653	13.2327396	1	1.0346983
Harvard	17327.2452	6714.77778	1048.48889	1668.86667	2777.27692	3079.28	3703.55714	4150.02	8181.32727	57	57	57	19.6562503	12.6804503	1.14521465	17.6370286	13	1.1527375
Haymarket	9795.40323	5062	1170.44444	2016.23333	3131.81539	3339.54	3934	4046.88	6509.05455	65	65	85	110.782999	2.05482115	16.5784057	21.9907772	12	1.02889284
Hynes Conver	6797.81936	2747.22222	359.4	645.966667	1321.90769	1465.44	2003.28571	2323.36	3963.75455	15	15	15	42.2704285	1.41901328	1.26404971	27.7968037	5	1.41159611
Jackson Squa	5162.84516	3237	889.044444	1181.56667	1800.41539	1895.9	2194.02857	2138.72	3145.74546	18	18	34	7.04198334	0.75607436	4.1999107	18.2670095	5	1.81118746
JFK/UMass	7637.25484	3398	622.066667	1044.56667	1540.49231	1617.56	1807.9	1939.46	3864.22727	15	34	34	5.65822461	2.25561161	0.30064661	9.81820432	4	1.50492516
Kendall/MIT	16493.5613	5095.55556	575.533333	1135.23333	1947.6	2199.44	2767.48571	2860.28	6079.57273	118	118	191	39.2820944	6.57967492	0.64206758	9.74894667	4	1.33608628
Kenmore	7014.23548	2554.55556	474.888889	895.866667	1391.75385	1581.4	1950.92857	2878.52	4948.30909	43	43	43	14.0440304	1.29422926	1.80754739	21.8264837	10	1.49965095
Lechmere	5446.44194	2209.44444	464.222222	NA	NA	NA	NA	NA	NA	41	41	41	24.3646183	1.63447307	2.73610057	10.2456025	5	1.13767987
Malden Cent	10928.1968	5188.11111	1130.97778	1903.56667	2967.15385	2935.56	3297.4058	2698.7561	5020.27273	0	0	0	6.37304658	0.77647566	1.42846681	9.79180587	13	1.39328856
Massachuset	5536.94839	2829.11111	696.933333	1042.13333	1673.26154	1781.58	2155.77143	2042.68	3249.81818	38	54	54	39.3104921	5.40522122	1.7498407	34.5124405	4	1.53343739
Maverick	11192.4742	6834.88889	1604.32558	2729.23333	4643.95385	4716.14	5579.7	5455.02	7961.57273	49	49	68	4.09156172	0.00754465	1.45123904	14.723811	8	1.58089062
North Quincy	6819.64194	2603.11111	489.977778	778.7	1232.81539	1277.72	1477.51429	1467.24	2457.41818	0	0	0	7.10236923	0.04874959	0.20018031	8.46872788	5	1.08838885
North Statior	16571.6613	6486.77778	1043.73333	2326.33333	3563.32308	3649.36	4161.27143	4281	8149.69091	72	72	92	80.5806934	1.17736342	26.769331	20.9183242	13	1.03072838
Oak Grove	6280.54194	2691.77778	389.377778	689.3	1055.84375	1106.44	1278.22059	1134.1579	2208.93519	0	0	0	2.73969421	0.33725752	0.54040181	7.06966235	4	1.19066007
Orient Heigh	4412.70323	2779.44444	640.642857	1038.86667	1791.18462	1775.5	2106.95714	2093.7	3020.19091	19	19	19	1.52267106	0.05788338	0.07741362	8.12438946	3	1.3862283
Park Street	16066.5129	6007.33333	786.044444	1490.43333	2515.33846	2677.36	3073.35714	3664.16	7070.59091	34	34	34	128.518034	4.35158429	13.3951598	20.658656	7	1.19126796
Porter	7953.66129	3007	476.4	727.4	1274.30769	1410.06	1768.58571	1821.58	3690.42727	34	53	53	5.886453	0.54603356	0.38462201	17.3756133	4	0.7710254
Prudential	3150.1129	1146.11111	159.066667	248.733333	727.676923	619.78	844.1	914.86	1744.22727	33	33	33	64.2262397	2.16095209	1.76585871	33.6900582	6	1.27538122
Quincy Adam	4004.69355	1711	292.288889	301.9	718.707692	742.84	853.828571	885.22	1602.02727	0	0	0	3.80163422	0.01834926	0.8137718	5.50369963	4	0.95486271
Quincy Cente	6899.4871	3699.77778	953.066667	1771.9	2157.86154	2245.1	2551.07143	2444.54	3726.53636	0	0	0	9.25692334	1.54924177	2.16802579	6.42919815	17	1.08370769
Revere Beacl	3053.50323	2020.44444	565.048781	919.222222	1700.04615	1573.5	1799.21429	1724.64	2423.28182	0	0	0	1.01628669	0.03158141	0.15874881	8.20560964	3	1.52192994
Riverside	1649.49677	634.444444	99.2444444	92.0333333	323.338462	283.74	304.4	383.08	703.045455	0	0	0	3.7879902	0.4089224	0.50986533	2.88654967	1	0.55555764
Roxbury Cros	4370.38387	2334.44444	429.066667	680.4	1069.93846	1115.7	1322.25714	1638.94	2505.31818	23	42	42	25.5310056	14.2901065	8.18147804	18.624705	11	1.76342021
Ruggles	9004.09355	4531.44444	1008.57778	1310.5	2326.64615	2685.56	3020.54286	2798.12	4515.64546	18	18	18	26.5547548	17.6214529	4.32926778	25.7998263	15	1.89330651
Savin Hill	2102.28065	1119.44444	247.044444	415.333333	690.738462	710.58	826.5	847.38	1260.21818	14	14	14	3.47751115	0.49979575	0.37366776	10.2980236	2	1.31333337
Science Park	758.03871	202.111111	41.1777778	NA	NA	NA	NA	NA	NA	91	106	106	55.9366162	0.54392827	29.9159095	15.5521053	1	1.1228227
Shawmut	2117.48387	1333.44444	352.911111	487.9	689.676923	584.48	818.971429	824.94	1287.66364	0	19	19	2.83217688	0.14576661	0.75984377	16.0105145	3	1.62006197
South Statior	23621.9645	9113.33333	1288.44444	2038.66667	3230.87692	3337.6	3712.54286	4068.76	8190.30909	85	112	112	132.585903	3.80857752	5.94999952	12.5945112	11	1.39721594
State Street	12982.7097	6249.88889	863.8	1773	2803.90769	2860.2	3222.62857	3314.38	5799.52727	67	67	82	145.53195	2.68014102	8.13483777	19.1957041	13	1.09762895
Stony Brook	3346.89355	1565.77778	253.911111	427.733333	707.384615	790.26	923.628571	917.7	1626.28182	15	15	15	4.21620444	0.15559118	1.83638668	17.9032498	0	1.40762268
Suffolk Dowr	674.009677	471.888889	113.658537	214.96	330.646154	338.86	379.642857	262.86	314.045455	0	0	0	1.00990933	0.05259635	0.04691763	4.92585098	1	1.3910851
Sullivan Squa	8056.16129	4375	1122.97778	1826.96667	2681.98462	2871.06	3512.54286	4389.2	5411.63636	19	38	38	8.83770388	1.07467241	1.17075375	8.54666229	14	0.99797962
Symphony	1646.60323	725.888889	142.022222	188.1	234.377049	383.7	474.642857	502.12	866.954546	19	35	35	43.4680596	5.62988203	2.01839636	32.2321931	4	1.49257368
Tufts Medica	5863.87742	3187.88889	791	1070.8	1811.01539	2015.38	2506.3	2197.42	3428.48182	75	90	90	104.991851	5.40625306	8.18963654	18.851773	10	1.45364357
Wellington	7266.83548	3341	684.844444	1102.96667	1827.2	1826	1969.62857	1254.18	2695.08182	0	0	0	4.86985887	0.16931493	0.24930091	4.89436754	9	0.96264764
Wollaston	3017.88387	1714.33333	342.777778	611.7	920.476923	999.42	1172.58571	1189.76	1902.46364	0	0	0	3.82385696	0.28096378	0.11859231	7.43385258	4	1.04969139
Wonderland	6694.93548	4057	972.674419	1760.68	2385.12308	1940.54	2564.65714	2658.38	3931.00909	0	0	0	0.721124	0.00194724	0.10640511	5.87405555	12	1.37360319
Wood Island	2017.07097	1331	314.422222	472.866667	857.507692	726.08	982.771429	997.1	1439.85455	0	0	0	3.30464727	0.07239026	0.12049974	8.56318341	6	1.66080747

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