The Effect of Bicycle Sharing Programs on Pollution Levels in North America

Xiuzhen Cao

Trevor Barnes

Supervisor: Prof. Dr. Hendrik Wolff

Simon Fraser University

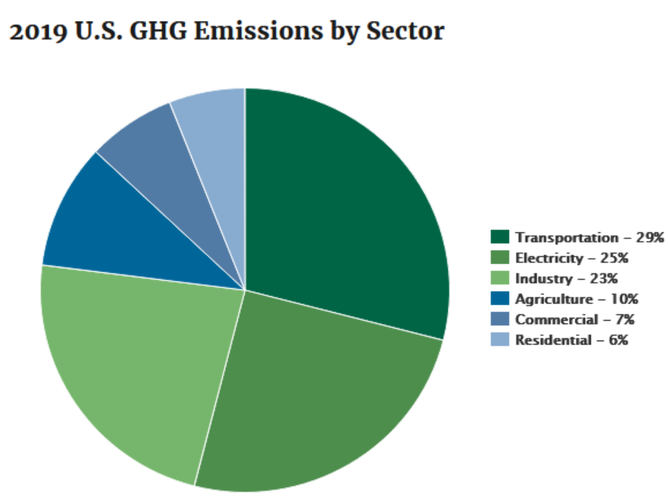
August 2021

Abstract

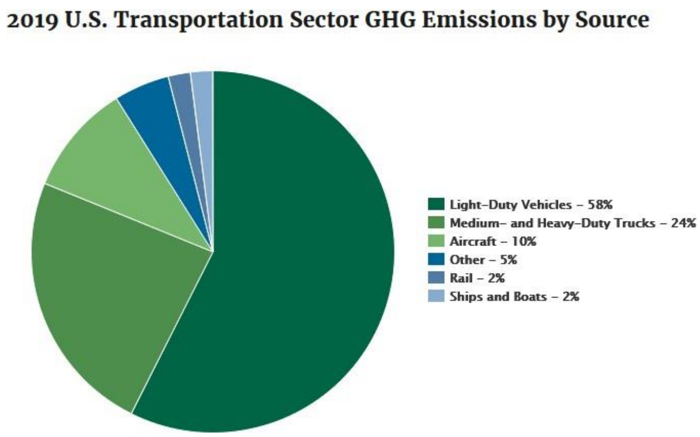
Bicycle sharing programs have experienced rapid growth in North America over the past decade. Our study investigates the role these programs have in reducing pollution levels in United States urban city centers. We empirically analyze if shared bike programs are used to substitute trips from other transportation alternatives, such as private light-duty vehicles. Using a difference-in-difference approach, we show that expanding the number of bikes in the existing bike share program in Boston increased substitution ridership. However, we conclude that furtheranalysis is needed to understand what transportation method is being substituted to draw results about reduction in actual pollution levels.

1. Introduction

North American nations have set aggressive emission reduction targets, including both Canada and the United States being net-zero by 2050 (Government of Canada, 2021; The White House, 2021). As shown in Figure 1a, below, a major source of greenhouse gas emissions is from the transportation sector. Moreover, light duty vehicles (defined as any vehicle up to 10,000lbs) produce the majority of emissions in the transportation sector, as shown in Figure 1b. Therefore, light-duty vehicle usage in the United States offers significant potential to be disrupted from its status-quo and reduce emission contributions and aid in reaching 2050 emission targets.



(a)



(b)

Figure 1: (a) United States Greenhouse Gas emission contributors by sector in 2019 **(b)** United States Greenhouse Gas emission contributors by source for the transportation industry in 2019 (United States Environmental Protection Agency, 2021)

Worldwide, a popular trend in the mobility sector has been the introduction of bicycle sharing programs. These programs grant customers access to a fleet of public bicycles distributed throughout a city, for a subscription based or one time usage fee. The objective of these programs can vary from country to country. Developed nations, such as the United States or the United Kingdom, may introduce bike sharing programs as a method to combat obesity and promote healthier lifestyles (Rojas-Rueda et al., 2011). While developing nations, such as China or India, may implement shared bicycle programs as a method for cheap, individual transportation options to reduce traffic congestion (Shaheen et al., 2010). A common trend between the implementation of bike share programs is that emission reductions are often auxiliary benefits, not necessarily the primary purpose (Midgley, 2011).

Shared bicycle programs offer customers the ability to commute to and from their target location in a cheap and environmentally friendly way. However, the actual effects of these programs on pollution levels has been a contested topic among economists. For example, documentation on the bicycle share program in Saint Paul, Minnesota, stated that 20 percent of their daily bike users have substituted their cars for bikes (National River and Recreation Area Minnesota, 2019). This equates to a reduction of 1.3 million lbs of CO_2 emitted per year. However, reports such as those compiled by Midgely argue that bicycle programs have minimal effect on car usage(Midgley, 2011). Rather, the majority of the population who incorporate shared bicycles into their commute previously utilized public transit. This exaggerates the reduction in CO_2 emissions from these programs. These conflicting results indicate further research is needed in this field to understand how bicycle share programs are connected to emissions.

Our study aims to evaluate how the expansion of shared bicycle programs in the United States will affect pollution levels in urban cities. We utilize openly accessible operational data from 2015 to 2020 to empirically estimate the number transportation trips shared bikes are replacing ina United States metropolitan. This allows us to understand the impact bicycle share programs have on combating transportation sector emissions. If significant substitution occurs, large-scale policy adoptions and initiatives should be encouraged to promote shared bicycle program use and contribute to the United States reaching its 2050 net-zero target.

Section 2 will provide a quick overview of the evolution of bike share programs and present existing literature in this research field. Section 3 will review our empirical strategy, our data sources, and how we estimate substitution trips. Section 4 will present results from our empirical analysis and discuss the limitations of our study. Section 5 will state our conclusions, and finally section 6 will discuss future work that can build upon this study.

2. Literature Review

We separate the literature review into two sections. The first section describes the history of bike share programs with a focus on the growth seen in North America. The second section describes the existing field of research and how our study contributes to the current literature.

2.1. Evolution of Bike Share Programs

In the early 2000s bicycle sharing programs operated in five countries, namely Denmark, France, Germany, Italy and Portugal, with a total fleet of roughly 4,000 bicycles (Midgley, 2011). Fast forward almost 20 years, and in 2018 more than 1,600 programs operate worldwide with over 18 million bicycles (Richter, 2018). The initial rapid expansion of these programs occurred mainly in developing countries, including China, India and Thailand. These nations have established successful bicycle sharing programs in metropolises such as Hangzhou , Mumbai, and Bangkok (Urban Sustainability Exchange, 2021), demonstrating how bike programs can integrate into existing public transportation systems. For example, the Chinese government treats the bicycle sharing programs as the first mile or last mile complement to the urban public transportation system. The system is set up so residents can utilize bicycle sharing services to replace the on foot transportation trip in their current commute with a bike (Qiu & He, 2018).

The United States was considerably slower to introduce bicycle share programs into its cities. The initial establishment and phase in period of these programs occured around 2007-2012 (Shaheen et al., 2013). However, after the introduction of these programs, rapid growth such as that seen in other nations has also been experienced in the United States. Ridership grew from 320,000 trips in 2010 to 50 million in 2019 (National Association of City Transportation Officials, 2019). Today, bike share programs, and general shared mobility systems, in North America are widely accepted and mainstream. Contributing to the success of these programs are the popular subscription based model pricing, the health benefits, and the perceivedenvironmental benefits (Webster & Cunningham, 2012).

2.2. Existing Research

Research of bicycle sharing programs can be classified into three categories; program planning, factors affecting usage, and system impact analysis. Program planning research investigates how bicycle sharing programs will integrate into a city to ensure program success upon introduction. After implementation of a program, research shifts towards analyzing what factors positively and negatively affect ridership, such as weather and demographics. Finally, system impact research incorporates big-data techniques to understand system operation and estimate its effectiveness. Our study is firmly situated in the third research area (system impact research), however, we provide sample literature on all areas to give the reader background information on the current research field.

Bicycle sharing programs require extensive planning before being implemented in any city. This analysis is done in the planning phase of the program's lifecycle. For example, Wuennenberg et al. utilize transit data, mobility pattern data, and survey results to analyze if key objectives of a proposed shared bicycle program in New Dehli will be met, before finalizing the investment in the program (Wuennenberg et al., 2020). These objectives included providing equitable transportation to all citizens, serving as first-mile and last-mile compliments to public transit, reducing road congestion, and offsetting environmental impacts from private cars. The study showed that the infrastructure and operating expenses are hard to justify from a purely financial viewpoint. However, taking into account all objectives (including environmental, social, and economic) the program showed promise. Consideration of the wider reaching benefits of bike share programs have also been supported by other research, such as that by DeMaio, who reviewed the history of bicycle sharing programs and investigated the future of it (DeMaio, 2009). He concluded his research by stating shared mobility programs will continue to grow as a method to combat traffic congestion, population overcrowding, and climate change.

Once a bicycle sharing program is established, research shifts to evaluating factors that affect the program. Research such as that done by Chan and Wichman investigate the impact of recreational bike usage due to changes in weather (Chan & Wichman, 2020). Using an econometric methodology they show that cold temperatures reduce recreational bicycle usage much more than warmer temperatures. Other research focuses on how the geography of the city will affect bicycle usage. For example, Midgely discusses how steep inclines in cities candiscourage cyclists from taking certain routes (Midgley, 2011). He continues by explaining inclines can create an imbalance between shared bicycle availability at stations situated at the topor bottom of hills. Finally, other research investigates the flow patterns of shared bicyclesthroughout a city. Within this operations focused research field, visualization techniques are utilized to analyze and optimize systems. Research, such as that done by Wood et al., present different methods for visualizing bicycle flows between stations (Wood et al., 2011). Visual analysis approaches allow complex systems to be presented in comprehensible images to easethe process of identifying trends, patterns, and bottlenecks.

With the success of bike share programs comes a wealth of data that economists can utilize to investigate impacts of the program. Zhang and Mi utilized historical data from Shanghai's bike share program to estimate pollution reductions (Zhang & Mi, 2018). Their study concluded that in 2016 the bike share program reduced $CO2$ emission by roughly 55 millions pounds. With this result, the authors also note that emission savings increased in more densely populated regions. A caveat with their study is that they worked with a pre-processed data set as the bike share company does not release raw data. This could introduce unintended bias if pre-processing methods are not publicly available. Similar studies, such as those completed by Qui and He support the emission reduction findings of Zhang and Mi (Qiu & He, 2018). In this study the authors empirically showed that bicycle sharing programs in Beijing successfully reduced worker travel time, reduced harmful emissions, and improved overall health.

In the current research field, there is generally less research focused on North American specific studies. This is likely due to North America being slower to adopt bicycle sharing programs than nations like China. However, North America has experienced significant growth in these programs over the last five years and offers a wealth of research opportunities. Due to differences such as culture, political influence, weather, and existing infrastructure, there is no guarantee that results from Asian or European studies will produce the same results in a North American context. Currently, studies investigating operational challenges in North America, (Han et al., 2018; Zhang & Zhang, 2018) and research investigating benefits of bike share programs, such as the health benefits (Clockston & Rojas-Rueda, 2021), have been conducted. However, there is a gap to perform an empirical study to estimate pollution reductions due to the introduction of shared bicycle programs in a United States city. Our research fills this gap through utilizing recent historical shared bicycle program data to analyze if riders are replacing commuting trips with eco-friendly shared bicycles in the United States.

3. Methods

Our study empirically estimates the effect shared bicycle programs have on transportation habits, and subsequently emission levels, in United States metropolitans. We separate our methods into three sections: our empirical strategy where we discuss our model, our process for selecting a treatment and control city, and our dataset utilized.

3.1. Empirical Strategy

To empirically estimate if shared bicycle programs reduce light-duty vehicle emission levels, we employ a difference-in-difference (DD) strategy. This methodology allows us to measure the average change in an outcome variable between a control and treatment city, and is an acceptable quasi-experimental method. (Deschenes & Meng, 2018).

One seemingly obvious choice for the outcome variable is pollution or particulate measures (such as CO2 or PM2.5 levels). We can compare changes in these levels between a treatment city (implementation of a bicycle share program) and a control city (no implementation of bicycle share program). However, two issues exist with this initial thought. Firstly, the ability to directly measure pollution levels in a city without spillover effects is difficult. Secondly, identifying a control city that has not implemented a bicycle sharing program was not feasible.

The United States Environmental Protection Agency has thousands of monitoring stations scattered throughout the country recording levels of various pollutants and particulates. This data is freely available for download to be used in research (United States Environmental Protection Agency, 2021). However, as Deschenes and Meng discuss in their paper, spillovers exist in quasi-experimental methods which may bias results. (Deschenes & Meng, 2018). They specifically call out the example of pollution abatement policies. When pollution levels changein one location, all downwind locations are also exposed to the effects of the policy. This translates into noisy data. An example of noisy pollution data is shown in Figure 2, where PM2.5and air quality levels for all Boston monitoring stations are plotted. To reduce external effects, such as wind and precipitation, we do not use pollution measures as our outcome variable.

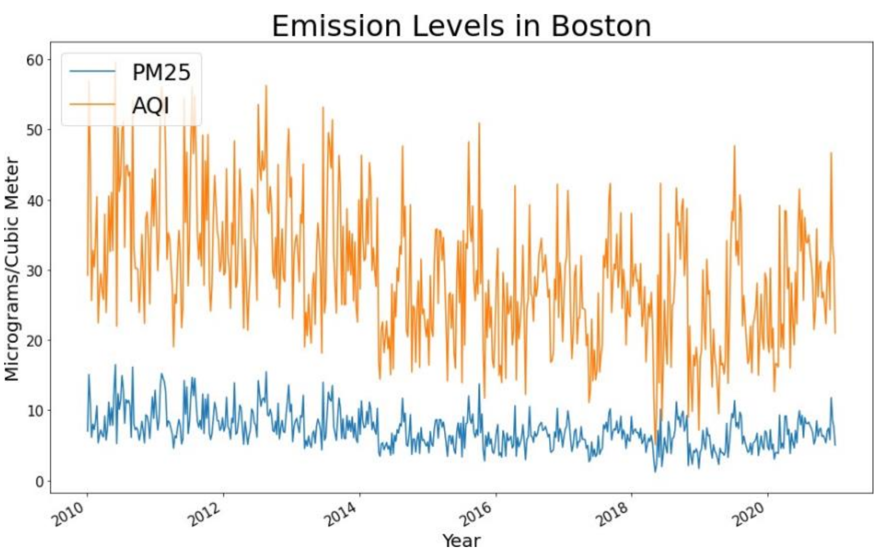


Figure 2: Aggregated Boston monitoring stations reported PM2.5 and Air Quality Index (AQI) levels for 2010 through mid 2021 (United States Environmental Protection Agency, 2021)

As an outcome variable, we instead utilize the number of substitution trips occurring in the system. We define a substitution trip as any trip where a commuter substitutes a private vehicle that emits pollutants with an eco-friendly bicycle trip. If the number of substitution trips after a treatment shows significant increase, we assume this will have a positive effect on total pollution levels. A substitution trip is different from a compliment trip through the type of transportation method being replaced. An example of a compliment trip is replacing a walk to a public transit station with a bicycle trip — this has net-zero impact on emission levels. We review our methods to identify substitution trips later in the Data section.

Identifying a treatment and control city has its own set of unique challenges. Firstly, we can no longer use the implementation of a shared bicycle program as a treatment, as we do not have a measure for substitution trips in a city without a shared bicycle program. Secondly, due to the wide adoption of bike share programs in the United States, most major cities have implemented bicycle share programs years ago. Therefore, if we want to use the recent bicycle usage data it will be difficult to identify a control city that has not implemented a bike share program. Instead,we utilize the expansion of an existing program, through a sharp increase in the number of bicycles in a fleet, as the treatment.

Equation 1 below shows our difference-in-difference model. The number of substitution trips occurring in the city (*c*) at time (*t*) is given by the variable y_{ct}. D_c is an indicator variable equal to 1 if the city (*c*) experiences an expansion of its bicycle sharing programs at time (*t*), and 0 otherwise. T_t is a dummy variable that equals to 1 if the treatment has been applied at time (*t*), and zero otherwise. X_{ct} is a vector of control variables, including temperature, proportion of college aged students, size of the population and number of bicycle stations. Finally, σ_t and Ω_c represent time and city fixed effects respectively, while ε_{ct} is the error term.

$$y_{ct} = \alpha + \beta_1 D_c + \beta_2 T_t + \beta_3 D_c T_t + \beta_4 X_{ct} + \sigma_t + \Omega_c + \varepsilon_{ct} \tag{1}$$

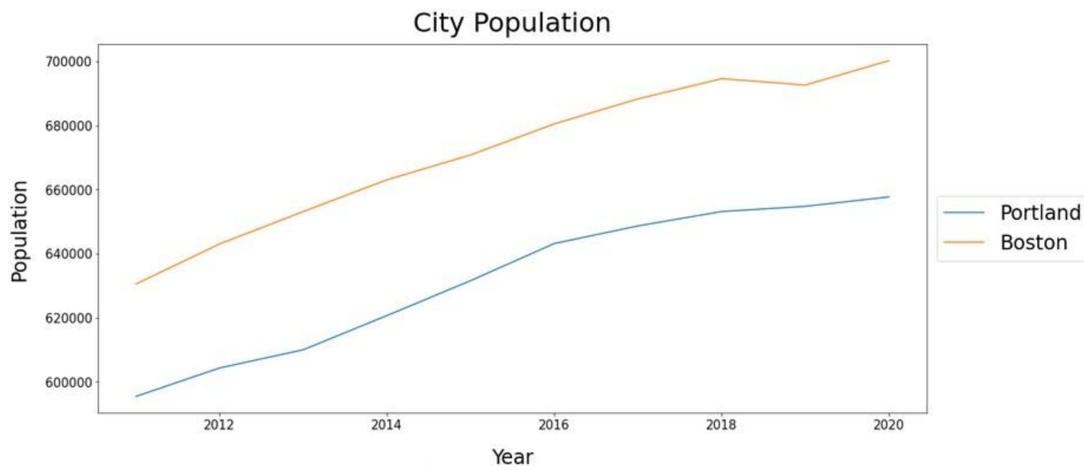
3.2. Treatment and Control City

Implementing our difference-in-difference model requires a treatment and control city. We first create a shortlist of major cities where bike data is freely provided by the operating companies. The cities included Boston, Las Angeles, Pittsburgh, Philadelphia, Portland, and New York. Initial research showed that the New York bike share program is significantly larger than the other five cities. Therefore, we eliminated New York from further analysis to reduce unforeseen results coming from large program size differences.

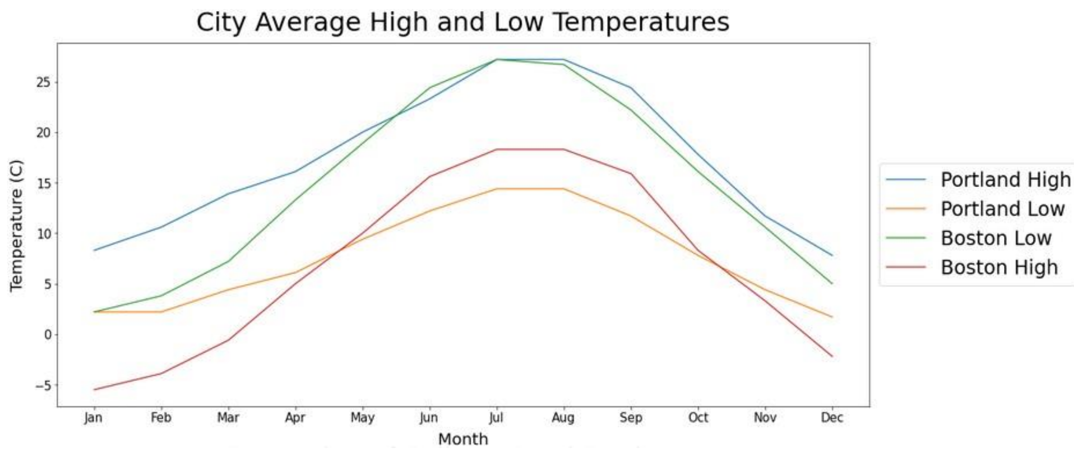
Reducing external variabilities between these cities needs careful attention. For example, if the treatment and control city have significantly different weather patterns or demographics, this could introduce external causal relationships which can increase or decrease substitution trips. We want our treatment (expansion of the existing bicycle share program) to be the only major change occurring between the treatment and control cities. Therefore, we develop criteria to compare external factors in these cities.

Through our literature review, a common trend of factors affecting shared bicycle program usage is identified. Notably, the temperature, population density, and demographics are all seen as confounding factors that need to be controlled. Research has shown cold weather is likely to deter bicyclists, while warmer weather has a less significant impact (Chan & Wichman, 2020; Gatersleben & Appleton, 2007). This finding suggests we should find cities whose temperature trends during peak usage are similar. Research has also shown that increased population density and proportion of college students will contribute to more general bicycle usage (Zhang & Mi, 2018; Dill & Carr, 2003). This suggests we should be comparing cities who have similar demographics and population densities within the geography covered by a bike share program.

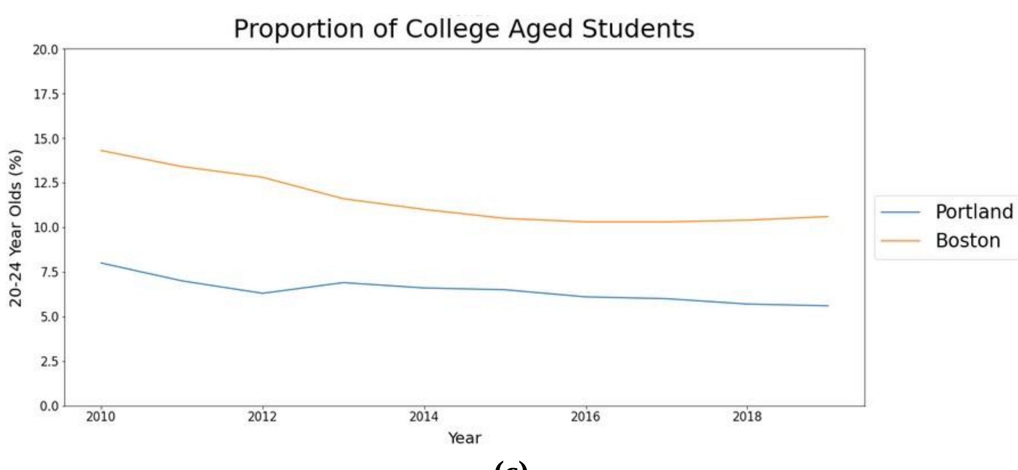
Figure 3 below compares the population (United States Census Bureau, 2021), temperature (US Climate Data, 2021), and proportion of college aged students (United States Census Bureau, 2021) between Boston and Portland. These two cities have the most common trends and are used as our treatment and control groups, however, the results for all five cities can be found in appendix Figure A1. Instead of comparing reported city densities, we compared the general population due to the geographical reach of shared bicycle programs. Programs are usually situated in the downtown cores of cities. However, city limits can often encompass suburban areas which have drastically different densities from their downtown core. Comparing the city population estimates the amount of people who can quickly access shared bicycle stations. Moreover, since we do not have exact data on the percentage of the population that attends college, we estimate the statistic by looking at the demographic we expect to have the highest college attendance — 20 to 24 year olds.



(a)



(b)



(c)

Figure 3: (a) Populations of Boston and Portland from 2011 to 2020 (United States Census Bureau, 2021) **(b)** Monthly average temperature variations of Boston and Portland from 2007 to 2019 (US Climate Data, 2021) **(c)** Percentage of population that is aged 20-24 between 2010 to 2019 as an estimate for potential college students (United States Census Bureau, 2021)

The comparison between Boston and Portland show that they follow similar trends between our three criteria. While Boston consistently has a roughly 5% larger population than Portland, they follow very similar year-over-year increases. Boston has significantly colder winters than Portland, however, we remove these data points due to low usage, as discussed in our next section. Moreover, the city's summer temperatures are quite similar. Their average highs are within 1°C of each other and their lows are only roughly 3°C apart. We are not concerned with the difference in low temperatures because this will occur overnight when bicycle usage significantly drops off due to visibility. Finally, Boston does have a larger proportion of college aged students, but follows a similar year-over-year trend as that seen in Portland. We prioritize seeing similar trends over having exactly the same proportions because of city geography.Portland includes a fair amount of suburban homes which are not covered by the bike share program and are less likely to house college students. Therefore, we estimate the majority of 20-24 year olds in Portland are situated near downtown and thus near a bike share station.

3.3. Data

Our primary data source is bicycle operation data supplied by the operating companies. In this section we will review the bike share services in Boston and Portland to provide the reader with all relevant background information. After, we discuss how we used the operational data to obtain our outcome variable data and our treatment data.

3.3.1. Bike Share Services

Boston and Portland's bike share programs are operated by two separate companies. BlueBikes is currently responsible for the operation of the Boston program which originally launched in 2011 (BlueBikes, 2021). While Lyft operates the Portland bike share program called Biketown which launched in 2016 (BikeTown, 2021). Both programs offer comparable annual and single-use pricing, however, BlueBikes also offers monthly subscriptions. Moreover, the Boston program is considerably larger and more utilized than the Portland program. BlueBikes recorded roughly 2.5 million trips in 2019 with a current fleet of 3,500 bikes distributed over 350 stations. Comparatively, BikeTown recorded only 325,000 trips in 2019 with a current fleet of 1,000 bikes over 180 stations. While the utilization rates of the programs differ, this is not necessarily a cause for concern. Boston is considerably more popular with tourists when compared to Portland (Best

Choice Reviews, 2019). Tourists are likely to use shared bikes for sight-seeing or as a public transit alternative. Both of these reasons can contribute to the higher utilization rate, but will not affect light-duty vehicle usage.

BlueBikes and BikeTown both freely provide their operating data in database friendly formats for researchers to use. Similarities between the data sets include start date and time, end date and time, start location coordinates, end location coordinates, start station id, end station id, and bike id. We utilized data from 2015 onwards for BlueBikes and from the introduction year of 2016 for BikeTown.

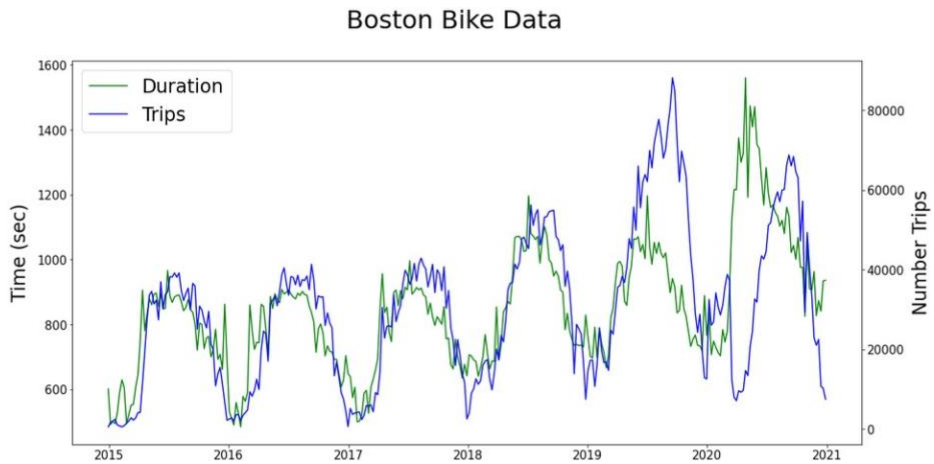
Upon initial analysis, we noticed some anomalies with the provided data. For example, there are frequent trips with a zero distance travelled, trips which have an end date and time earlier than the start date and time, trips that last multiple days, and trips that have obviously wrong dates. Table 1 below provides an example of these four errors, all coming from the January 2018 data for Portland. We expect trip distance is reported based on the coordinates of the start and end station, rather than on distance pedalled. Therefore, if the trip is a round trip, the distance will appear as zero. Moreover, we expect the multi-day trips to be subscribers (rather than single use customers) who keep the bike overnight for convenience.

Table 1
Common errors found in bicycle data

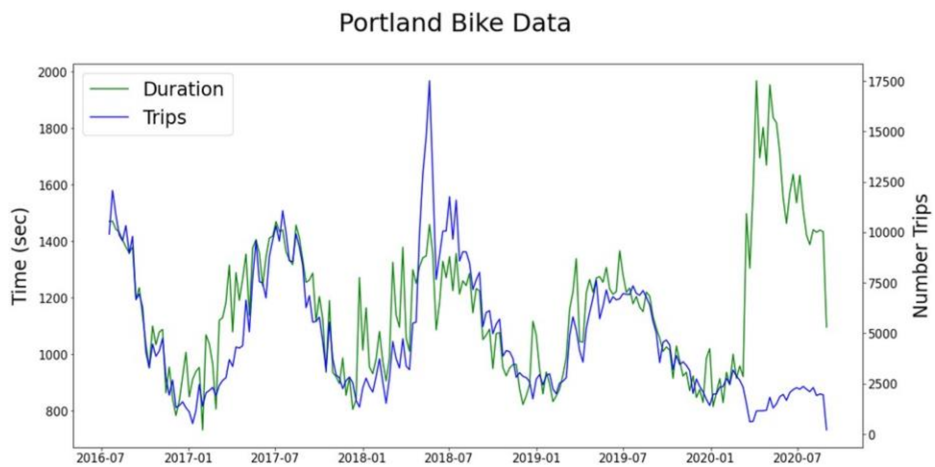
Start Date	Start Time	End Date	End Time	Distance (Mi)	Description
1/7/2018	1:22:00 PM	1/7/2018	1:29:00 PM	0	Zero Distance
1/1/2018	1:21:00 PM	1/1/2018	1:20:00 PM	0	Negative Trip Duration
1/14/2018	1:07:00 PM	1/15/2018	7:54:00 AM	0.72	Multi-day Trip
1/6/2018	6:21:00 PM	12/31/1969	4:30:00 PM	0	Wrong End Date

Example taken from Portland January 2018 data set (BikeTown, 2021).

Whatever the reason for the anomalies, we remove them from the datasets through filtering. Any trip that has a negative duration, a duration greater than three hours, or a distance of zero is removed. We choose to remove the multi-day trips as this goes against the principle of shared bike programs. At this point we can plot the weekly aggregated average trip duration and the weekly number of trips for both Boston and Portland, as shown in Figure 4, below.



(a)



(b)

Figure 4: (a) Boston weekly aggregated total trips and average trip duration from 2015 through 2020 (BlueBikes, 2021). **(b)** Portland weekly aggregated total trips and average trip duration from program start in 2016 through 2020 (BikeTown, 2021).

The above figure shows very clear trends. Consistent with our literature review, we see that bike usage peaks during the warmer summer months and drops off during the cold winter months. Moreover, in Boston there are clear year-over-year summer increases in the number of trips from 2017 to 2020. While in Portland we see a peak in usage during 2018. Finally, in 2020 for both cities we see deviations from their normal trends, which we attribute to Covid-19.

3.3.2. Outcome Variable Data

As discussed in the Empirical Strategy section, our outcome variable is the number of substitution trips occurring in the system. We have previously defined a substitution trip as any trip where a commuter substitutes a private vehicle that emits pollutants with an eco-friendly bicycle trip. Since data does not explicitly measure substitution trips, we develop criteria to estimate if the bicycle trip is a substitution trip instead of a compliment/recreational trip. All filtering criteria is listed below:

- Minimum and maximum trip duration. Incorporating a shared bike into a commute can either complement or substitute the pre-existing trip. We do not want to capture complimentary trips as they do not contribute to pollution reduction. Midgley discusses distances commuters are willing to walk and bike respectively (Midgley, 2011). He notes people are willing to walk up to 10min for a commute, and are willing to bike up to 5km. Therefore, we only want to capture bicycle trip durations which are longer than a 10min walk and less than 5km. As travel speed is unique to each commuter, we approximate that trips between 7 min and 45 min will classify as substitution trips.

- Weekday trips only. Bicycle habits will vary between workdays and non-workdays. We want to capture commuting trips rather than recreational trips. This is more likely to occur on weekdays rather than weekends, therefore, we eliminate all weekend trips.

- Summer months only. Figure 4, above, shows the consistent increase in number of trips during the warmer summer months. These are the periods we want to capture because there will be less chance of unpredictable weather introducing confounding factors.Therefore, we only analyze data from June, July and August.

- Low precipitation days. Building on our point of warmer weather encouraging bicycle usage, rain heavily deters riders. Therefore, any days that experience a moderate amount of rain (greater than 5mm) we remove (US Climate Data, 2021).

- Removal of Covid-19 data. We remove all data from 2020 onwards due to Covid-19 altering transportation needs in 2020 and 2021.

- Removal of incomplete years of data. Boston data includes a full 2015 year, and the bike system was established several years earlier. Therefore, we are not concerned about the phase-in period. In Portland, the program started in mid 2016. This mid year start can introduce unintended bias due to it being new, therefore, we remove Portland’s 2016 data.

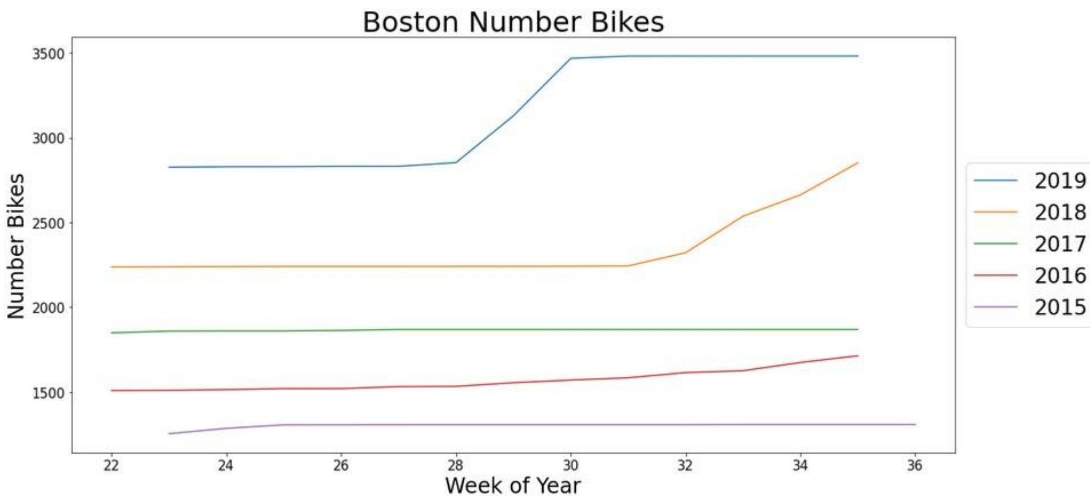
An important check to complete after applying cleaning criteria is to review the number of data points. If we remove a significant amount of data our results may be biased due to a small sample size. Table 2 highlights the raw number of data points available to us (including the anomalies highlighted in Table 1), and the remainder after applying all filtering criteria. While both sets have lost about 90% of their available data, there are still well over a hundred thousand data points in each city. We consider this an acceptable sample size. We include the plotted number of weekly trips and average trip duration in the appendix after applying filtering criteria for reader interest (Figure A2 and Figure A3).

Table 2
Number of Data Points for Each City

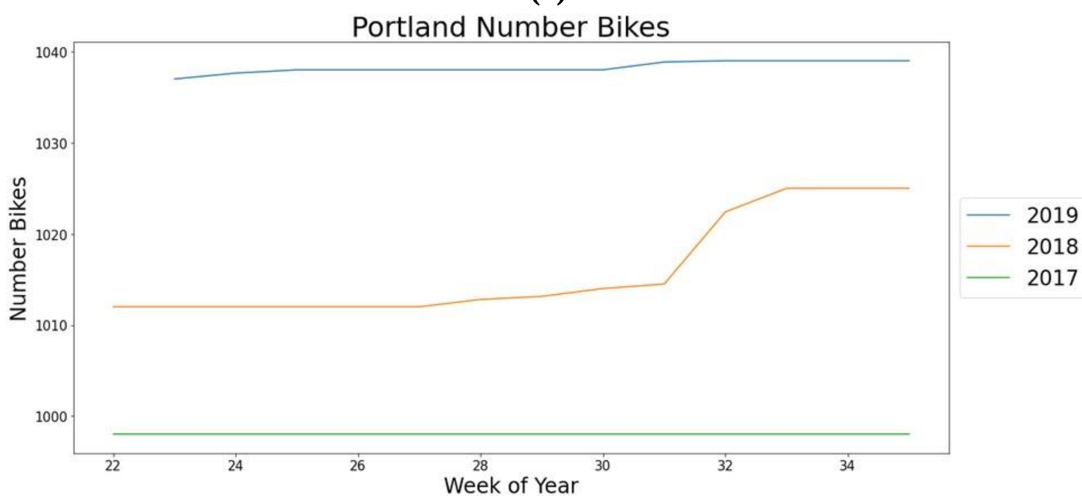
Criteria	**Boston**	**Portland**
Raw Number of Data Points	10,036,560	1,290,053
Filtered Number of Data Points	1,235,997	127,678
Reduction (%)	87.7	90.1

3.3.3. Treatment Data

Our treatment is the expansion of an existing bike share program in a city. We have two variables available to measure expansion; the number of stations in the system and the number of bicycles in the system. Furthermore, we need to identify a treatment date where one city sees an expansion (treatment) and one does not. Figure 5, below, shows the approximate number of bicycles in the system during the same time period for each city. There is roughly a 400 bike addition from 2017 to 2018 in Boston, adding 20% capacity to the system. In Portland, only 12 new bikes are added to the system, adding roughly 1% capacity to the system. Therefore, we use the treatment of expanding the number of bicycles in Boston in 2018 as our treatment, while Portland acts as our control city. We include plots showing station expansion in the appendix for reader interest (Figure A4). Both cities had consistent station expansion, so we opted to use bicycle additions due to the low addition of numbers seen in Portland.



(a)



(b)

Figure 5: (a) Estimated number of shared bicycles in the Boston program from 2015 to 2019 during our study period (June to August) **(b)** Estimated number of shared bicycles in the Portland program from 2017 to 2019 during our study period (June to August)

An important note on our treatment data (Figure 5) is that they are estimated numbers only. Program operators do not include daily numbers of available bikes and stations in the system, as we can assume occasionally some will be out of service for maintenance or repair. Rather they provide a bike ID and station ID associated with each trip. We can calculate the program lifetime total number of bikes and stations simply by counting the number of unique IDs in the data. In Portland, we see very little deviation in the number of bikes in the system (addition of roughly 4% over three years) so we assume the lifetime total numbers accurately depict the current fleet. Boston's system operator, BlueBikes, provides estimates on the number of stations and bikes in the system at the start of each year. These numbers are significantly lower than our calculated lifetime numbers. This signifies bikes and stations are being modified/removed from the system at the same time while new bikes and stations are being added. To account for this, we manually reduced our start of year value (in January) to match the values reported by BlueBikes. Therefore, we capture growth trends throughout the year, while also having reasonable estimates on bikes and stations in the system.

Our empirical strategy section discusses the use of the difference-in-difference methodology. To employ this technique we need to validate the parallel trend assumption. This assumption states that in the absence of treatment, we should see the same change in the treatment group as the control group (Deschenes & Meng, 2018). In Figure 6, below, we show the aggregated number of trips (outcome variable) for both cities and our treatment date. While the two cities have changing differences, there are some noticeable trends. Portland has very minimal change in number trips throughout the entire analysis period. Furthermore, before the treatment date the cities had a relatively steady difference, with the exception of the low point at the start of 2018 data. This point represents the low point for both cities, indicating there may be an externalfactor affecting data nationwide at this point. Finally, in Boston (treatment city) we see a clear increase in the number of trips after the treatment date. While there is some inconsistency in establishing consistent differences between Boston and Portland, we do not expect the data to be perfect due to the natural nature of the experiment. Therefore, to obtain preliminary results, the data is considered acceptable in meeting the parallel trend assumption.

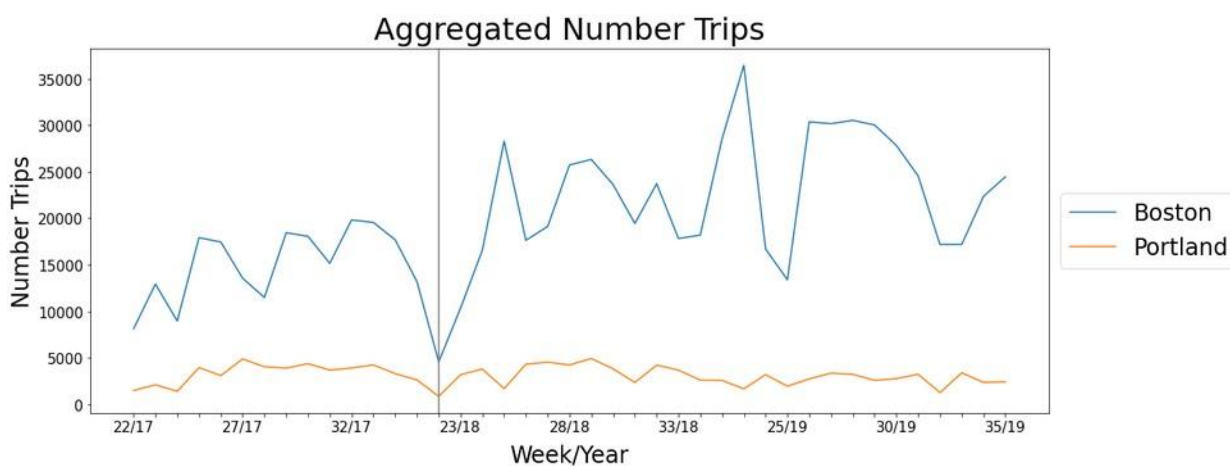


Figure 6: Weekly number of substitution trips from 2017 to 2019 for Boston and Portland. The vertical grey line represents our treatment intervention date.

4. Results

Table 3, below, shows the results from our difference-in-difference analysis. Looking at the Expansion of Bicycle Fleet term, we see that the introduction of roughly 400 bikes into the Boston bicycle share program in 2018 increased the number of substitution trips by 3,100 each week. Furthermore, we see that low temperatures have positive effects on substitution usage, while high temperatures have negative effects. This is initially concerning because our literature review indicated the opposite results should be seen. However, since we only analyze summer months, low temperatures are relatively mild and high temperatures can spike making it uncomfortable outside. Therefore, this result is not entirely unexpected. Wind speed did not deterridership, while increased humidity did. Again, these results are reasonable. Summer winds actas a cooling mechanism for riders, while wet weather causes uncomfortable, often sweaty, rides. The most surprising result is the negative coefficient in the number of stations. This indicatesthat the station changes made in the treatment year decreased the likelihood of substitution trips being taken. However, if we fix the number of bicycles and only introduce more stations, there will be less bicycles available at each station, including heavily trafficked stations. Therefore, weshould expect substitution trips to decrease. We also include results in appendix Table A1 that show our difference-in-difference results without city and time fixed effects for reader interest.

Table 3
Difference-in-difference estimate of expanding bicycles fleet on substitution trips

Criteria	
Expansion of Bicycle Fleet	3099.52 (0.553122)
Low Temperature	1096.32 (0.000183)
High Temperature	-788.36 (0.001542)
Wind Speed	687.59 (0.128099)
Humidity	-180.60 (0.107523)
No. Stations	-76.72 (0.681855)
No. Observations	38

Our study shows that bicycle share programs are an effective method to increase substitution ridership in the United States urban cities. We suggest programs scale up their bicycle fleet and that policy makers incentivise the use of shared bicycle programs, particularly in the summer months, to introduce new members to the program. Incentives can be direct, such as offering to reimburse a certain amount of trips, or more subtle, such as allowing public transit passes to be utilized on shared bike programs. Once new users have been convinced to try the service, theyare more likely to become repeat customers and continue to substitute other transportationmethods for a bike. Furthermore, while stations need to be scaled up with the system, we suggestprioritizing increasing fleet numbers first to ensure substitution trips are not being lost due to bicycle availability. Once the fleet has expanded, further operations analysis, such as that discussed in the literature review, can be completed to optimize the system station locations.

While our results suggest expanding bike share services in United States metropolitans will increase substitution trips, it is important to understand the limitations of our study. Mostnotably, we have not yet incorporated transit data or private bicycle usage data into our model.To attach values on how these programs affect light-duty vehicle usage, we need to increase our confidence in where substitution trips are coming from. If people are switching from other eco-friendly transportation methods (such as private bicycles or public transit systems), light-duty vehicle usage is not actually decreasing and other methods to reduce usage need to be explored. We further discuss this point in Section 6, Future Work.

5. Conclusion

Light-duty vehicle usage in the United States is the single biggest contributor of CO2 emissions in the transportation sector. Reducing vehicle usage will in turn reduce CO2 emissions and help the United States reach its 2050 net-zero emission target. To encourage city residents to reduce car usage, bicycle share programs have been implemented in numerous cities across the United States. In this study we utilize operational data from bicycle system operators to empirically estimate, through a difference-in-difference technique, the number of commuting trips replaced by shared bicycle programs. We find that expanding the current shared bicycle fleet in Boston byroughly 20% resulted in an additional 3,100 weekly substitution trips. This is an extremely positive result and we propose policy intervention be made to increase the shared bike fleet and gain new substitution customers. However, we also suggest further analysis to be done todetermine the source of the substitution ridership before drawing conclusions on light-duty vehicle usage. Our model does not currently build in public transit or private bike data. Without knowing these factors, it is difficult to know what transportation method riders are replacing withshared bicycles and how pollution levels are affected.

6. Future Work

This study provides an estimation on the impact bicycle share programs have on commuting habits. To expand the conclusions that can be drawn from our model, several factors have been identified to improve accuracy. Notably, improving our methods for identifying substitution trips, incorporating transit and private bicycle usage data, and analyzing the casual relationship between the substitution effect and pollution emissions.

We currently estimate a substitution trip primarily based on trip duration, however, a more accurate method is to look at distance travelled as it will not take into account external factors increasing trip time. Operational data includes start and end location longitude and latitudes. Using software, such as the Google Maps API, to calculate actual trip distance based on these coordinates will allow us to identify substitution trips based on only distance. Furthermore, when identifying substitution trips we do not take into account people switching from other public transportation options or from private bikes. Since these trips will not affect light-duty vehicle usage, we are not able to draw conclusions about vehicle use. Collecting, cleaning, and adding transit and private bike data into our model will allow us to expand our conclusions anddefinitively say if light-duty vehicle use, and more generally transportation sector emissions, reduce with expanding shared bicycle programs. Finally, we can run an instrumental variable regression, using the substitution effect as the instrument, to establish the causal relationship between the expansion of bicycle-sharing programs and pollution emissions. Our treatmentwould remain the same (expansion of the bicycle fleet), however, our outcome variable will be pollution levels. The logic behind this idea is that the substitution effect correlates with the expansion of bicycle-sharing programs, but is not correlated with any other determinants of pollution levels. This approach may allow us to obtain estimates on shared bicycle programs variations in pollution emissions.

7. References

Best Choice Reviews. (2019). *America's 30 Most Popular Cities for Tourists 2019*. Best Choice Reviews. https://www.bestchoicereviews.org/travel/popular-tourist-cities-us/

BikeTown. (2021). *BikeTown*. https://www.biketownpdx.com/homepage

BlueBikes. (2021). *BlueBikes*. https://www.bluebikes.com/

Chan, N., & Wichman, C. (2020, 4 22). Climate Change and Recreation: Evidence from North American Cycling. *Environmental and Resource Economics*, *76*, 119-151. https://doi.org/10.1007/s10640-020-00420-5

Clockston, R. L., & Rojas-Rueda, D. (2021, 7 14). Health impacts of bike-sharing systems in the U.S. *Environmental Research*, *202*. https://doi.org/10.1016/j.envres.2021.111709

DeMaio, P. (2009). Bike-sharing: History, Impacts, Models of Provision, and Future. *Journal of Public Transportation*, *12*(4), 41-56. http://doi.org/10.5038/2375-0901.12.4.3

Deschenes, O., & Meng, K. (2018, 8). *Quasi-Experimental Methods in Environmental Economics: Opportunities and Challenges* [Working Paper]. National Bureau of Economic Research. https://www.nber.org/papers/w24903

Dill, J., & Carr, T. (2003, 1 1). Bicycle Commuting and Facilities in Major U.S. Cities. *Transportation Research Record*, *1828*(1), 116-123. https://journals.sagepub.com/doi/10.3141/1828-14

Gatersleben, B., & Appleton, K. (2007, 5). Contemplating cycling to work: Attitudes and perceptions in different stages of change. *Transportation Research Part A: Policy and Practice*, *41*(4), 302-312. https://doi.org/10.1016/j.tra.2006.09.002

Government of Canada. (2021, 4 29). *Net-Zero Emissions by 2050*. Canada's climate plan. https://www.canada.ca/en/services/environment/weather/climatechange/climate-plan/net-zero-emissions-2050.html

Han, X., Wang, P., Gao, J., Shah, M., Ambulgekar, R., Jarandikar, A., & Dhar, S. (2018, 6 28). Bike sharing data analytics for silicon valley in USA. *IEEE*. 10.1109/UIC-ATC.2017.8397557

Midgley, P. (2011, 5). *Bicycle Sharing Schemes: Enhancing Sustainable Modibily in Urban Areas*. United Nations Department of Economic and Social Affairs. https://static.un.org/esa/dsd/resources/res_pdfs/csd-19/Background-Paper8-P.Midgley-Bicycle.pdf

National Association of City Transportation Officials. (2019, 12 31). *Shared Micromobility in the U.S.: 2019*. National Association of City Transportation Officials. https://nacto.org/shared-micromobility-2019/

National River and Recreation Area Minnesota. (2019, 4 22). *Alternative Transportation Plan: New Bike Share Will Reduce Congestion and Pollution*. National Park Services. https://www.nps.gov/miss/learn/management/atp-bikeshare.htm

Qiu, L.-Y., & He, L.-Y. (2018). Bike Sharing and the Economy, the Environment, and Health-Related Externalities. *Sustainability*, *10*(4). https://doi.org/10.3390/su10041145

Richter, F. (2018, 7 3). *Bike-Sharing Clicks Into Higher Gear*. Statista. https://www.statista.com/chart/14542/bike-sharing-programs-worldwide/

Rojas-Rueda, D., de Nazelle, A., Tainio, M., & Nieuwenhuijsen, M. (2011). The health risks and benefits of cycling in urban environments compared with car use: health impact assessment study. *bmj*, *343*. https://www.bmj.com/content/343/bmj.d4521

Shaheen, S., Guzman, S., & Zhang, H. (2010, 1). Institute of Transportation Studies. https://www.researchgate.net/publication/46439835_Bikesharing_in_Europe_the_Americas_and_Asia_Past_Present_and_Future

Shaheen, S., Martin, E., & Adam, A. (2013, 12). Public Bikesharing in North America: Early Operator Understanding and Emerging Trends. *ournal of the Transportation Research Board, 2387*, 83-92. https://www.researchgate.net/publication/272716592_Public_Bikesharing_in_North_America

United States Census Bureau. (2021). *Explore Cencus Data*. United States Census Bureau. https://data.census.gov/cedsci/

United States Environmental Protection Agency. (2021, 4 14). *Fast Facts on Transportation Greenhouse Gas Emissions*. Green Vehicle Guide. https://docs.google.com/document/d/1DUjtaB12TJi_ObSrsv09jOuhlpJMIKH8riUt3BznBT8/edit#

United States Environmental Protection Agency. (2021, 5 18). *Pre-Generated Data Files*. Air Data. https://aqs.epa.gov/aqsweb/airdata/download_files.html

Urban Sustainability Exchange. (2021). *Case Studies*. Urban Sustainability Exchange. https://use.metropolis.org/

US Climate Data. (2021). *US Climate Data*. https://www.usclimatedata.com/

Webster, K., & Cunningham,, C. (2012, 7 5). Preparing for Bike-Sharing: Insight From Focus Groups and Surveys, Chattanooga, Tennessee, 2010. *Health Promotion Practice*, *14*(1), 62-68. https://doi-org.proxy.lib.sfu.ca/10.1177/1524839912447191

The White House. (2021, 4 22). *President Biden Sets 2030 Greenhouse Gas Pollution Reduction Target Aimed at Creating Good-Paying Union Jobs and Securing U.S. Leadership on Clean Energy Technologies*. FACT SHEET. https://www.whitehouse.gov/briefing-room/statements-releases/2021/04/22/fact-sheet-president-biden-sets-2030-greenhouse-gas-pollution-reduction-target-aimed-at-creating-good-paying-union-jobs-and-securing-u-s-leadership-on-clean-energy-technologies/

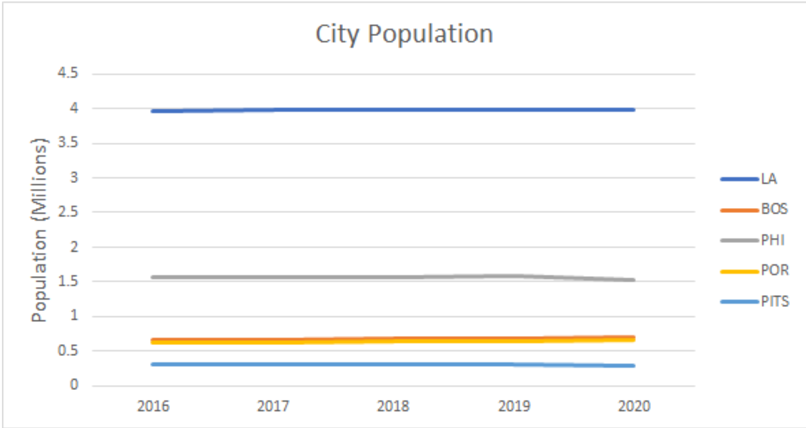
Wood, J., Slingsby, A., & Dykes, J. (2011). Visualizing the Dynamics of London's Bicycle Hire Scheme. *Cartographica*, *46*(4), 239-251.

Wuennenberg, L., Bassi, A., & Pallaske, G. (2020, 1 1). Sustainable Asset Valuation (SAVi) of a Public Bicycle Sharing System in Dwarka, New Delhi, India: A focus on the environmental, social and economic impacts of non-motorized transport infrastructure. *International Institute for Sustainable Development*. http://www.jstor.org/stable/resrep21987.4

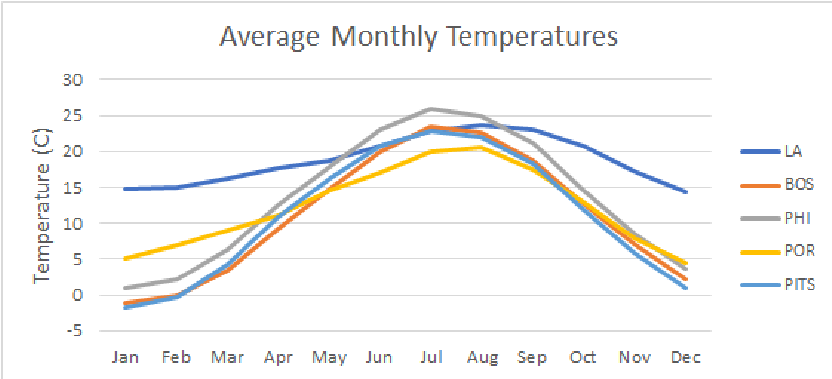
Zhang, Y., & Mi, Z. (2018, 6 15). Environmental benefits of bike sharing: A big data-based analysis. *Applied Energy*, *220*, 296-301. https://www.sciencedirect.com/science/article/pii/S0306261918304392

Zhang, Y., & Zhang, Y. (2018, 6 4). Associations between Public Transit Usage and Bikesharing Behaviors in The United States. *Sustainability*, *10*(6). https://doi.org/10.3390/su10061868

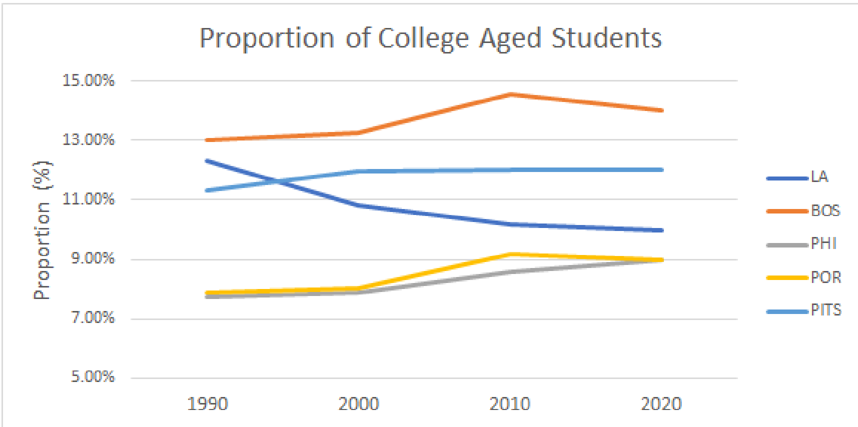
8. Appendix



(a)

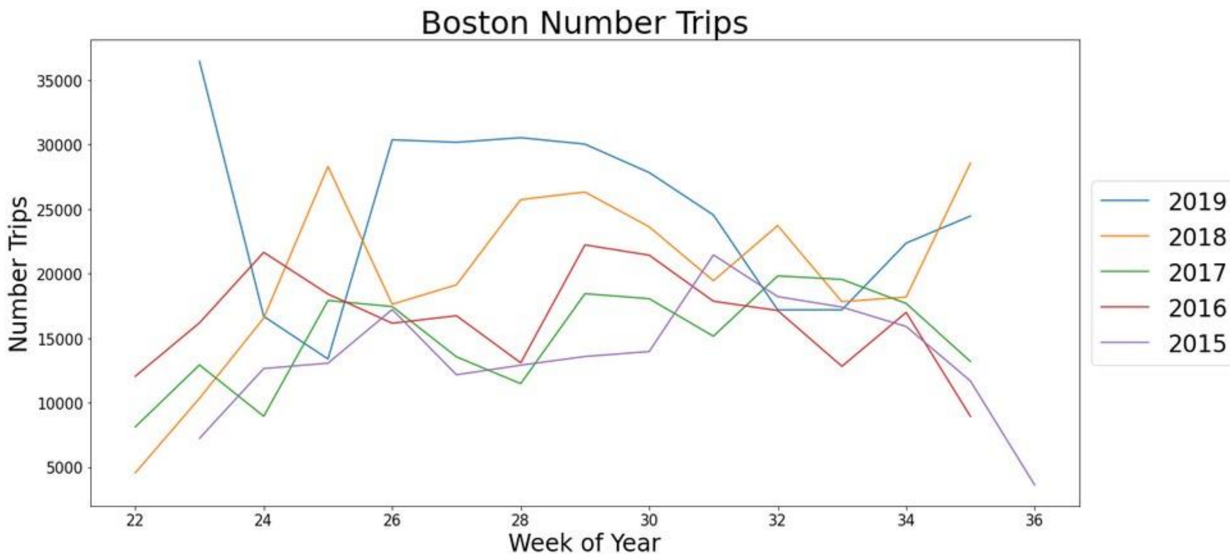


(b)

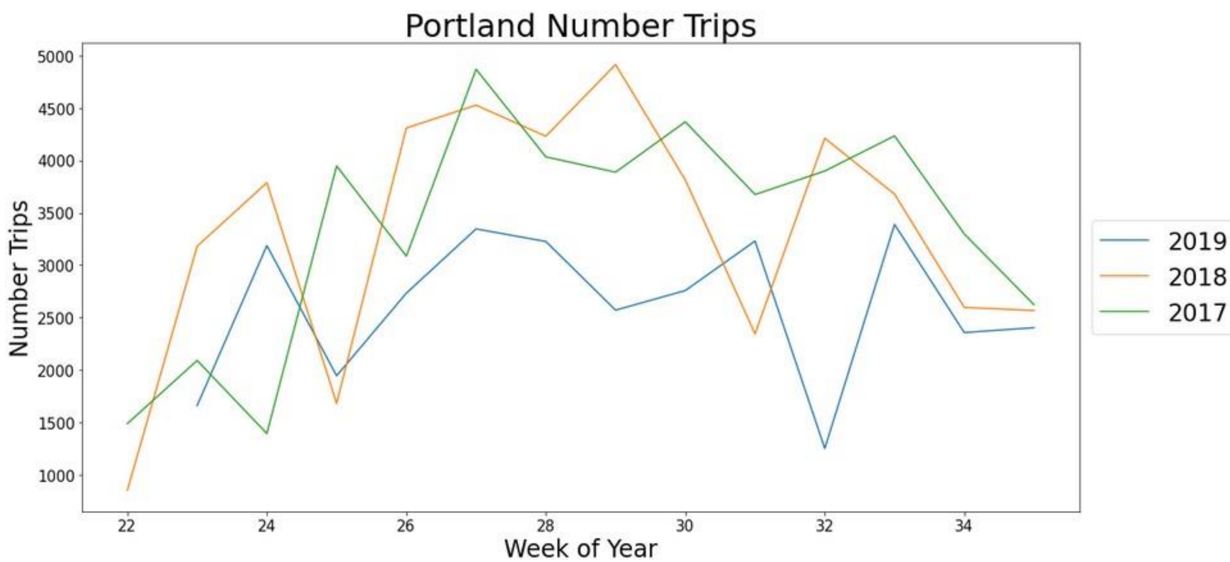


(c)

Figure A1: (a) Populations of cities considered for out study from 2016 to 2020 **(b)** Monthly average 2020 temperatures of cities considered for our study **(c)** Percentage of college aged students living in cities considered for our study

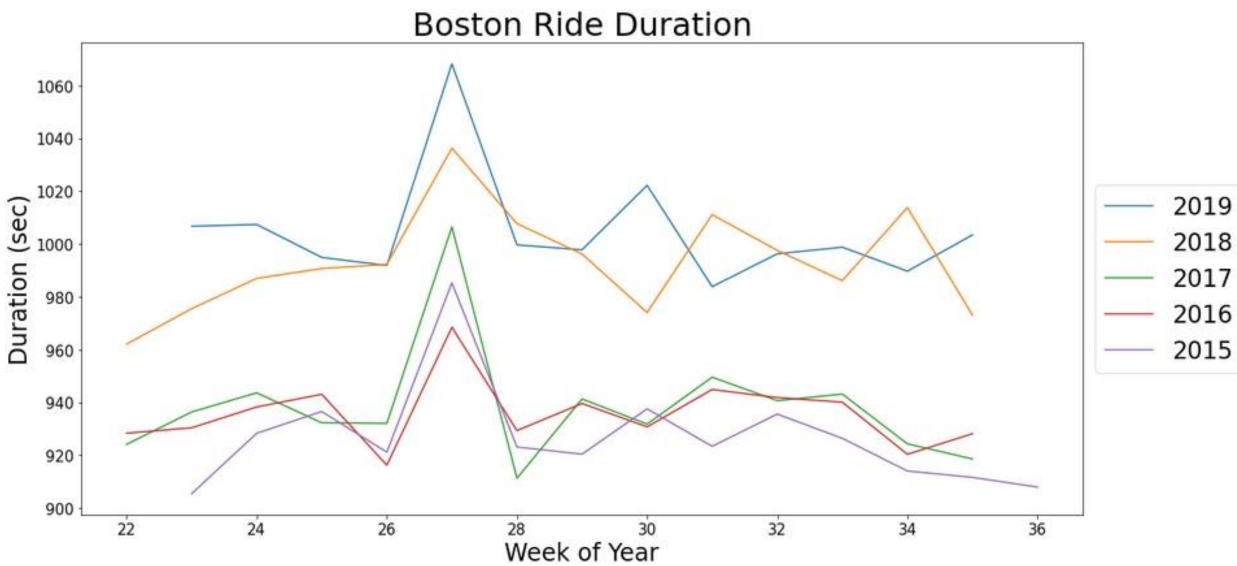


(a)

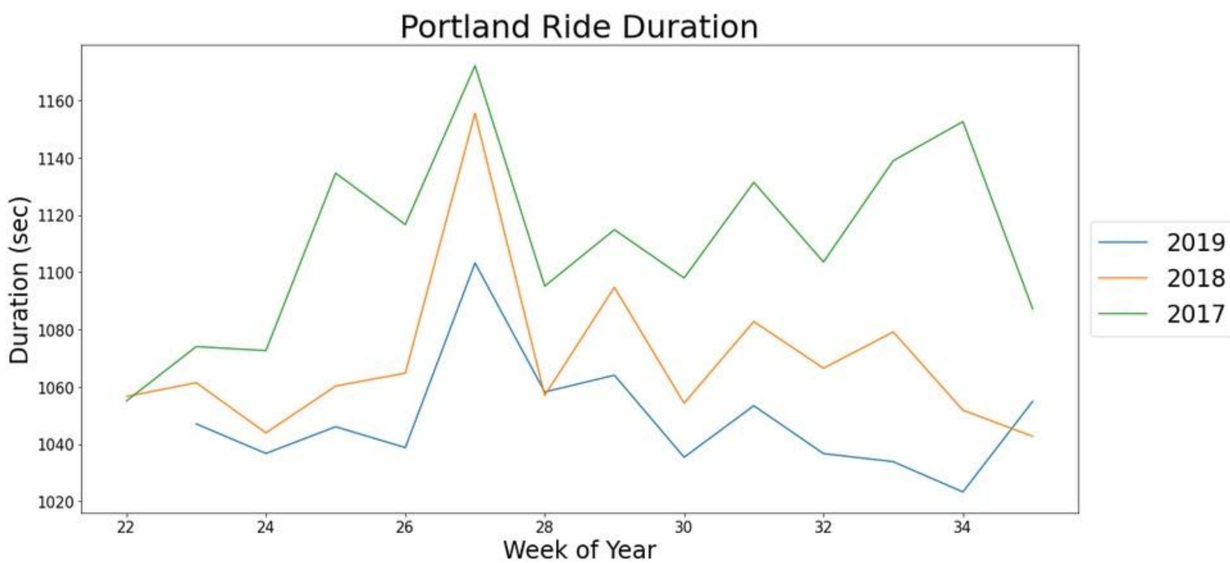


(b)

Figure A2: (a) Boston weekly aggregated total trips after applying substitution trip filtering during our study period (June to August) **(b)** Portland weekly aggregated total trips after applying substitution trip filtering during our study period (June to August)

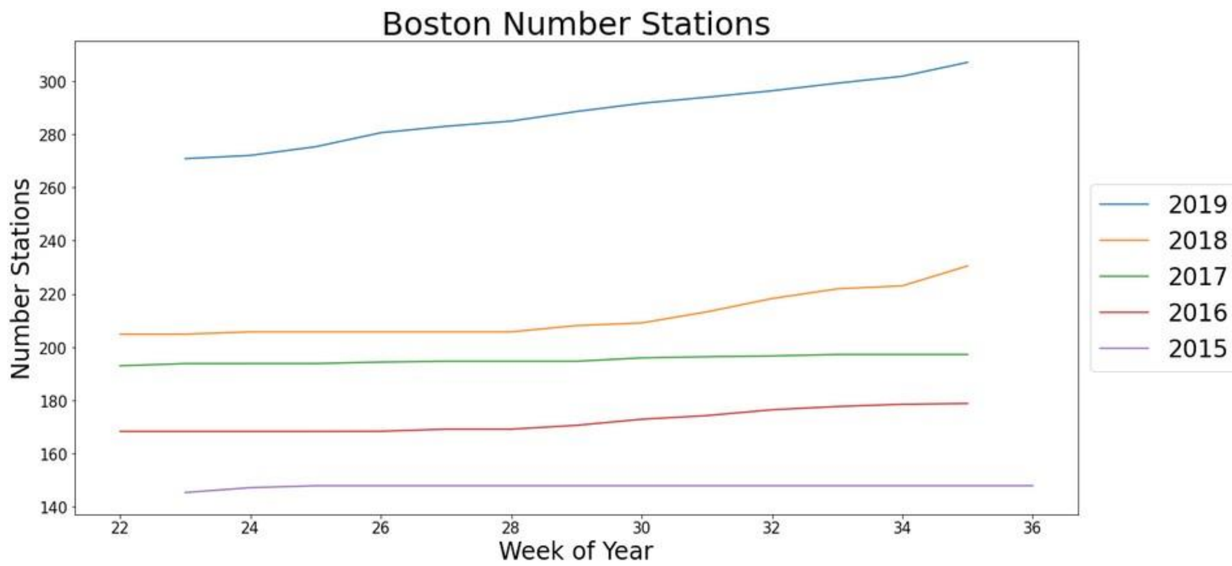


(a)

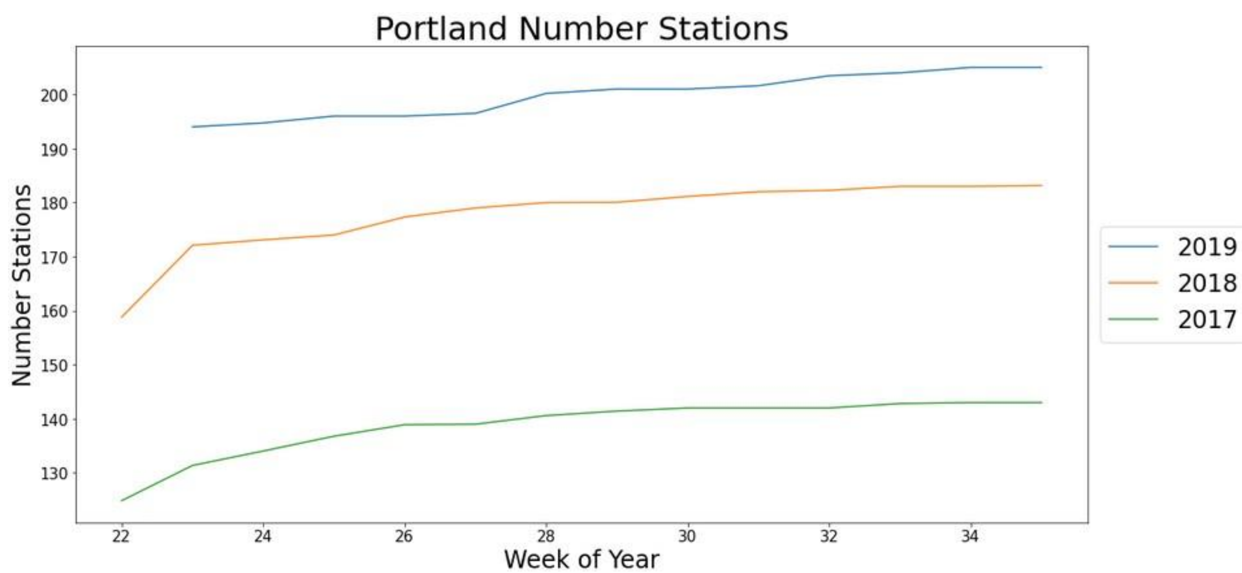


(b)

Figure A3: (a) Boston weekly average trip duration during our study period (June to August) **(b)** Portland weekly average trip duration during our study period (June to August)



(a)



(b)

Figure A4: (a) Estimated number of bicycle sharing stations in Boston during our study period (June to August) **(b)** Estimated number of bicycle sharing stations in Portland during out study period (June to August)

Table A1
Difference-in-difference estimate of expanding bicycles fleet on substitution trips including no city and time fixed effects

Criteria	**(1)**	**(2)**	**(3)**
Expansion of Bicycle-Sharing Pogram	5264.635 (0.064131)	3099.52 (0.553122)	3099.52 (0.553122)
Low Temperature	1111.971 (0.000113)	1096.32 (0.000183)	1096.32 (0.000183)
High Temperature	-821.037 (0.000566)	-788.36 (0.001542)	-788.36 (0.001542)
Wind Speed	607.457 (0.142017)	687.59 (0.128099)	687.59 (0.128099)
Humidity	-182.986 (0.098190)	-180.60 (0.107523)	-180.60 (0.107523)
No. Stations	9.772 (0.876975)	-76.72 (0.681855)	-76.72 (0.681855)
No. Observations	38	38	38
City Fixed Effects	No	Yes	Yes
Time Fixed Effects	No	No	Yes