THE UNIVERSITY OF CHICAGO

Evaluating the Impact of Lyft App Integration on the Public Bike Share Programs in Four Major U.S. Cities Using Synthetic Control[1]

By

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[1] I'd like to thank my roommate Boxuan Zhou for joining me in numerous divvy biking adventures as we explored various neighborhoods in Chicago. For the data and code of this project, see:
https://github.com/william-wei-zhu/thesis_public_bike_share_programs

Introduction

Since 2013, public bike sharing programs have been expanding across major cities in the United States. Through these bike sharing programs, riders can rent out and return bikes from bike stations installed across each city. In each city, a third-party contractor company operates each city’s bike sharing program through a licensed agreement with the city council. These contractors were responsible for maintaining the bikes and bike stations as well as building web and mobile platforms to process payments for riders. Before 2019, riders in each city can either pay at a kiosk next to each bike station, or through a city-specific phone app or website. Every public bike sharing program has two types of payment options: (1) one-time or day pass, which allows riders to pay by trip or day, and (2) monthly or yearly membership, which allows riders to pay a monthly or yearly fee for unlimited rides.

In 2018, Lyft acquired a company called Motivate, which operates the bike sharing service of cities including Boston, Chicago, New York City, Washington DC, Columbus (Ohio), and Portland (Oregon). As a result of the acquisition, riders in these cities can use their Lyft mobile app to unlock bikes for one-time usage. Boston, Chicago, NYC, and DC rolled out the Lyft app integration in June of 2019, while Columbus and Portland rolled out the integration in January and September 2020. Meanwhile,the bike share systems in Philadelphia and Pittsburgh are not integrated with the Lyft app as they are operated by different third-party contractors. Table 1.1 summarizes the public bike share programs of these 8 major cities.

Table 1.1: Public Bike Share Systems of Eight Cities

City	Name	Launched in	Stations #	Bicycles #	Operator before 2019	bike trip data source
Boston	Bluebikes	2011	393	3800	Motivate	https://www.bluebikes.com/system-data
Chicago	Divvy	2013	659	5837	Motivate	https://www.divvybikes.com/system-data
New York City	Citi Bike	27 May 2013	1000	20000	Motivate	https://ride.citibikenyc.com/system-data
Washington DC	Capital Bikeshare	2010	658	5400	Motivate	https://www.capitalbikeshare.com/system-data
Columbus, OH	CoGo	July 2013	80	600	Motivate	https://www.cogobikeshare.com/system-data
Portland, OR	Biketown	19 July 2016	133	1000	Motivate	https://www.biketownpdx.com/system-data
Philadelphia	Indego	23 April 2015	140	1400	Bicycle Transit System	https://www.rideindego.com/about/data/
Pittsburgh	Healthy Ride	2015	100	650	Pittsburgh Bike Share	https://healthyridepgh.com/data/

This project aims to test the impact of the Lyft mobile app integration on the monthly casual trips and casual trip rates. Monthly casual trips are defined as the number of bike trips in a month that are paid via one-time or day pass options. Monthly casual trip rate is the percentage of all bike trips in a month that are casual trips. The hypothesis is that, when riders are able to unlock one-time rides from their Lyft mobile app, the monthly casual trips and casual trip rates both increase because of low sign up friction: before the Lyft app integration, renting out bikes for casual trips required riders to either pay via a kiosk next to the bike stations or download a city-specific app and sign up for an account. The process of signing up and entering the payment information can be very cumbersome for casual riders. As a result, many potential casual riders choose membership options or are discouraged from signing up.

After Lyft app integration, riders who have the Lyft app installed on their phone can easily unlock bikes for casual trips without needing to sign up for a new account or enter additional payment information. The reduced friction should encourage more riders to try out the public bike share on a casual basis. Hence, this project aims to test the hypothesis that the Lyft mobile app integration caused an uplift in monthly total casual trips and casual trip rates.

Furthermore, if the Lyft app integration did contribute to an increase in monthly casual trips, was this uplift drawn from new first-time riders, or previously membership riders? To answer this question, this project also explores the impact of the Lyft app integration on monthly total trips and membership trips. If the increase in monthly casual trips are drawn from mostly new first-time riders, then we should observe an uplift in total trips and no significant changes in membership trips. Meanwhile, if the uplift was drawn from previously membership riders, we should observe a decline in monthly membership trips and no changes in total trips.

This project applies a causal inference method called synthetic control to answer these questions. Results show that **the Lyft mobile app integration caused a significant uplift in both monthly casual trips and casual trip rates in Chicago, New York City, and Boston from June 2019 to December 2019**. Meanwhile, the app integration is associated with a decline in monthly total trips and membership trips in Chicago and Washington DC, and non-significant impact in Boston and New York City. It suggests that the increase in casual trips are mainly drawn from previously membership riders rather than first-time new riders.

The rest of the paper is organized as follows: “Literature Review" section describes the background behind Uber and Lyft’s expansions into the public bike share market. “Method and Data” section introduces the motivation behind synthetic control and the description of the four time series that experienced interventions and the eight time series in the control pool. The first three subsections of the “Result” section show that in Chicago, New York City, and Boston, the actual casual trip rates and monthly casual trips are significantly higher than the synthetic control counterfactuals from June to December 2019. It suggests that interventions in June 2019 were effective at uplifting casual trip rates and monthly casual trips. The third and fourth subsection of the “Result” section shows that the interventions in June 2019 were not effective at improving monthly total trip counts and membership counts in these cities. It suggests that the increase in monthly casual trips are likely to be drawn from previous membership riders. Lastly, the “Visualization” section enriches the analysis by presenting the public bike share network of the eight cities included in this project.

Literature Review

Over the past decade, ride sharing companies like Uber and Lyft have tremendously changed how people make urban travels. Diao el al. (2021) showed that these ride sharing services led to an increase in urban road congestion and decline in public transportation ridership. Because of these major impacts to urban mobility, as well as Uber and Lyft’s oligopolistic dominance of the ride sharing market, scholars and public policy researchers have called for government regulators to step in to ensure that these ride sharing companies act for the interest of efficient, sustainable, and environment friendly urban future (Bulger et al 2019).

Partly in response to the pressure of reducing urban congestion and vehicle pollution, ride sharing companies have expanded into public bike share services as a solution. In 2018, Uber acquired JUMP bike, which operated dockless bike share programs in San Francisco, San Diego, and Sacramento. Also In 2018, Lyft acquired a Motivate, which operated the public bike share programs in 8 major metropolitan areas in the United States (San Francisco Bay Area, Portland, Boston, Chicago, New York City, Washington DC, Columbus, and Minneapolis-St Paul). Interestingly, Gozen and Tosun (working draft) found that Lyft’s acquisition of Motivate caused an 10% increase in the ride-sharing compared to Uber. Gozen and Tosun argue that this uplift is mainly because rebranding public bikes with the Lyft logo on them give Lyft more brand presence in these cities. This research project suggests that Lyft’s integration of ride sharing and public bike share features in one mobile app is another potential cause for the uplift in ride-sharing: to use the public bike share service, more people are willing to download and use the Lyft mobile app on their phone. More usage of the bike sharing feature in the Lyft mobile app drives usage of the ride sharing feature due to convenience and frequent exposure in the same app.

As Lyft and Uber expanded into the public bike share market, more regulatory concerns ensued. For example, there is a big discussion over dockless vs docked public bikes. Docked bikes are public bikes that must be checked out and returned to designated public bike stations. Meanwhile, dockless bikes can be checked out and locked on most public streets. On the one hand, researchers found that dockless public bikes allowed residents in less urban areas to access the public bike share service (Lazarus et al 2019). On the other hand, allowing riders to lock bikes on the sidewalk led to congested sidewalks. Because Uber and Lyft have so much power in shaping the urban public landscape in major cities, public policy researchers called for more active collaborations and communications between city regulators and these two private bike share service operators (Moon-Miklaucic 2018).

This project contributes to this line of discussion by showing that Lyft’s acquisition of public bike systems in major cities in the United States and the subsequent mobile app integration improved the convenience and payment flexibility of urban residents when using these public bikes. More travelers choose to use these public bikes on causal trips, rather than become bounded by monthly or yearly subscriptions.

Method and Data

The main objective of this study is to test whether the Lyft app integration in May 2019 caused an improvement in monthly casual trips and casual trip rates in the four major cities in the United States (Boston, Chicago, New York City, Washington DC). To demonstrate a causal impact, the biggest challenge is to identify a convincing counterfactual to simulate the trend of casual trip rates since May 2019 in a hypothetical scenario in which the intervention of the Lyft app integration never took place.

Two groups have the potential to serve as the counterfactual for the Lyft app integration in the four major cities in May 2019. The first group is the public bike share data of four other cities from April 2018 to December 2019: Columbus, Portland, Philadelphia, and Pittsburgh. The public bike share systems of these four cities had not experienced Lyft app integration by the end of 2019. While this group is able to control time-specific trends in April 2018 to December 2019, the challenge is that the scale of the public bike share systems in these four cities were much smaller than those that received the intervention. Therefore, it’s likely that certain confounding factors (e.g. scale of public bike share system, population density) may not be controlled. Hence, the first group by themselves cannot serve as convincing counterfactuals.

The second group is the prior year public bike share data of the four major cities that received the intervention in 2019 (from April 2017 to December 2018). This group controls the scale of the public bike share systems, but is unable to control seasonal confounders that differentiate bike share trends in 2017-2018 from those in 2018-2019. Hence, the second group of data by themselves cannot serve as satisfactory counterfactuals either.

This paper applies synthetic control, a causal inference technique that combines the strength of both groups of data previously mentioned to generate a more convincing counterfactual (Abadie et al. 2010, Abadie 2021)[2]. The core idea of synthetic control is that it collects a pool of data that has potential to serve as the control group, and applies linear regression to identify weights for each data in the pool such that the linear combination of these data trends best simulates the trend of the intervention data during the time period before intervention. In this way, this method combines a pool of data to create a “synthetic” counterfactual. The gap between the trend of the intervention data and that of the “synthetic control” data during the time period after the intervention represents the impact of the intervention.

For each of the four casual trip rate time series that experienced the intervention (Boston, Chicago, NYC, and Washington DC from April 2018 to Dec 2019), a synthetic control time series is generated based on a pool of 8 time series: Philadelphia, Pittsburgh, Portland, and Columbus from April 2018 to Dec 2019, as well as Boston, Chicago, NYC and Washington DC from April 2017 to Dec 2018. For the four time series from April 2017 to Dec 2018, their timestamps are manually adjusted by adding 1

[2] For a detailed description of synthetic control, see https://matheusfacure.github.io/python-causality-handbook/15-Synthetic-Control.html

year before feeding into the control pool, so that all time series in the control pool have consistent starting and ending time periods. Table 2.1 summarizes the 4 intervention time series and the 8 control time series.

Table 2.1 Overview of intervention and control time series data

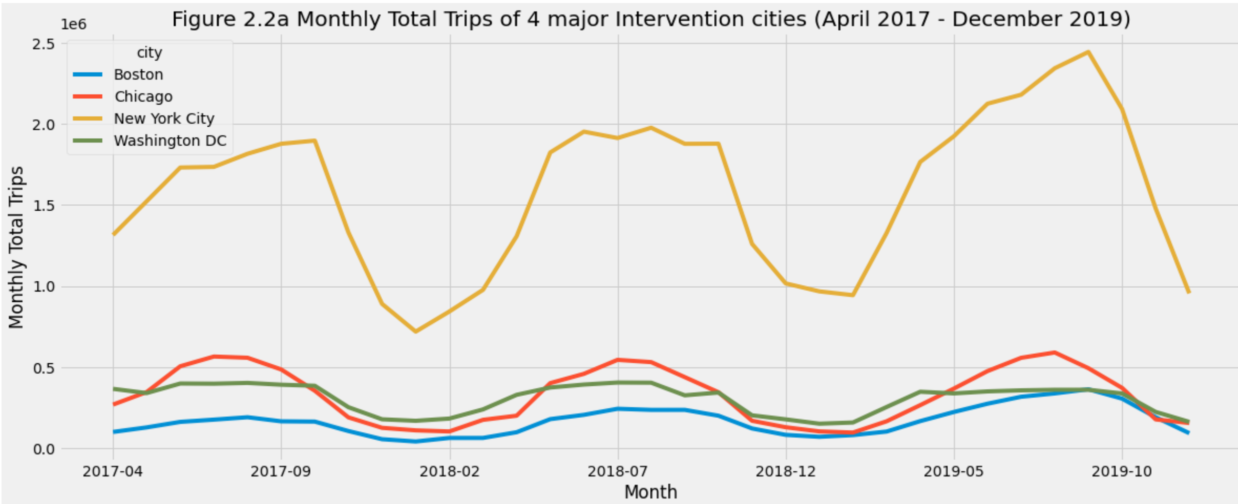
time series data	intervention group or control pool	total number of trips
Chicago April 2018 - Dec 2019	intervention	7,033,941
Boston April 2018 - Dec 2019	intervention	4,123,843
New York City April 2018 - Dec 2019	intervention	35,561,256
Washington DC April 2018 - Dec 2019	intervention	6,351,135
Chicago April 2017 - Dec 2018	control pool	7,000,405
Boston April 2017 - Dec 2018	control pool	3,013,537
New York City April 2017 - Dec 2018	control pool	31,667,008
Washington DC April 2017 - Dec 2018	control pool	6,653,951
Columbus April 2018 - Dec 2019	control pool	74,658

Pittsburgh April 2018 - Dec 2019	control pool	182,664
Philadelphia April 2018 - Dec 2019	control pool	1,317,085
Portland April 2018 - Dec 2019	control pool	675,505

All 12 sets of trip record data are publicly available on the official website of each city’s public bike share system[3]. The trip data is stored in csv files. Each row represents a bike trip with features including starting and ending time stamps and coordinates, the trip type (one-time, day pass, month pass, year pass), and bike type (normal and e-bike). For each dataset, the monthly casual rate is calculated as the total number of casual trips (one time and one day pass) divided by the total number of trips in the month.

Figure 2.2a and 2.2b show the monthly total trips of the eight cities in the analysis. Because the total trips of four cities that received the intervention are so much larger than those that did not receive the intervention in 2019, they are presented in two separate figures. Seasonality plays an important role in affecting monthly total trips. In all cities, summer months have more bike trip rides than winter months. We can see that New York City has by far the most amount of monthly total trips, followed by Chicago, Washington DC, and Boston. For all eight cities except Washington DC and Portland, the total number of trips in the summer of 2019 increased from those in the summer of 2018. In contrast, the total number of trips in Washington DC witnessed a decline in the summer of 2019 compared to the summer of 2018. It is likely because alternative traveling options (e.g. scooters) became increasingly popular in Washington DC in 2019, which took away the market share from public bike services[4].

[3] See the last column of Table 1.1
[4] For information about the rise in popularity of scooters in Washington DC in 2019, see the follow articles:



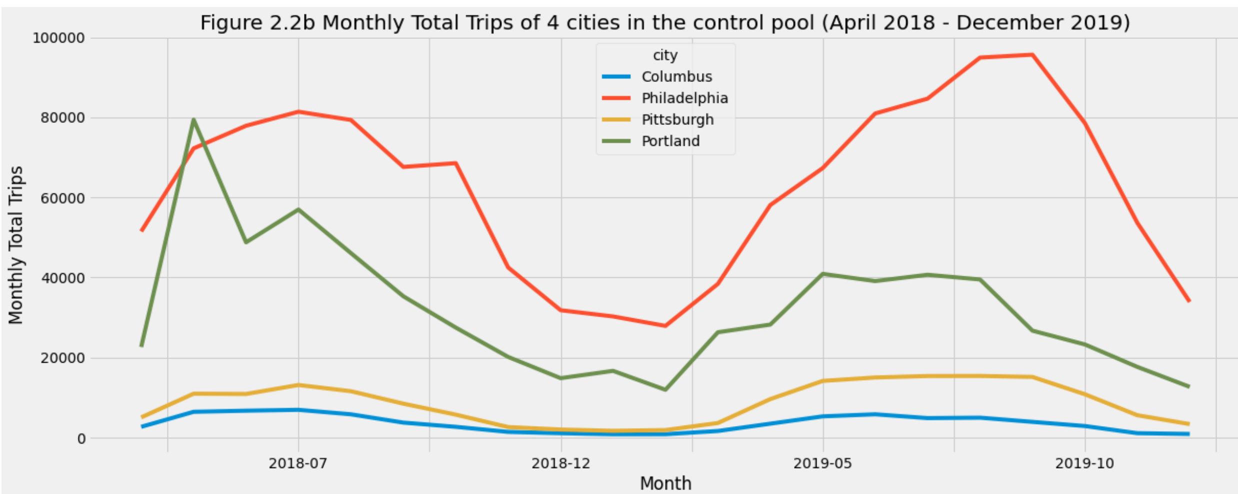


Figure 2.3 shows the monthly casual trip rates of all eight cities from April 2017 to December 2019. Interestingly, the three cities with the lowest total trip counts have the highest casual trip rates. It is likely because the relatively small scale of the public bike systems in these cities made their monthly or yearly membership less useful relative to casual payment options. Furthermore, the casual trip rate also shows a seasonality

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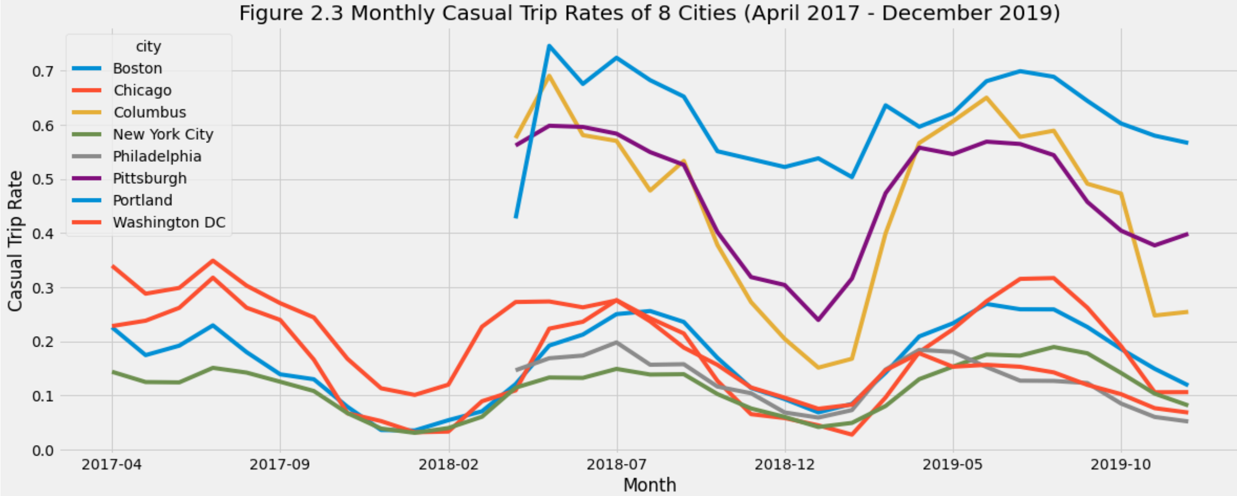
https://www.npr.org/2019/03/30/703102986/as-electric-scooters-proliferate-so-do-minor-injuries-and-blocked-sidewalks
https://www.usnews.com/news/cities/articles/2019-05-30/electric-scooter-safety-issues-as-more-people-ride-in-washington-dc

effect across all eight cities. Casual trip rate increased during the summer months and dipped in winter. A rough glimpse seems to show that the casual trip rates of three cities (New York City, Chicago, and Boston) were higher during the summer months of 2019 relative to the summer months of 2018. However, this figure cannot tell us how much of the increase in casual trip rates in the summer of 2019 was caused by Lyft mobile App integration. Therefore, synthetic control is needed for further analysis.

Figure 2.3 Monthly Casual Trip Rates of 8 Cities (April 2017 - December 2019)



Results

This section contains four subsections. The first two subsections show that interventions that took place in June 2019 in Chicago, Boston, and New York City caused a significant improvement in the monthly casual trip rate from June 2019 to December 2019, using synthetic controls with and without weight constraints. The third subsection shows that there is a significant increase in monthly casual trips in Chicago, Boston, and New York City from June 2019 to December 2019 relative to the synthetic controls with and without weight constraints. The fourth and fifth subsections show that both total trips and membership trips declined in Chicago and Washington DC, and experienced no significant change in Boston and New York City from June 2019 to December 2019 relative to the synthetic controls.

Synthetic control on monthly casual trip rates (first iteration)

In the first iteration of the analysis on monthly casual trip rates, the eight time series in the control pool generated four synthetic control time series, one for each of the four cities that experienced Lyft App integration in June 2019. In Table 3.1, the four rows represent the four cities that received the intervention. The eight columns show the eight time series in the control pool. The values in each row are the weights that each time series in the control pool contributed to the four synthetic control time series.

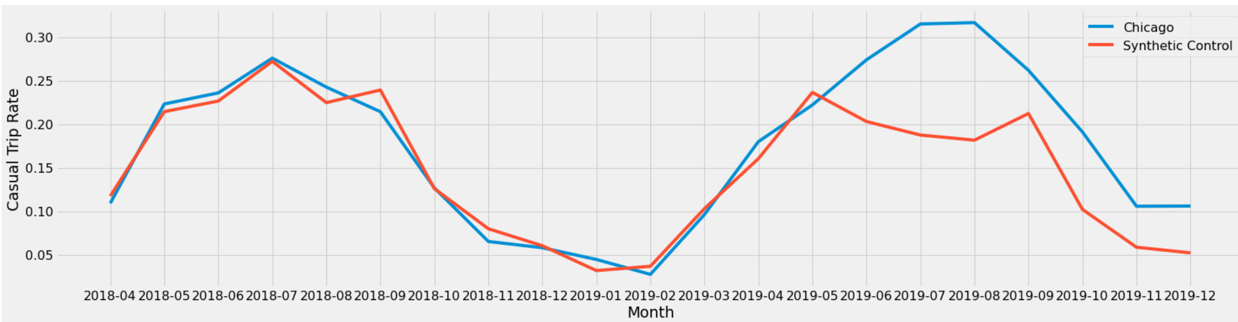
Table 3.1: Weights of the eight time series in the control pool for synthetic controls on casual trip rates (no weight constraints)

	Columbus	Pittsburgh	Portland	Philadelphia	Chicago Previous	Boston Previous	Washington DC Previous	New York City Previous
Chicago	-0.513	0.881	-0.036	1.104	1.545	0.026	-0.003	-1.016
Boston	-0.849	0.461	-0.240	2.223	1.442	0.175	0.018	-0.842
New York City	0.120	0.050	0.000	1.059	0.422	0.060	0.021	-0.376
Washington DC	0.188	0.331	0.171	-1.320	-1.062	0.123	0.023	0.965

Figure 3.2 shows the monthly casual trip rate of Chicago (blue line) versus its synthetic control (red line) from April 2018 to December 2019. Before June 2019, the two lines almost coincide with each other. It means that before June 2019, the synthetic control is effective at simulating the monthly casual trip rate of Chicago. The line of the synthetic control from June 2019 to December 2019 represents the monthly casual trip rate trend of the counterfactual, in which no Lyft mobile application was introduced. We can see that there is a clear gap between the actual monthly casual trip rate trend line and the synthetic control line from June 2019 to December 2019. **The gap shows that the**

interventions that took place in Chicago in June 2019 caused a significant improvement in the monthly casual trip rate from June 2019 to December 2019.

Figure 3.2 Monthly Casual Trip Rate (Chicago vs the synthetic control of Chicago) (April 2018 to December 2019) (No Weight Constraints)



From figure 3.3 and 3.4, we can draw similar conclusions for the impact on casual trip rates in Boston and New York City. In both figures, the synthetic control lines were effective at simulating the casual trip rates in the two cities before June 2019. From June 2019 to December 2019, large gaps appeared between the actual casual trip rate line and the synthetic control line. **It means that in both Boston and New York City, interventions that took place in June 2019 caused a significant improvement in the monthly casual trip rate from June 2019 to December 2019.**

Figure 3.3 Monthly Casual Trip Rate (Boston vs the synthetic control of Boston) (April 2018 to December 2019) (No Weight Constraints)

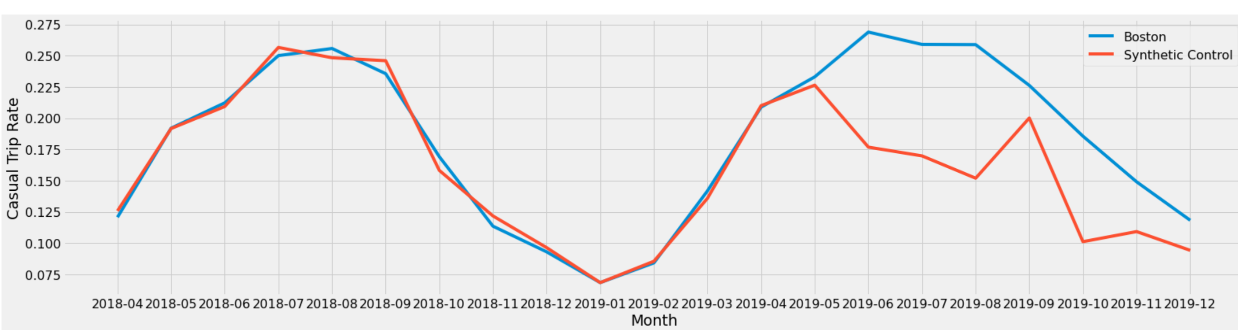
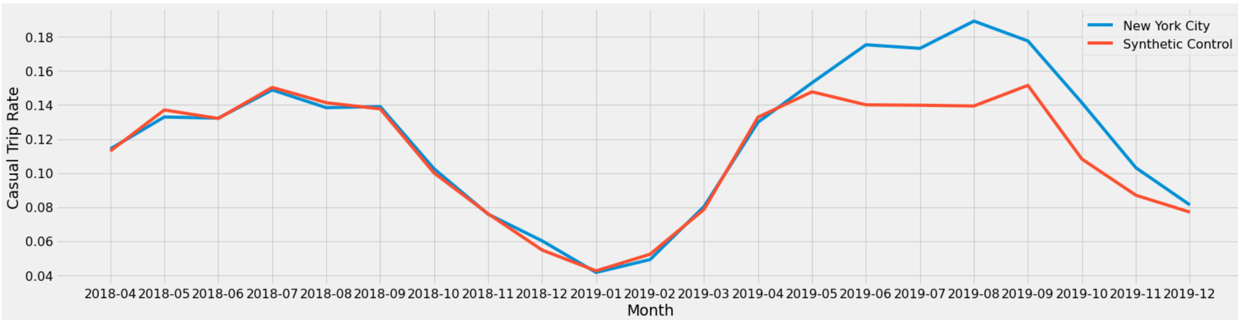
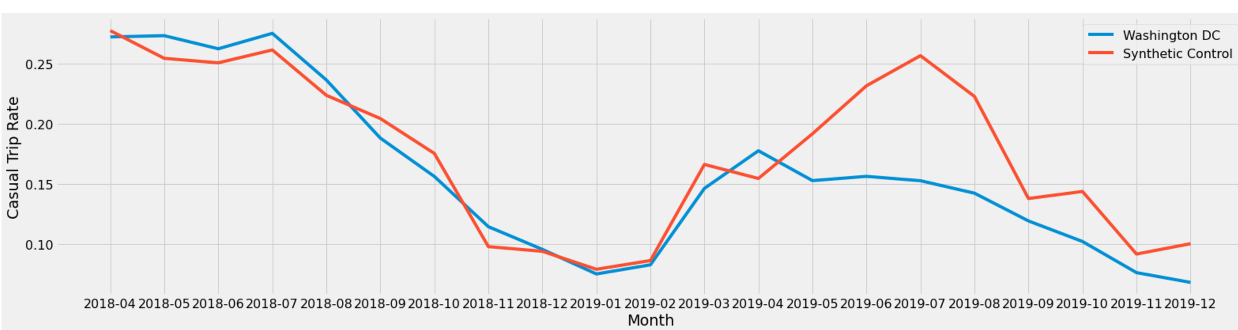


Figure 3.4 Monthly Casual Trip Rate (New York City vs the synthetic control of New York City) (April 2018 to December 2019) (No Weight Constraints)



In contrast to the patterns in Chicago, Boston, and New York City, the pattern in Washington DC looks different. From June 2019 to December 2019, there is a gap between the actual trend line and the synthetic control line. The difference is that in this case, the actual trend line is beneath the synthetic control line. It means that in Washington DC, there was a decline in casual trip rates from June 2019 to December 2019 compared to the counterfactuals. It is likely because the scooters became a very popular means of transportation in the summer of 2019, which took the casual riders away from public bike share systems.

Figure 3.5 Monthly Casual Trip Rate (Washington DC vs the synthetic control of Washington DC) (April 2018 to December 2019) (No Weight Constraints)



Synthetic control on casual trip rates (second iteration)

A major limitation with the previous analysis is that many weights used to generate the synthetic control time series are negative. It is problematic because in reality, having a negative casual trip rate does not make logical sense. Therefore, an improved iteration of the analysis adds a new constraint: all weights must be non-negative. Table 3.6 shows the weights of the four new synthetic control time series.

Table 3.6: Weights of the eight time series in the control pool for synthetic controls on casual trip rates (weights must be non-negative)

	Columbus	Pittsburgh	Portland	Philadelphia	Chicago Previous	Boston Previous	Washington DC Previous	New York City Previous
Chicago	0.000	0.558	0.000	0.000	0.440	0.000	0.002	0.000
Boston	0.000	0.219	0.000	0.147	0.563	0.000	0.071	0.000
New York City	0.000	0.000	0.000	0.765	0.235	0.000	0.000	0.000
Washington DC	0.328	0.114	0.000	0.219	0.000	0.026	0.023	0.291

Figure 3.7 to 3.10 show the monthly casual trip rate comparisons between the four cities’ actual trend and the synthetic control trend lines, where the weights used to generate the synthetic controls are non-negative. The four figures show that all conclusions drawn from figure 3.2 to figure 3.5 remain robust: **in Chicago, Boston, and New York City, interventions in June 2019 caused a significant uplift in casual trip rates from June 2019 to December 2019. In contrast, in Washington DC, interventions in June 2019 caused a significant decline in casual trip rates from June 2019 to December 2019.**

Figure 3.7 Monthly Casual Trip Rate (Chicago vs the synthetic control of Chicago) (April 2018 to December 2019) (Non-negative Weights)

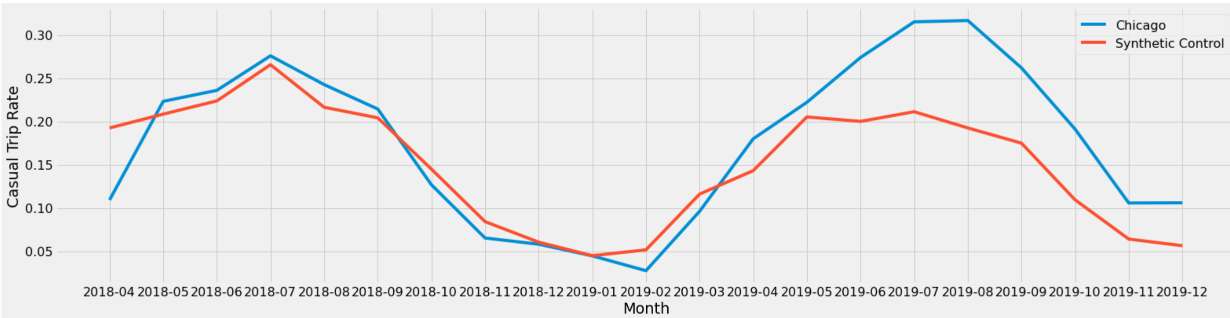


Figure 3.8 Monthly Casual Trip Rate (Boston vs the synthetic control of Boston) (April 2018 to December 2019) (Non-negative Weights)

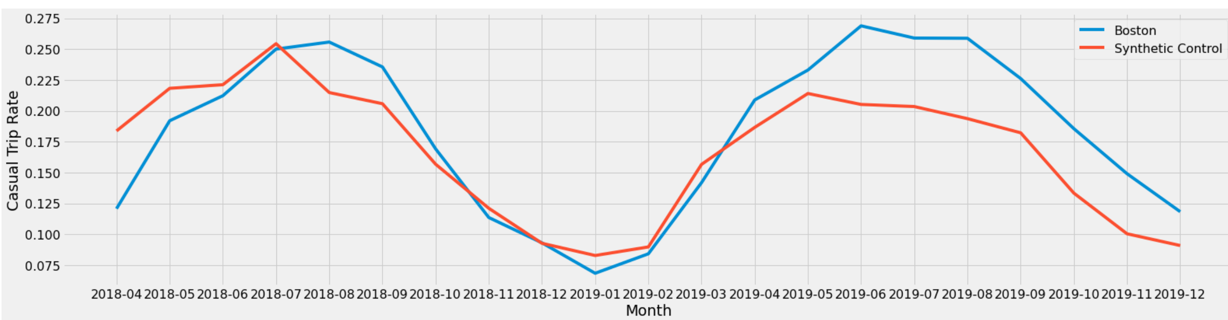


Figure 3.9 Monthly Casual Trip Rate (New York City vs the synthetic control of New York City) (April 2018 to December 2019) (Non-negative Weights)

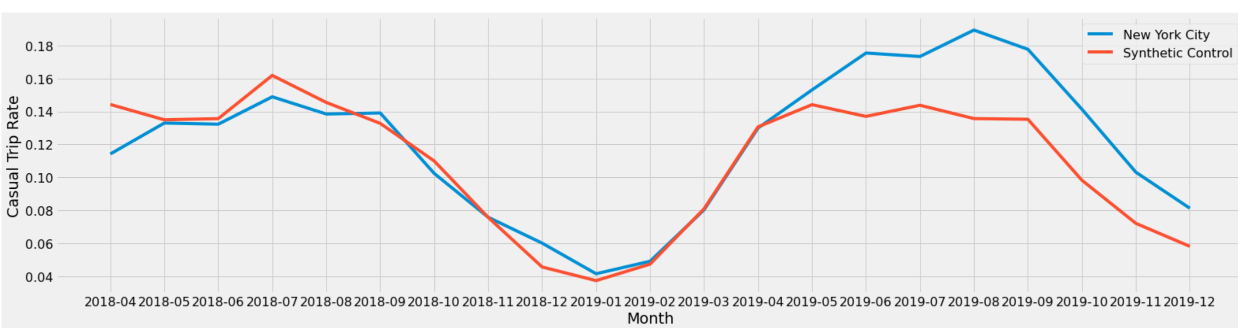
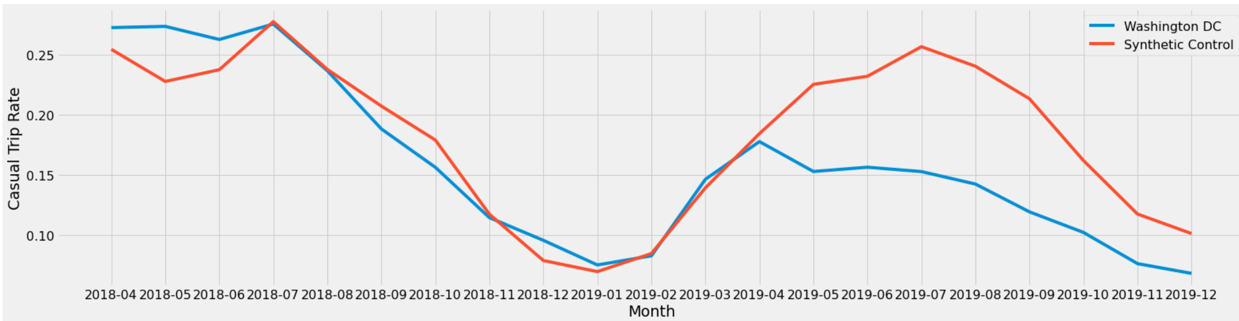


Figure 3.10 Monthly Casual Trip Rate (Washington DC vs the synthetic control of Washington DC) (April 2018 to December 2019) (Non-negative Weights)



Synthetic control on monthly casual trips

Last two subsections demonstrated that there is a significant increase in monthly casual trip rates in Chicago, Boston, and New York City from June 2019 to December 2019 relative to the synthetic controls with and without weight constraints. Is the increase in monthly casual trip rates mainly driven by an increase in casual trips, or a decrease in membership trips (non-casual trips)? This subsection applies the same method as the last two subsections to show that the monthly casual trips also increased significantly in Chicago, Boston, and New York City from June 2019 to December 2019 relative to the synthetic controls with and without weight constraints.

Table 3.11 lists the weights of the four synthetic control time series without weight constraints. Figures 3.12 to 3.15 tell a similar story as the figures in the last two subsections. In Chicago, Boston, and New York City, there were large gaps between the treatment time series and the synthetic control line after June 2019, especially during summer months (June to October of 2019). It means that in these three cities, interventions in June 2019 caused an uplift in monthly casual trips relative to the control cities. It is also interesting to note that in Figure 3.12 to 3.14, the gaps narrowed in the winter months (November and December 2019). Meanwhile, we did not see similar patterns in figures from the last two subsections. It suggests that the interventions also caused the membership trips to decline in winter months.

Table 3.11: Weights of the eight time series in the control pool for synthetic controls on monthly casual trips (no weight constraints)

	Columbus	Pittsburgh	Portland	Philadelphia	Chicago Previous	Boston Previous	Washington DC Previous	New York City Previous
Chicago	-1.241	0.791	-6.483	0.097	3.057	6.936	0.326	-0.415
Boston	-0.849	0.218	-10.853	0.232	2.898	5.206	0.117	-0.373
New York City	-2.760	-0.122	-13.974	0.969	12.152	14.392	0.229	-0.605
Washington DC	-0.469	0.162	11.626	-0.223	-2.206	-2.355	0.434	1.083

Figure 3.12 Monthly Casual Trips (Chicago vs the synthetic control of Chicago) (April 2018 to December 2019) (No Weight Constraints)

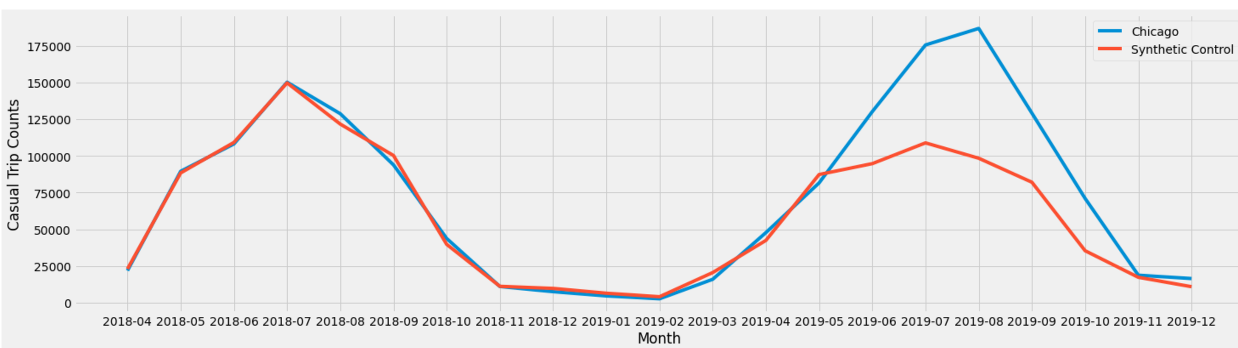


Figure 3.13 Monthly Casual Trips (Boston vs the synthetic control of Boston) (April 2018 to December 2019) (No Weight Constraints)

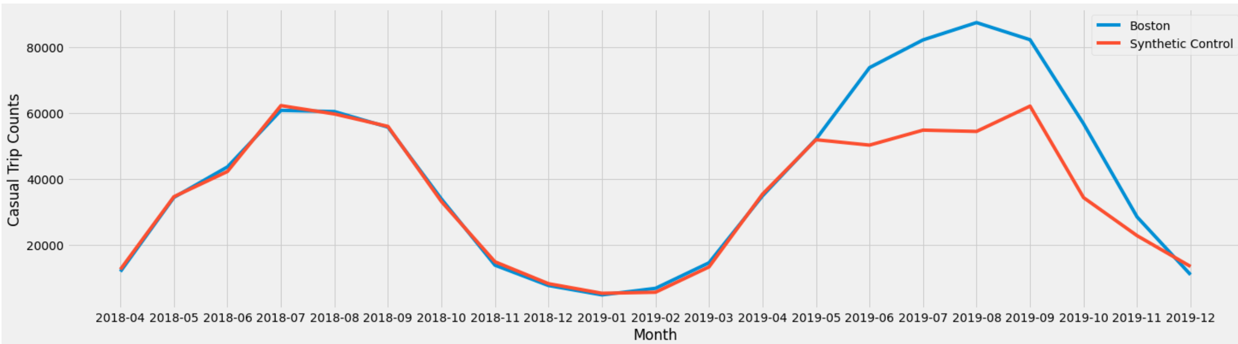


Figure 3.14 Monthly Casual Trips (New York City vs the synthetic control of New York City) (April 2018 to December 2019) (No Weight Constraints)

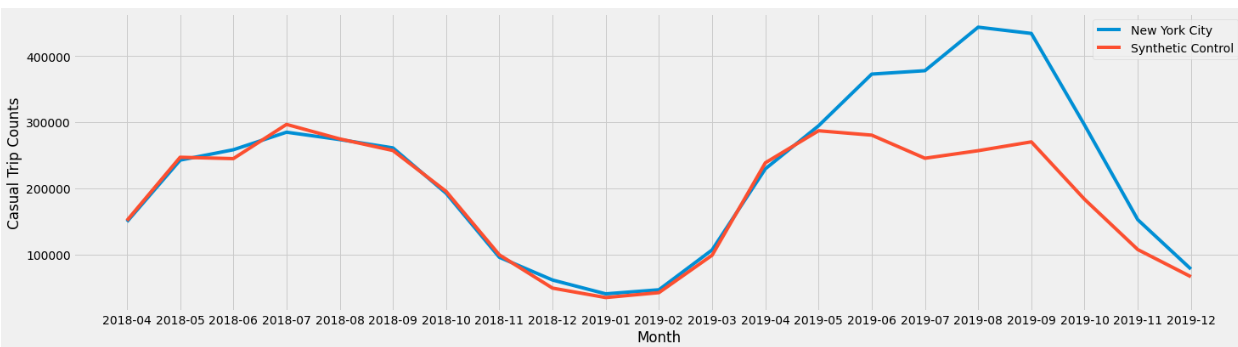


Figure 3.15 Monthly Casual Trips (Washington DC vs the synthetic control of Washington DC) (April 2018 to December 2019) (No Weight Constraints)

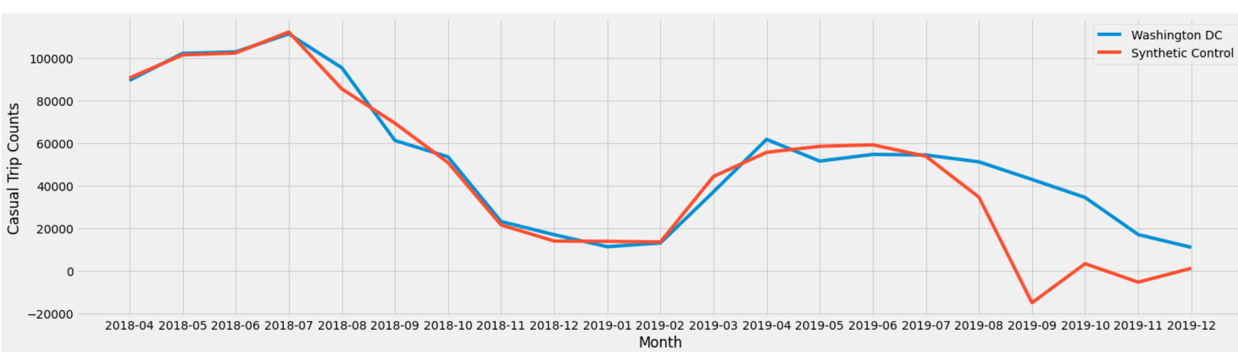


Table 3.16 summarizes the weights of the four synthetic control time series with non-negative weight. Figures 3.17 to 3.20 support the conclusion drawn in the previous sections. In Chicago, New York City, and Boston, interventions in June 2019 caused the treatment cities to have higher monthly casual trips than the synthetic control from July to December 2019. Meanwhile, there was a decline in Washington DC in monthly casual trips relative to the synthetic control with non-negative weights.

Table 3.16: Weights of the eight time series in the control pool for synthetic controls on monthly casual trips (non-negative weights)

	Columbus	Pittsburgh	Portland	Philadelphia	Chicago Previous	Boston Previous	Washington DC Previous	New York City Previous
Chicago	0.000	0.704	0.000	0.034	0.000	0.000	0.262	0.000
Boston	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
New York City	0.000	0.000	0.000	0.999	0.000	0.000	0.000	0.000
Washington DC	0.000	0.073	0.000	0.000	0.000	0.000	0.354	0.574

Figure 3.17 Monthly Casual Trips (Chicago vs the synthetic control of Chicago) (April 2018 to December 2019) (Non-negative Weights)

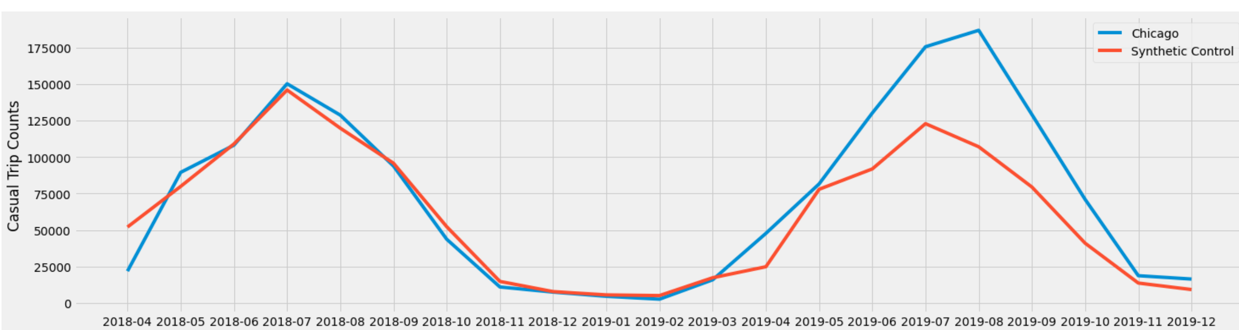


Figure 3.18 Monthly Casual Trips (Boston vs the synthetic control of Boston) (April 2018 to December 2019) (Non-negative Weights)

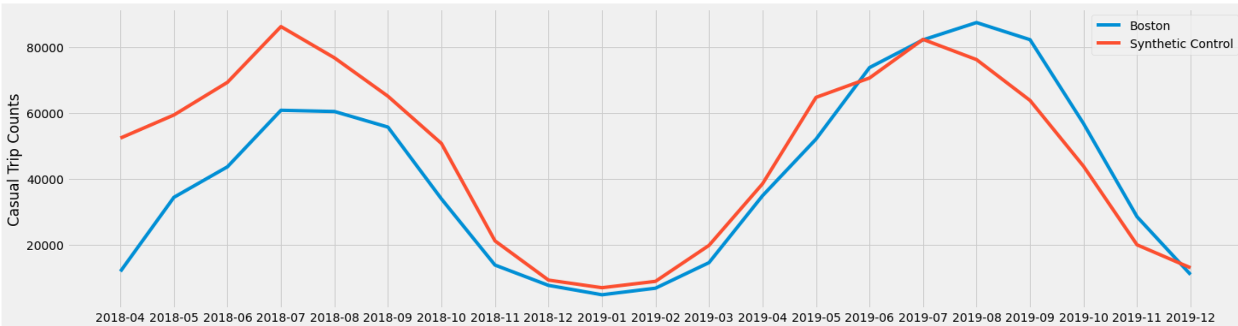


Figure 3.19 Monthly Casual Trips (New York City vs the synthetic control of New York City) (April 2018 to December 2019) (Non-negative Weights)

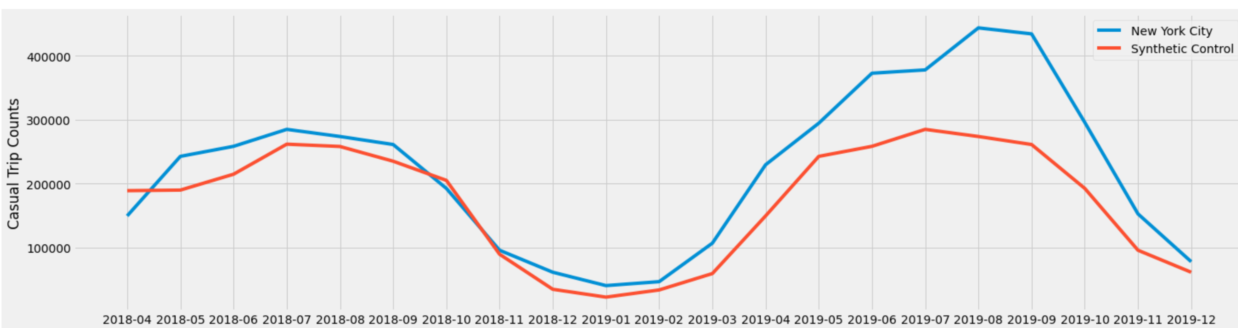
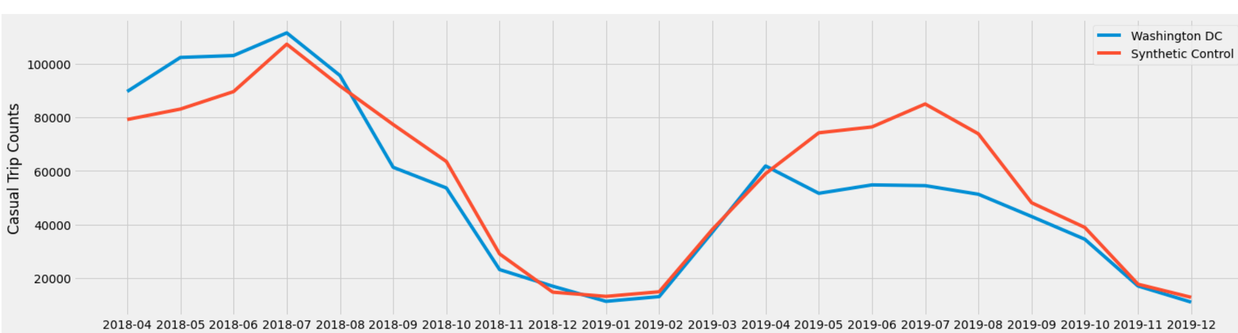


Figure 3.20 Monthly Casual Trips (Washington DC vs the synthetic control of Washington DC) (April 2018 to December 2019) (Non-negative Weights)



Synthetic control on monthly total trips

Previous analysis shows that certain interventions in June 2019 caused a significant uplift in monthly casual trip rates as well as casual trip counts from June 2019 to December 2019 in Chicago, Boston, and New York City. Were the increase in monthly casual trips in the three cities mainly drawn from residents who did not use public bike share service before, or residents who were previously membership riders with monthly or yearly subscriptions? This section demonstrates that monthly total trips did not significantly increase as a result of the intervention in June 2019 in the three treatment cities, which suggests that most of the increase in monthly causal trips were drawn from previous membership riders.

Table 3.21: Weights of the eight time series in the control pool for synthetic controls on monthly total trips (no weight constraints)[5]

	Columbus	Pittsburgh	Portland	Philadelphia	Chicago Previous	Boston Previous	Washington DC Previous	New York City Previous
Chicago	0.141	0.685	-28.871	-0.088	7.331	8.264	0.750	-0.648
Boston	-0.496	0.232	-22.058	0.107	2.853	10.935	-0.121	-0.514
New York City	-8.404	0.153	-96.634	1.048	26.864	55.198	-1.356	-1.553
Washington DC	-0.035	-0.099	-8.509	-0.134	4.569	2.766	0.397	0.831

Table 3.21 shows the weights of the four synthetic control time series without weight constraints. Figure 3.22 to figure 3.25 show the monthly total trips of the four cities and their synthetic control lines. In New York City and Boston, there were no significant gaps

[5] For this set of data, applying non-negative weight constraints led to poorly fitted synthetic control lines for Boston and New York City. The resulting figures were nevertheless consistent with the figures 3.22 to 3.25. Therefore, the version with weight constraints was excluded from this project report.

between the two lines from June 2019 to December 2019. It means that for these two cities, the interventions in June 2019 did not significantly impact the total trips from June to December of 2019. Meanwhile, in Chicago and Washington DC, the actual total trip lines are beneath the synthetic control lines. It means that the intervention in June 2019 reduced the total trips from June to December 2019 for the two cities. To conclude, **these four figures show that the interventions in June 2019 did not significantly affect the monthly total trips of the four cities from June to December 2019.** Therefore, even though there was a major uplift in casual trips in Chicago, Boston, and New York City, the total trips did not increase significantly in the three cities. It implies that the membership trips have declined in these three cities.

Figure 3.22 Monthly Total Trips (Chicago vs the synthetic control of Chicago) (April 2018 to December 2019) (No Weight Constraints)

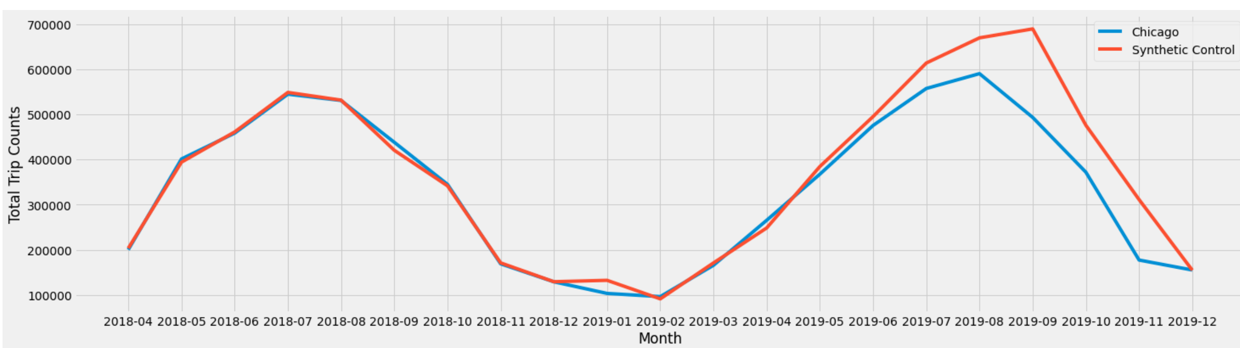


Figure 3.23 Monthly Total Trips (Boston vs the synthetic control of Boston) (April 2018 to December 2019) (No Weight Constraints)

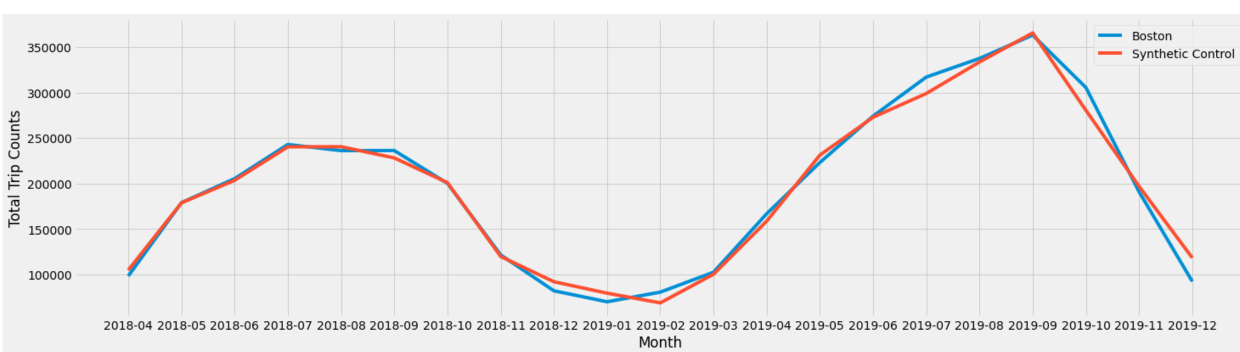


Figure 3.24 Monthly Total Trips (New York City vs the synthetic control of New York City) (April 2018 to December 2019) (No Weight Constraints)

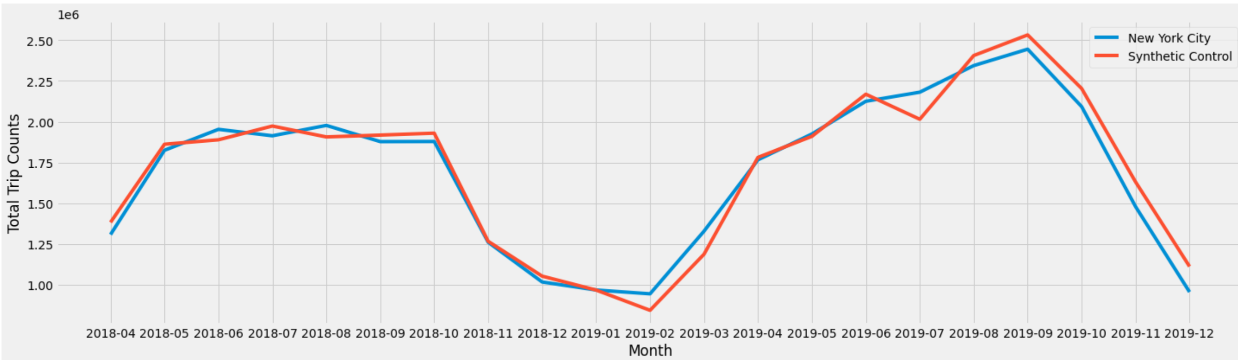
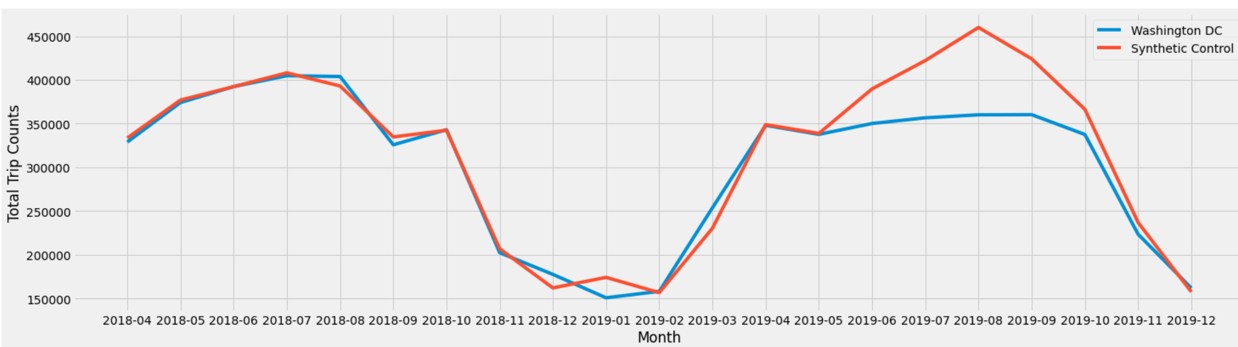


Figure 3.25 Monthly Total Trips (Washington DC vs the synthetic control of Washington DC) (April 2018 to December 2019) (No Weight Constraints)



Synthetic control on monthly membership trips

In previous sections, we arrived at the conclusions that in Chicago, New York City, and Boston, interventions caused significant increases in monthly casual trips and non-significant changes in monthly total trips from June to December 2019. It implies that there was a decline in monthly membership trips in these three cities. This subsection aims to test this hypothesis.

Table 3.26 lists the weights of the four synthetic control time series without weight constraints. Figures 3.27 and 3.30 show that there was a significant decline in monthly membership trips in Chicago and Washington DC from June to December 2019 relative to the synthetic control. However, figures 3.28 and 3.29 show that there were no significant changes in membership trips in Boston and New York City relative to the synthetic control. It poses a paradox for this analysis: for Boston and New York City, how could interventions cause a significant positive impact in monthly casual trips, but not in monthly total trips and membership trips?

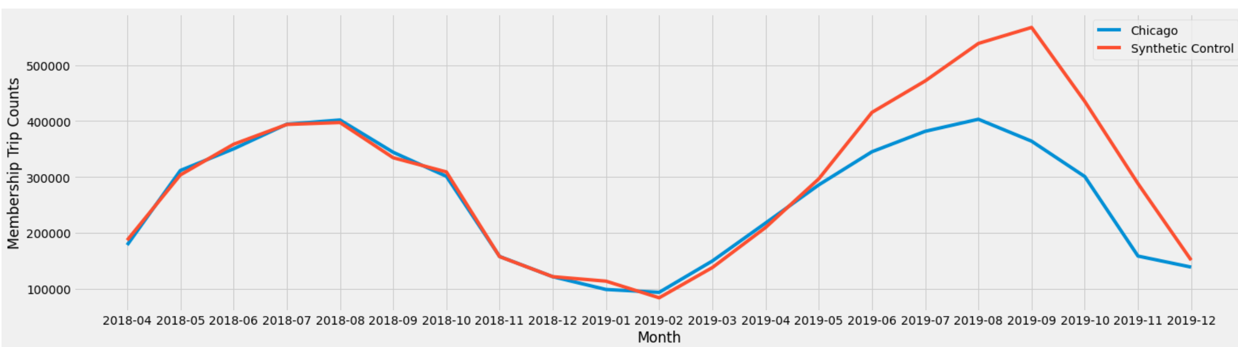
There could be two reasons: (1) For each synthetic control line, there were only 8 time series data in the control pool. It is likely that the insufficient amount of control pool data made the resulting synthetic control line inaccurate. (2). This study looks at 4 major outcomes (casual trip rates, monthly casual trips, monthly total trips, and monthly membership trips) of 4 treatment cities, which means that 16 hypotheses are being tested at once. It is likely that the multi-hypothesis testing led to false discoveries.

To overcome these limitations, future research on this area should include more relevant time series data in the control pool, as well as applying multiple testing correction techniques (like benjamini-hochberg correction) to test these hypotheses more rigorously.

Table 3.26: Weights of the eight time series in the control pool for synthetic controls on monthly membership trips (no weight constraints)[6]

	Columbus	Pittsburgh	Portland	Philadelphia	Chicago Previous	Boston Previous	Washington DC Previous	New York City Previous
Chicago	-0.405	0.611	-2.855	0.021	7.496	9.859	-3.918	-0.826
Boston	-0.640	0.100	-7.637	0.143	2.035	12.972	-3.737	-0.405
New York City	-8.577	-0.777	120.348	1.099	11.156	71.426	-17.510	1.286
Washington DC	-0.722	-0.113	7.337	-0.028	2.437	15.917	-2.551	0.968

Figure 3.27 Monthly Membership Trips (Chicago vs the synthetic control of Chicago) (April 2018 to December 2019) (No Weight Constraints)



[6] For this set of data, applying non-negative weight constraints led to poorly fitted synthetic control lines for Boston and New York City. The resulting figures were nevertheless consistent with the figures 3.27 to 3.30. Therefore, the version with weight constraints was excluded from this project report.

Figure 3.28 Monthly Membership Trips (Boston vs the synthetic control of Boston) (April 2018 to December 2019) (No Weight Constraints)

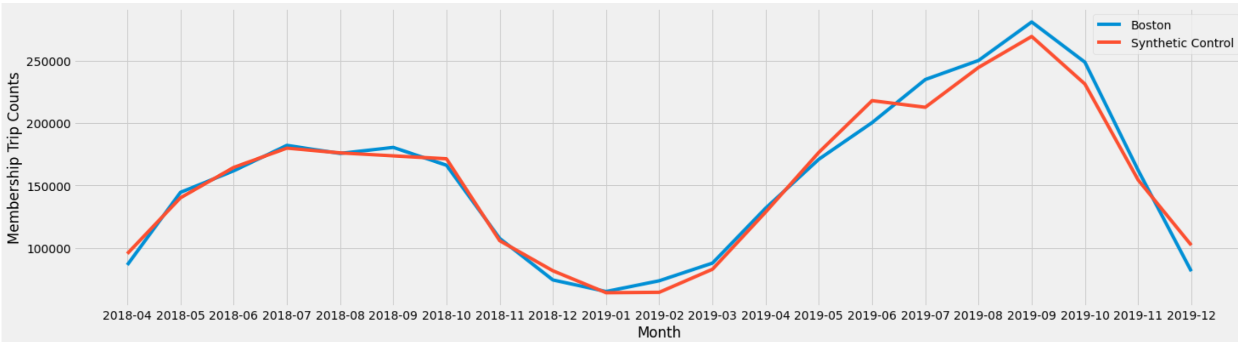


Figure 3.29 Monthly Membership Trips (New York City vs the synthetic control of New York City) (April 2018 to December 2019) (No Weight Constraints)

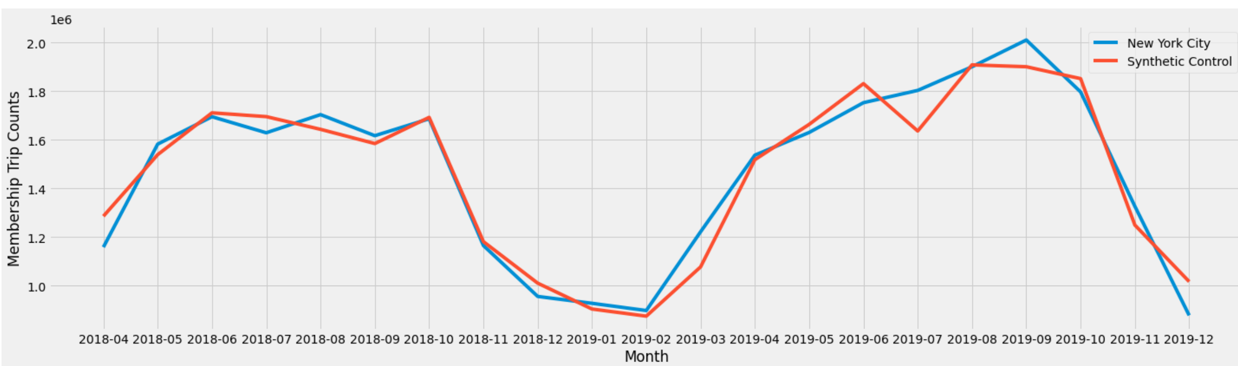
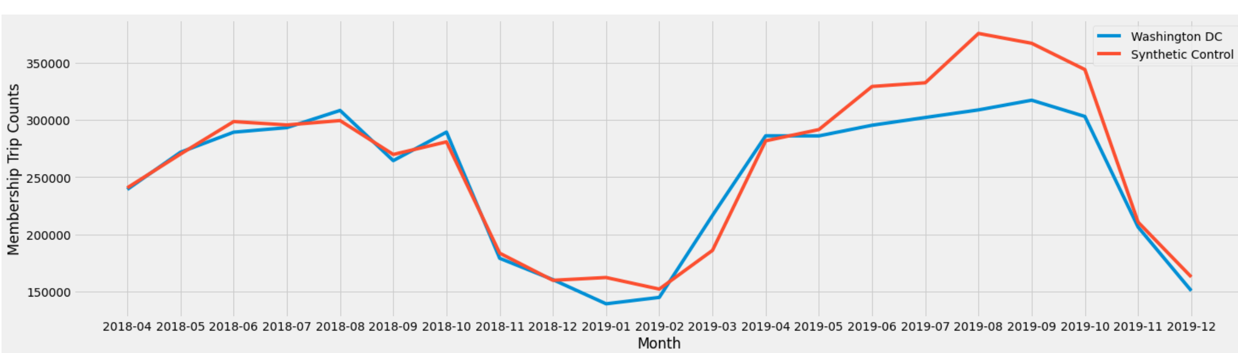


Figure 3.30 Monthly Membership Trips (Washington DC vs the synthetic control of Washington DC) (April 2018 to December 2019) (No Weight Constraints)



Visualizations of Bike Share Networks in Eight Cities

Figures 4.1 to 4.8 show the public bike share network of the eight cities based on trip records from July 2019. In each figure, each node represents a public bike station. Each edge represents bike trips from one bike station to the other. The width of an edge represents the number of trips between the two bike stations.

Figure 4.1: Public Bike Share Network of Chicago (July 2019)

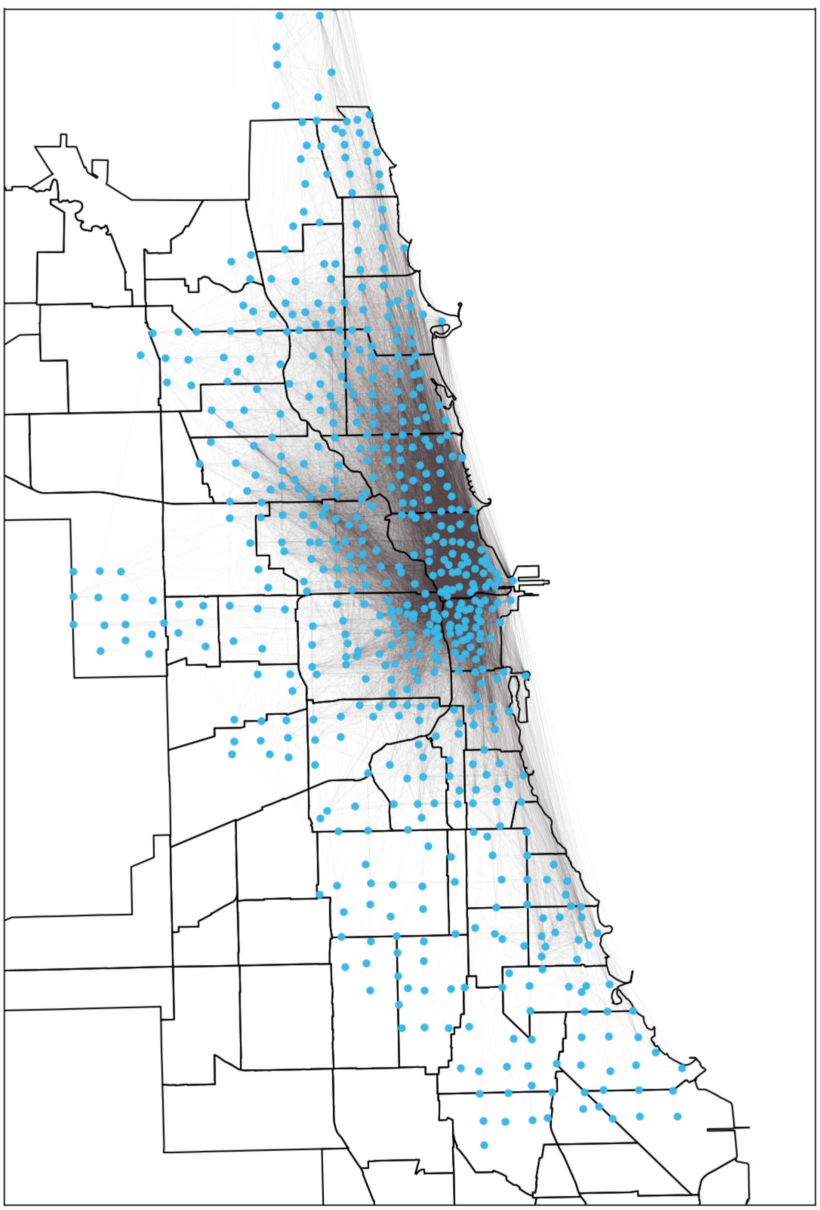


Figure 4.2: Public Bike Share Network of Boston (July 2019)

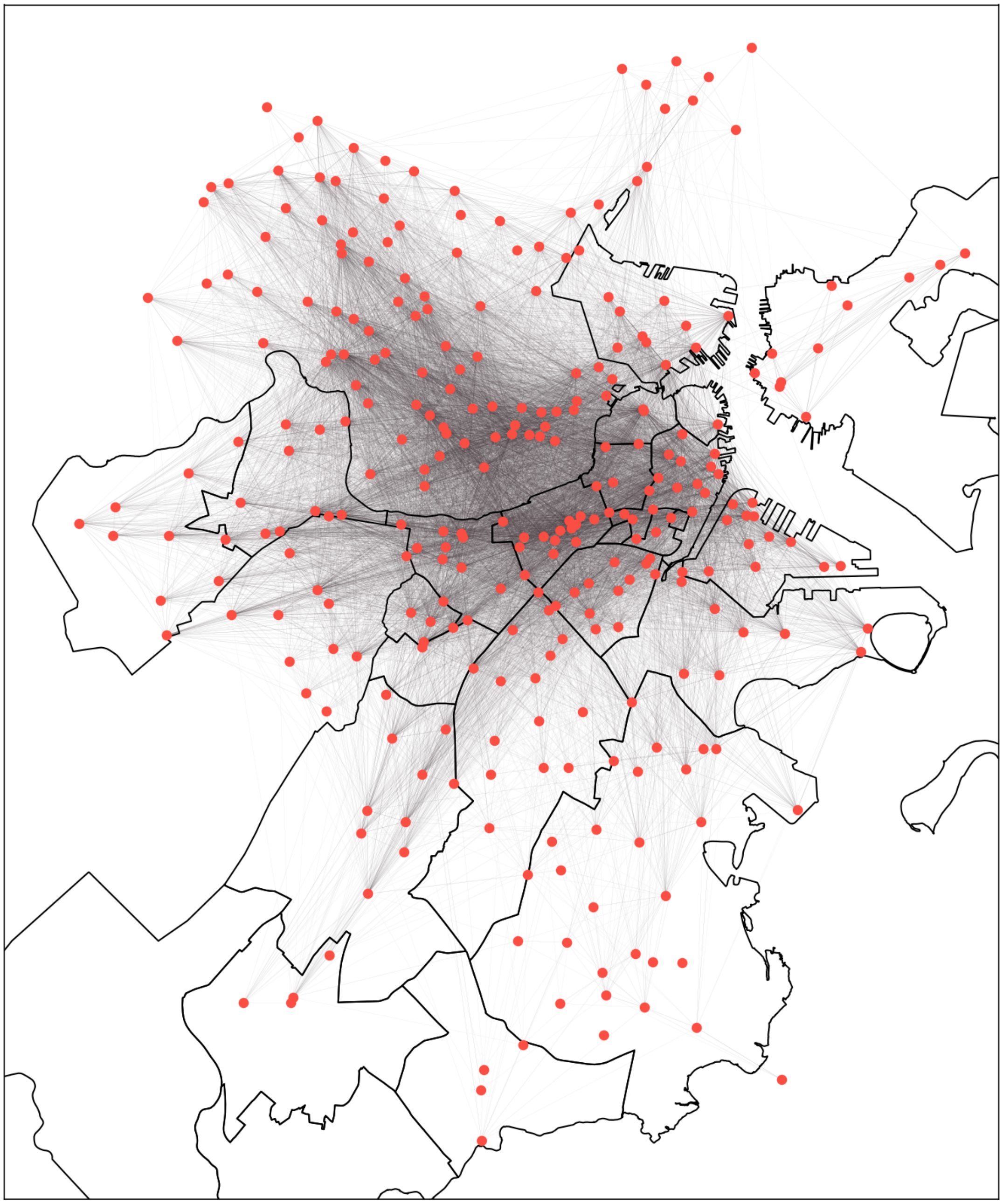


Figure 4.3: Public Bike Share Network of New York City (July 2019)

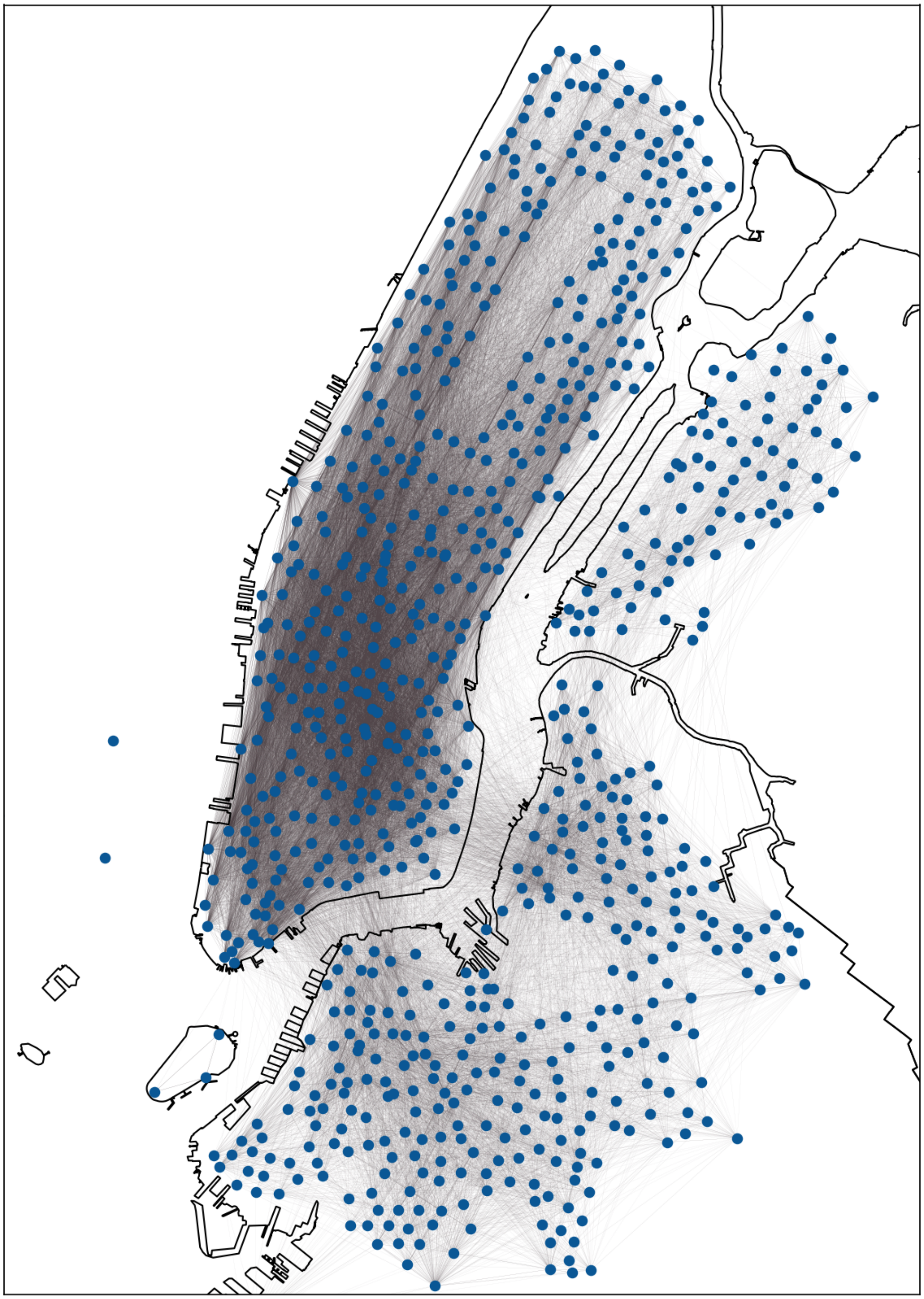


Figure 4.4: Public Bike Share Network of Washington DC (July 2019)

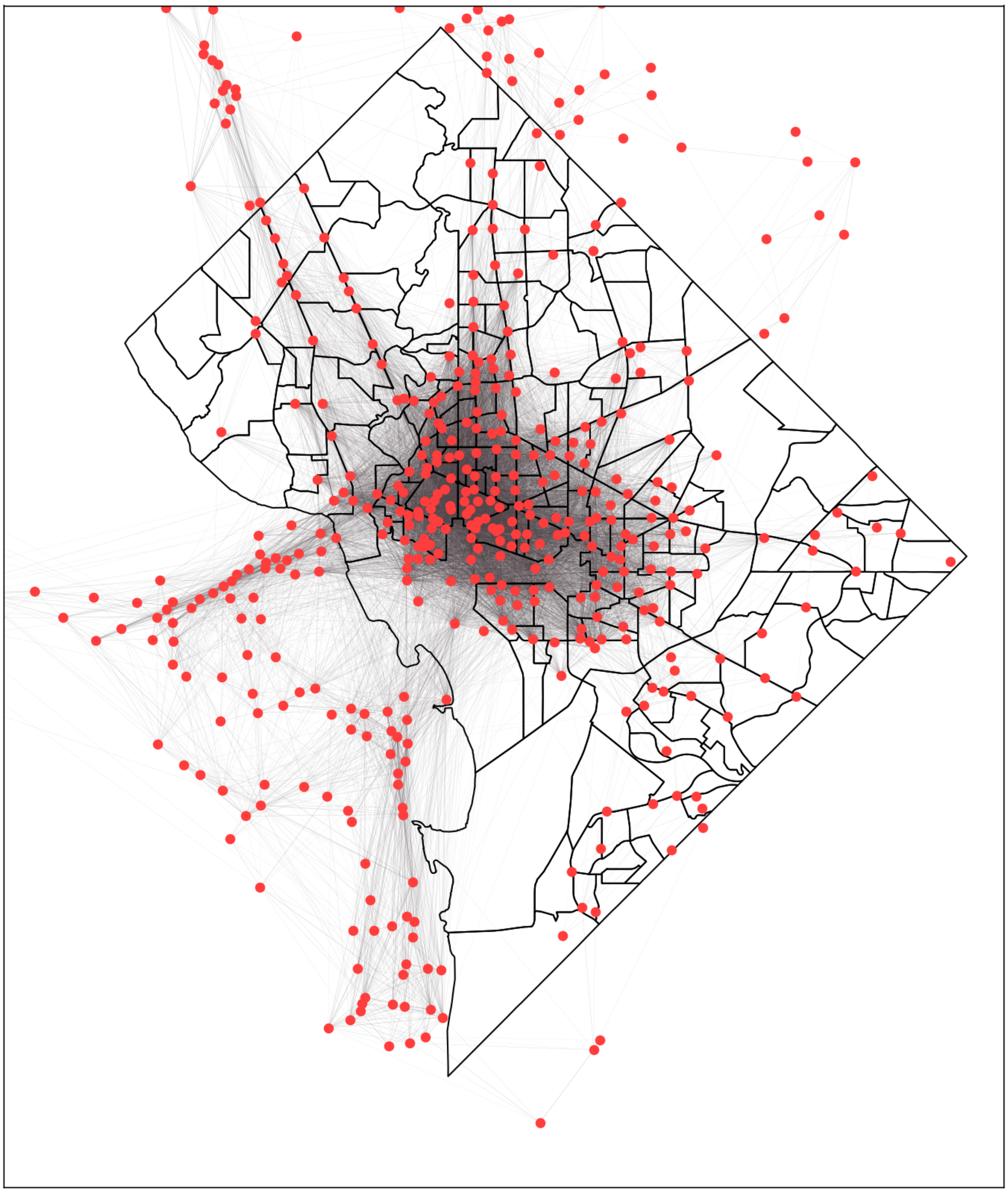


Figure 4.5: Public Bike Share Network of Philadelphia (July 2019)

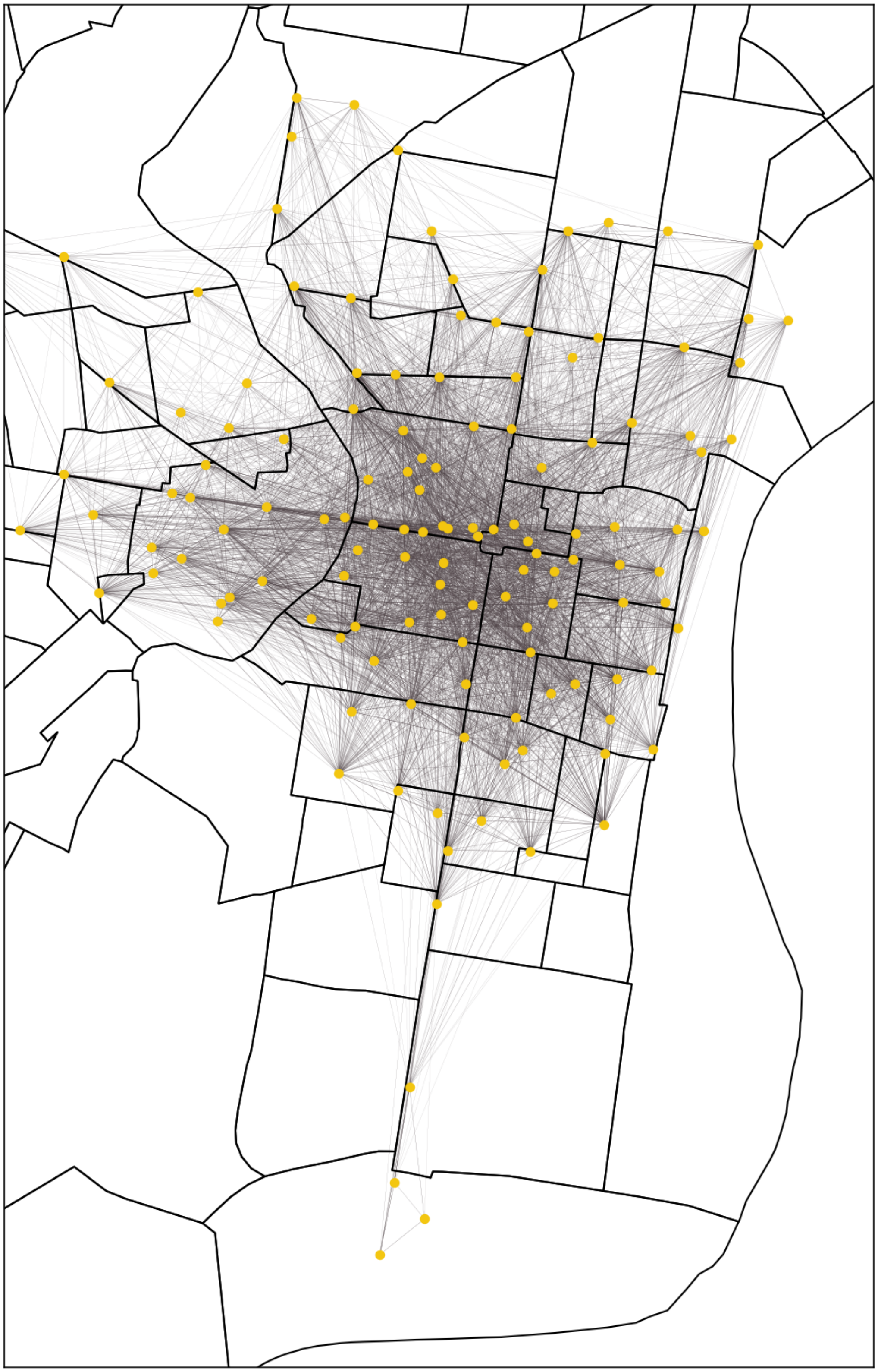


Figure 4.6: Public Bike Share Network of Portland (July 2019)

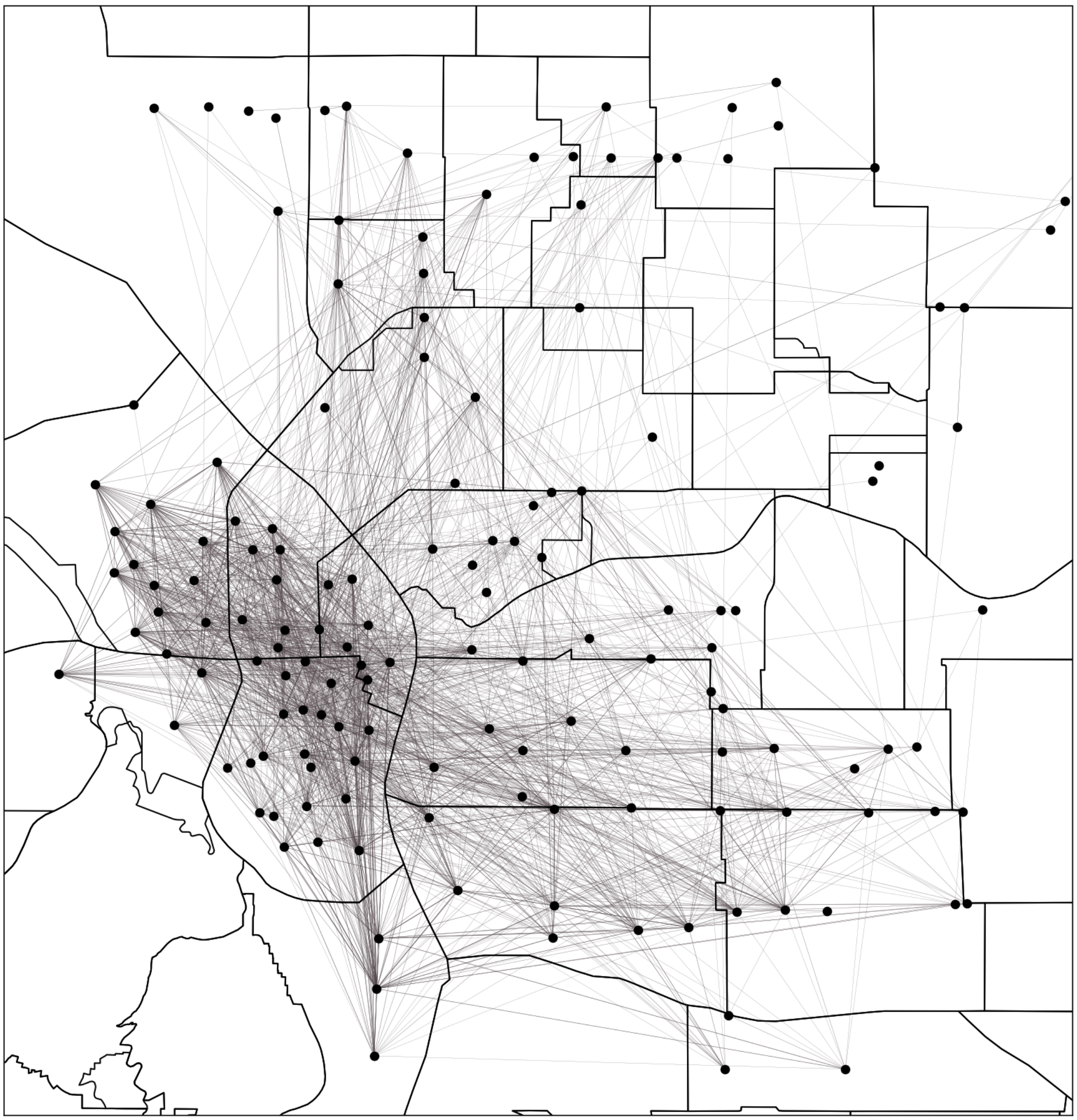


Figure 4.7: Public Bike Share Network of Pittsburgh (July 2019)

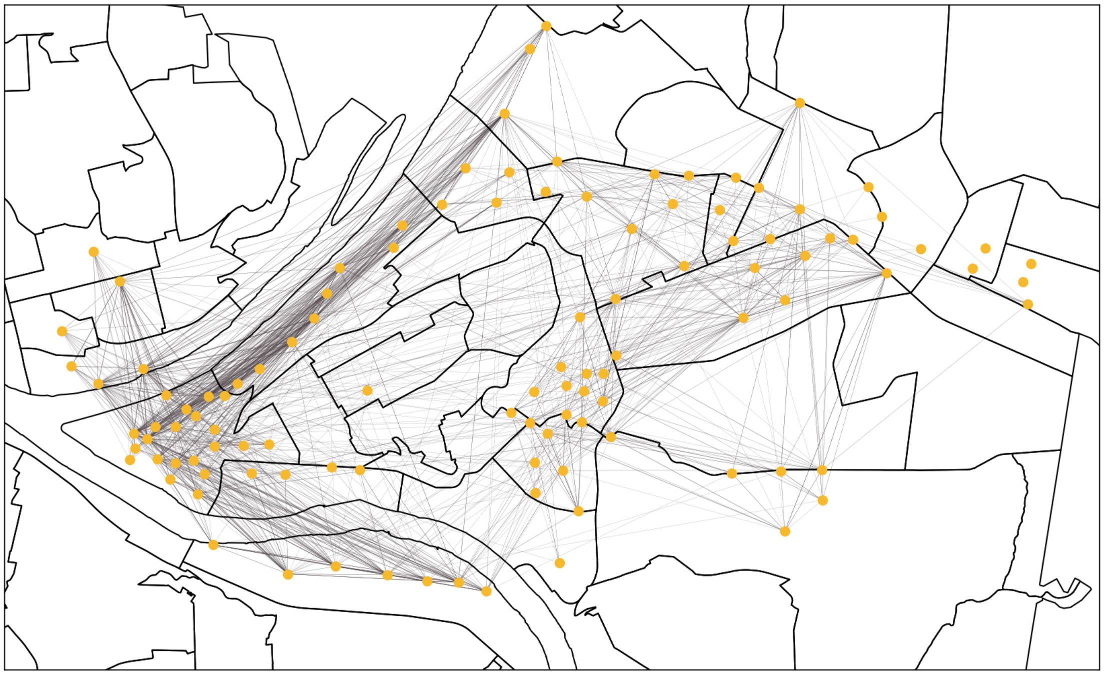
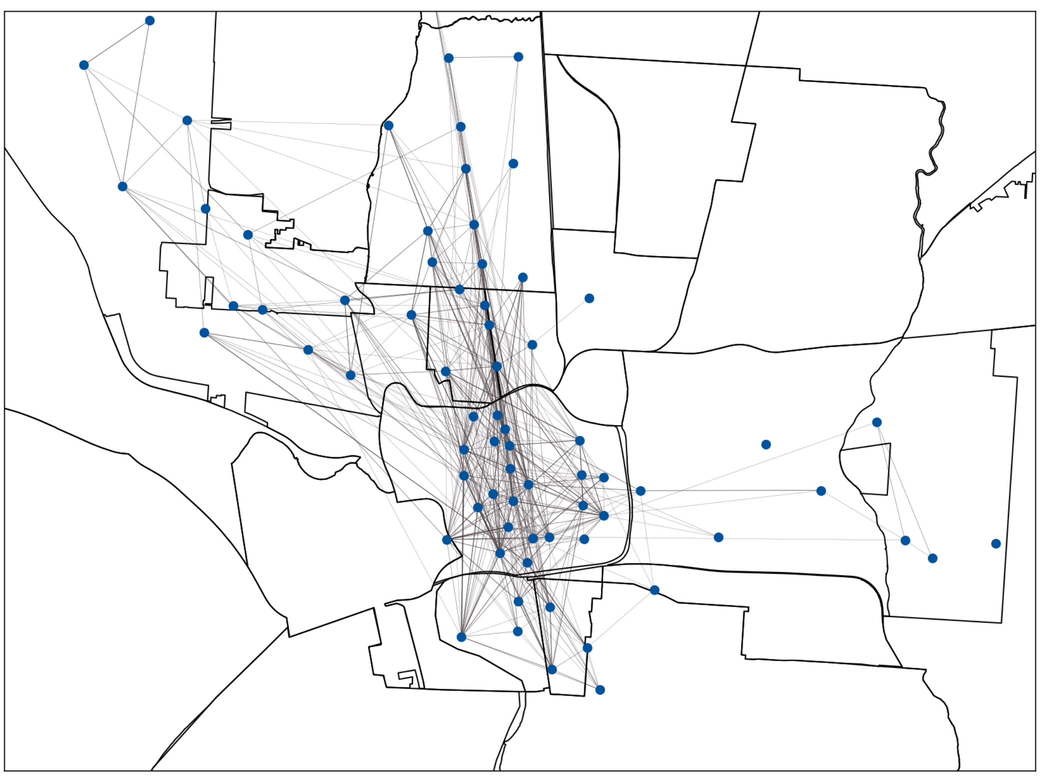


Figure 4.8: Public Bike Share Network of Columbus (July 2019)



Conclusions

This project applies synthetic control to show that (1) interventions in June 2019 caused an uplift in monthly casual trip rate and monthly casual trips in public bike share programs in Chicago, Boston, and New York City from June to December 2019, (2) the interventions did not led to increase in monthly total trips and monthly membership trips in these programs during the same time period. It suggests that the increase in monthly casual trips in the three cities are likely drawn from previously membership riders, rather than from new first-time public bike riders. Nevertheless, results of these analyses show internal inconsistencies, especially on the monthly membership trips in Boston and New York City. It suggests that for the conclusions to be trustworthy, future projects require more rigorous applications of the synthetic control methods, like including more time series data in the control pool, as well as applying multiple-hypothesis testing correction techniques.

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