Bike Infrastructure and Congestion - Evidence from Manhattan

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1 Introduction

Bike-sharing has increased in popularity and usage over the last decade, and most major North American cities have implemented one or multiple bike-sharing systems by now. The goal of bike-sharing is to increase bike ridership and at the same time, decrease the usage of cars for private transportation. Using cars for private transportation leads to environmental and economic damages due to pollution and traffic congestion (Hamilton & Wichman, 2018). Following the example of Braun et al. (2018) we want to know whether the introduction and expansion of bike-sharing systems are an expedient measure to combat traffic congestion. Furthermore, we also want to know if placing a bike-sharing station on a dedicated protected bike lane will lead to a higher uptake and, in turn a larger reduction in traffic congestion. There are four different kinds of bike infrastructure: protected bike lanes, bike lanes, shared lanes and signed routes. While protected bike lanes offer a safe way to travel by bike, with dedicated bike lanes away from motor traffic, shared lanes mean cars, trucks, buses and bikes alike share the same lane, making it significantly more dangerous for bikers. We expect a higher bike-sharing uptake for stations on protected bike lanes which in turn would mean a more traffic congestion alleviation effect.

Traffic congestion in North America has become an increasingly important topic, with the economic opportunity cost of congestion being around $124 billion per year just in the United States and a projected cost of $168 billion dollars in the year 2030 (Chang et al., 2017). At the same time, traffic is the biggest contributor to greenhouse gas emissions in the United States with a 29% share[1]. The causes for this are mainly combustion engines in cars, trucks, ships, trains and planes.

We focus our attention on Manhattan since it is one of the most congested areas in the US and has a single, rapidly expanding bike-sharing system. This bike-sharing system is called Citi Bike and has seen a swift increase in ridership and bike-sharing stations since its introduction in April 2013. Citi Bike went from 5.000 founding members in 2013 to 143.000 members in May 2018. Ridership exceeded 100.000 daily trips in for the first time in September 2019. Just in the month of December 2019, Citi Bike ridership is estimated to have offset 2,306,982 pounds of carbon[2], showing its positive environmental

[1]https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions
[2]https://www.citibikenyc.com/system-data/operating-reports

impact. Citi Bike works like most bike-sharing system, where members can start and end a ride on any Citi Bike station after purchasing a single ride, day pass or annual membership. The stations are mainly concentrated within Manhattan and Brooklyn and are mostly meant for short to medium distances, with the average trip in August of 2019 lasting around 15 minutes and covering around 1.9 miles.

We use New York City bike-sharing, bike lane and traffic data from 2015-2019 to answer the questions of whether the introduction and expansion of the Citi Bike bike-sharing system has lead to a decrease in traffic congestion in New York City and whether a better biking infrastructure, and placing bike stations on dedicated protected bike lanes has a higher congestion alleviating effect. We focus our attention on the morning rush hour on weekdays between 6 am and 10 am. This is when most people commute into Manhattan, causing the most congested time of the day. We also restrict our research from April to October, when bike ridership is high and riding a bike is a feasible alternative to commuting by car. We construct a traffic congestion measurement similar to Braun et al. (2018) on a traffic sensor basis and link these together with bike-sharing station data and bike lane status - whether a bike lane is protected or not - to census blocks. From there we find that Citi Bike has a traffic congestion reducing impact and this impact can be elevated by placing the stations on protected bike lanes.

2 Literature Review

The most recent literature covering the impact of bike-sharing system on traffic congestion are Wang and Zhou (2017) and Hamilton and Wichman (2018). Wang and Zhou employed the differences-in-differences to measure the effect of bike-sharing across different location and time (implementation of bike-sharing system), where Hamilton and Wichman took different approach by using the panel fixed effect model to measure the impact of bike-sharing. However, the reduced form analysis could potentially breach the endogeneity assumption that leads to biased estimation. The most promi- nent confounding variable is proposed by Noland et al. (2016), in which they found an positive association between cycling infrastructure and bike-sharingsystem, for example, the introduction of cycling infrastructure is accompanied by bike-sharing stations. Since cycling infrastructure also correlates with the endogenous variable, through the channel of, such as invoking higher willingness of people riding a bike or less traffic congestion due to dedicated bike lanes. Therefore, failing to control for cycling infrastructure could potentially deliver an biased estimate of the bike-sharing system.

A large part of previous literature also covers the impact of other traffic-reducing measures. Baghestani et al. (2020), for example, investigate the effect of New York City's congestion pricing on traffic and emissions and found a decreasing trend of car trips into Manhattan with an increasing congestion fee. Cao et al. (2016) show that rerouting vehicles and a planned traffic light strategy can help reduce traffic congestion. Arnott et al. (2005) show that a more micro-centered approach including downtown parking policy, encouraging bicycling, staggering work hours of employees and a fee that charges cars the same amount as the corresponding transit fare are all measures that can help to alleviate congestion. Beaudoin et al. (2015) show that public transit investment can lead to lower traffic congestion and better air quality. Other measures could be increases in gasoline prices, but Bento et al. (2009) show relatively inelastic reaction of demand to price increases. Spiller et al. (2012) do, however, show that an increase in gasoline prices will lead to a higher uptake in public transportation.

The environmental and health effects of traffic have also been extensively covered. Ogunsola et al. (1994) show a higher blood lead level as well as potential hearing damage in people directly affected by heavy traffic. Armah et al. (2010) show that traffic congestion causes a significant amount of air pollution.

We extend this literature with the following contributions: First, we can control for cycling infrastructure by including protected lanes into our empirical specification. Protected lanes are dedicated bike lanes on the side of a street. The inclusion of protected lanes would improve the accuracy of overall estimation. Second, we are empirically evaluating whether protected lanes reduce traffic congestion. As stated before, protected bike lanes should invoke higher willingness of people riding a bike, and reduce traffic accidents that keep traffic fluent both of these consequences should lead to the reduction in traffic congestion. Third, our empirical approach is inherited from Hamilton and Wichman (2018), in which they found bike-sharing systems reduce traffic congestion by up to 4%. Our paper verifies whether their result can also be applied to New York City. Lastly, our data set is more up-to-date than Braun et al. (2018). We include observations from 2015 to 2019, giving an updated view on the progress of bike-sharing in a traffic congestion context.

3 Data

3.1 Bike Station Data

Data on bike stations comes from Citi Bike NYC. The data is publicly available from 2013 to 2021 and contains every trip taken on a CB bike. In addition, it specifies the duration, the start and end time, the start and end station (unique bike station identifier), the unique bike identifier, user type (subscriber or customer), birth year, and gender of a trip.

We identify the introduction of a new bike station through the start station and the trip's start time. Over time, trips with new bike stations appear – this constitutes the introduction of a new bike station. The data is available at seconds; however, we use the hourly level as the smallest unit of time.

Figure 1 shows the increase in bike stations from 2015 (N=471) to 2019 (N=881). In 2015, bike stations are more concentrated in the lower half of Manhattan and Brooklyn, while in 2019, bike stations expanded further up north. Further, from a different angle, Figure 2 shows the gradual increase of bike stations over time.

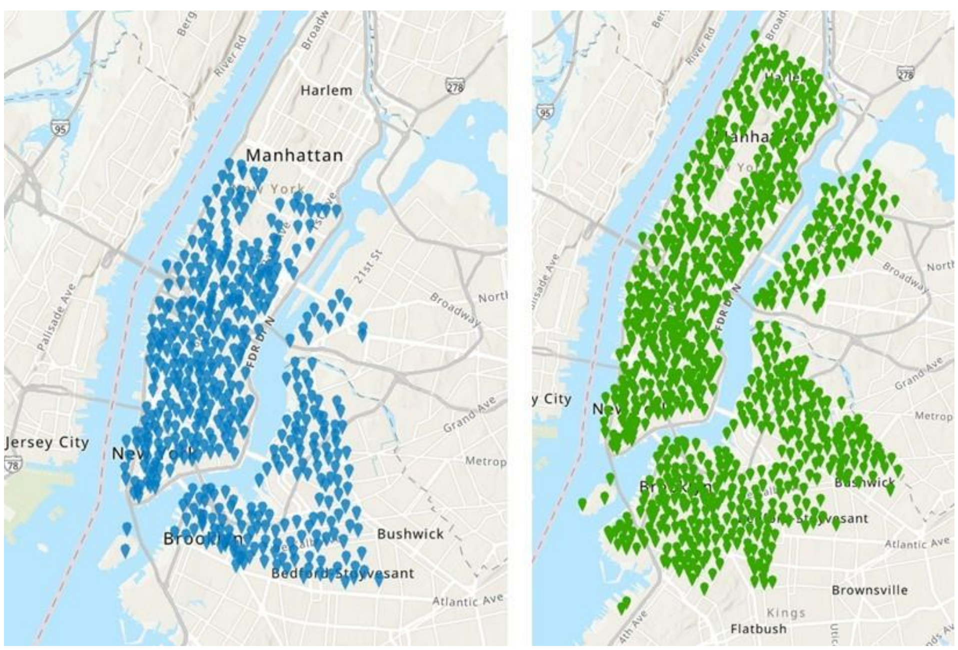

Figure 1: Bike stations in Manhattan and Brooklyn in 2015 (left) and 2019 (right)

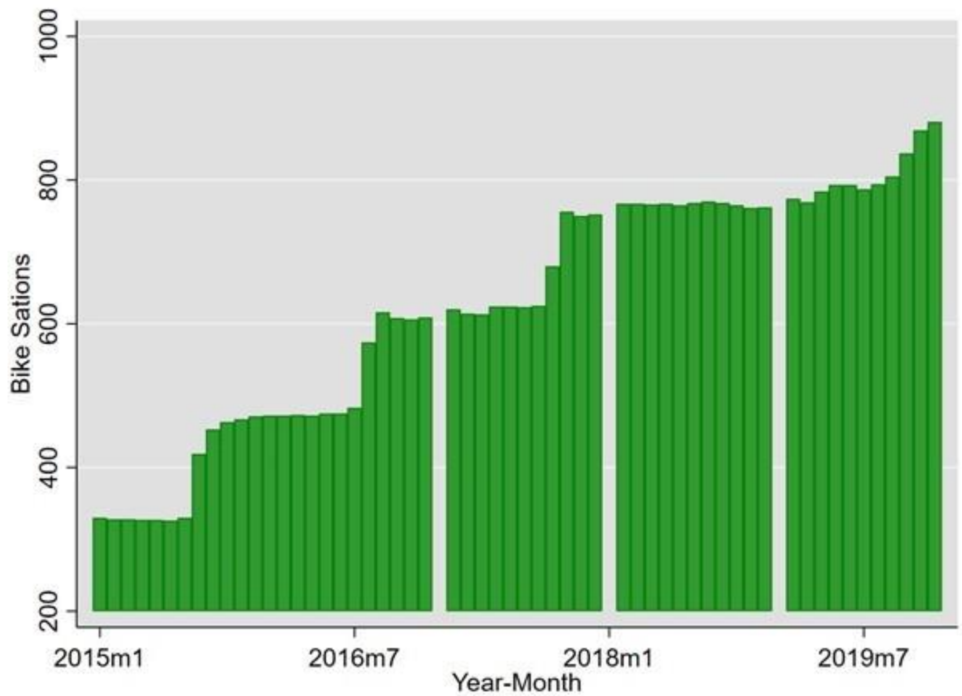

Figure 2: Number of bike stations in Manhattan from 2015 to 2019

3.2 Traffic Data

We obtain traffic speed data from the NYC Real Time Traffic Speed Data Feed through BetaNYC. The traffic information includes the speed, travel time (at the level of seconds), and the locations of each traffic sensor of a road. The data is available from 2015 to 2021. It contains traffic information for 35 roads in Manhattan from the NYCOT speed detectors. Each road consists of multiple traffic sensors. In total, 345 traffic sensors are making up 35 roads. Figure 3 shows the location of traffic sensors. Notably, traffic sensors are located on the border, entrances, and bridges of Manhattan. These locations of sensors are no severe problem since most cyclists will ride on Manhattan's border and take a bridge to enter Manhattan. However, it is a limitation as it does not include traffic speed information in the center of Manhattan. Therefore, as for the rest of this study, when we talk about congestion in Manhattan, we refer to congestion on Manhattan's border, entryways, and bridges.

Figure 3: All traffic sensors in Manhattan (N=345)
Notes: Each unique colour represents a road (N=35)

To build a measure of congestion, we define a reference speed, $Speed_d^R$, as the average speed between 3 AM and 4 AM. Figure 6 shows that during the early morning hours, there is little to no congestion. The reference speed captures the unique congestion characteristics for a certain road. Next, we define the speed at a specific hour, $Speed_{hd}^O$. Finally, by dividing $Speed_d^R$ by $Speed_{hd}^O$ we get a measure for congestion,

$$CONG_{hd} = \frac{Speed_d^R}{Speed_{hd}^O} \tag{1}$$

where a higher $Speed_{hd}^O$ leads to lower values of congestion.

Figure 4 shows a preliminary analysis of the average trend in congestion over time in Manhattan with outliers removed. Overall, it indicates a decreasing trend. Further, we see that congestion fluctuates throughout the year; average congestion peaks around November and dips around August. This overall decreasing trend in congestion may indicate that the increase in bike infrastructure effectively reduces traffic congestion. However, it is essential to keep in mind that this only applies to congestion on the border, the entrances, and the bridges of Manhattan.

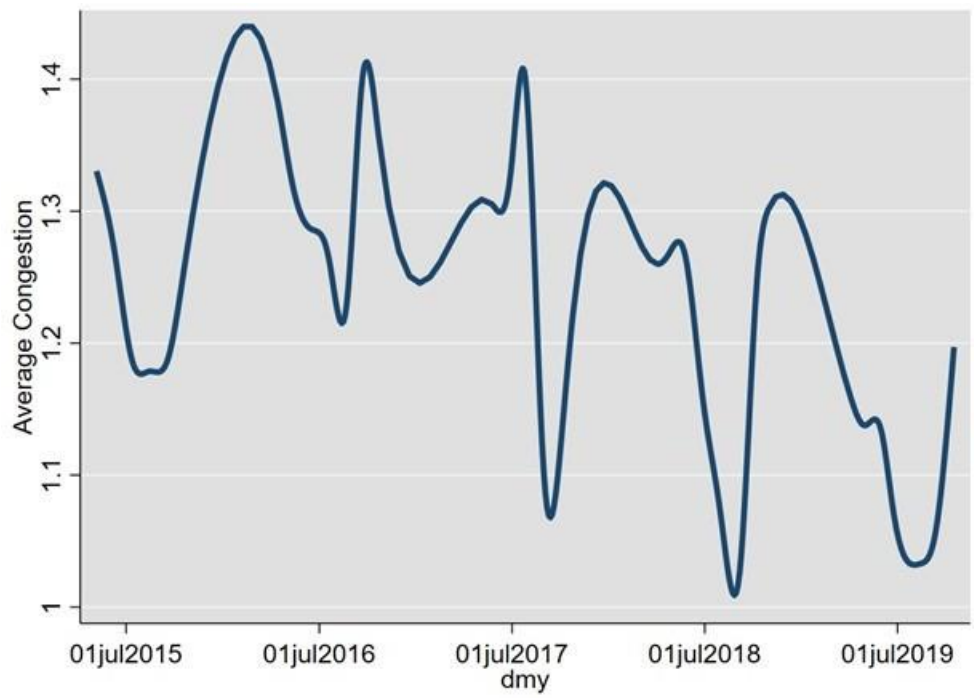

Figure 4: Average Congestion for April-October, weekdays, 6 AM to 10 AM with outliers removed

3.3 Protected Bike Lanes

Another of our interests is finding how the introduction of protected bike lanes affects traffic congestion. Overall, there are three main bicycle lanes in NYC: protected bicycle lanes, conventional bicycle lanes, and signed/marked lanes. Protected bicycle lanes physically separate cyclists from vehicle traffic with concrete medians, vertical elements, or other physical objects. Conventional bicycle lanes are not as safe as protected lanes but provide a delineated travel lane with street markings. Signed/marked routes are the least safe because they share the road with cars. However, they also include street markings and signed bicycle routes. We focus on protected bike lanes as they should be the most impactful on increasing cycling out of the three types.

As of this writing, there are no publicly available datasets indicating protected bike routes over time. There are, however, yearly bicycle maps of NYC ranging from 1997 to 2021. These maps visually indicate which route is protected. Therefore, we manually create our datasets through these visual maps on a yearly level.

We identify the introduction of protected bike lanes at the census block and year level. For each year, census blocks with new protected lanes appear – this constitutes the introduction of a protected bike lane.

3.4 Census Blocks and Census Block Groups

The US census blocks are the smallest geographic unit of observations. Data is from the US census and analyzed through ArcGIS pro. The purpose of census blocks is to spatially link traffic sensors to bike stations and protected bike lanes. The first number of a census block identifies the census block group to which it belongs. Census block groups are larger areas and contain multiple census blocks.

We first identify all the census blocks that contain one or more traffic sensors. Next, we identify all the census blocks that contain one or multiple bike stations and the census blocks that contain a protected bike lane. Then, we keep all the census blocks that contain one or more traffic sensors but remove all the bike station census blocks or protected lane census blocks with no traffic sensor. In this way, all observations have an outcome variable (congestion), for which some have zero bike stations and others have a positive number of bike stations. In addition, all observations have an outcome variable (congestion), for which some have a protected bike lane and others do not. Figure 5 illustrates the spatial link between traffic sensors with census blocks. Each census block (in red) corresponds to a census block that contains one more traffic sensor. This spatial link is done similarly forbike stations and protected bike lanes. Together, we have a spatial unit in common between bike stations, protected bike lanes, and traffic sensors

An important technicality when dealing with census block (group) data is that there can exist two or more different census blocks (groups) with the same census block (group) number. Therefore, the critical distinction we need to make is to include the census tract number to which a census block (group) belongs. This technique provides us with a unique identifier for every census block (group) in Manhattan.

Figure 5: Census blocks with one or more traffic sensors

3.5 Sample Restrictions

The first step is to isolate years that are in common with all datasets. Since congestion data is available only from 2015 to 2021, this will be our starting point. Next, we remove all observations from 2020 and 2021 because we do not want the COVID19 pandemic to bias our results. Thus, our timespan of interest on the yearly level becomes from 2015 to 2019. Next, on the monthly level, we only look at April to October to account for seasonality. We argue that these months biking is a reasonable option to commute into Manhattan. To further isolate commuters from tourists, we focus on the weekdays and remove weekend observations. Tourists are more likely to bike on the weekend and explore the city than on the weekdays. Also, residents are more likely to bike for recreational purposes on the weekend and may show different cycling patterns. Lastly, we focus on the hours between 6 AM to 10 AM since it is likely to focus on commuters during this time of day. Figure 6 shows a spike in congestion for an average weekday in 2019 during this timeframe. This spike in congestion from 6 AM to 10 AM is pretty typical for other years and specific months of years.

Furthermore, as mentioned in the section on weather data, we remove any days with precipitation. In addition, we remove all observations with a missing reference speed. Lastly, as shown in Figures 7 and 8, we remove seven outliers where congestion is greater than 60.

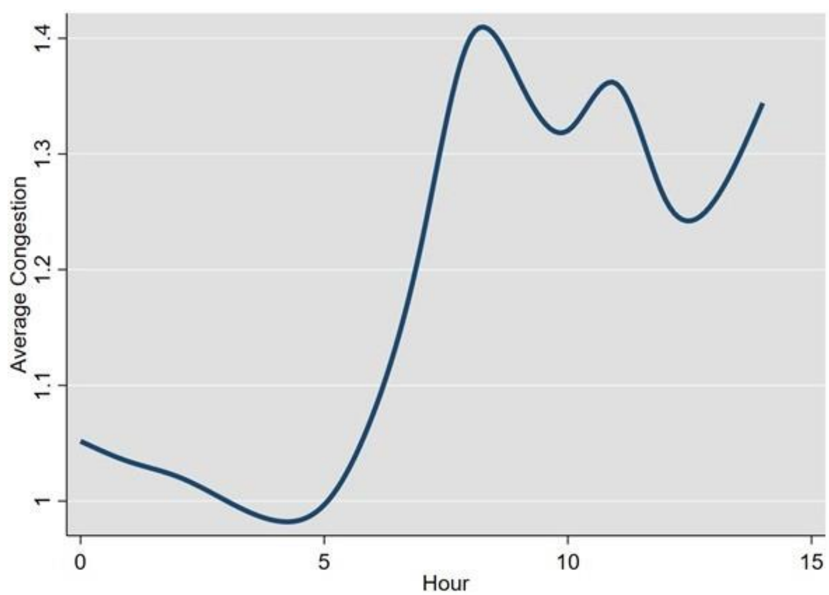

Figure 6: Average congestion pattern through a weekday (April to October)

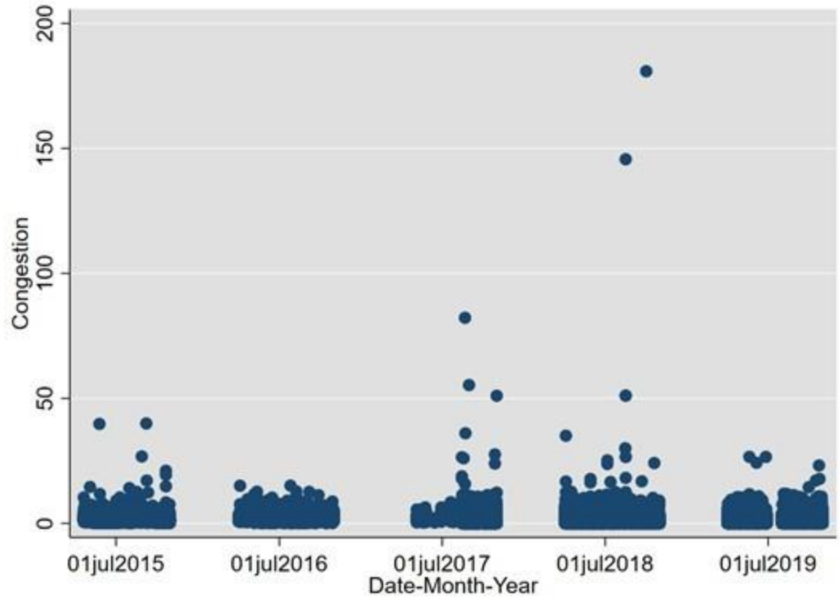

Figure 7: Average congestion scatter plot with outliers from 2015 to 2019 (April to October)

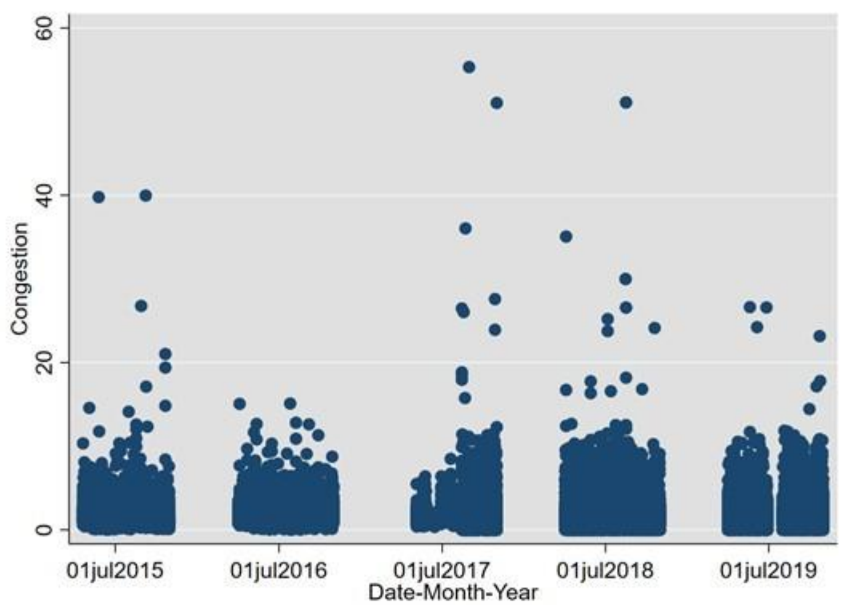

Figure 8: Average congestion scatter plot with outliers removed from 2015 to 2019 (April to October).

4 Identification

We identify the causal effect of the introduction of bike stations and protected bike lanes on motor vehicle traffic-induced congestion in Manhattan. By properly controlling for other important determinants of congestion that might be correlated with bike infrastructure, we are able to isolate the effects. These results should be helpful for policy makers as it gives feedback to (i) if bike infrastructure truly decreases traffic congestion, (ii) how big is the effect of bike infrastructure on traffic congestion, and (iii) weather bike stations or protected bike lanes are more effective at reducing congestion. To properly isolate the causal effect, we perform an OLS regression with multiple controls and fixed effects, specified as:

$$\begin{aligned} lnCONG_{jhdmt} = \alpha + \delta_j + v_h + \mu_m + \upsilon_t + \eta TEMP_{dmt} + \varphi AWND_{dmt} \\ + \gamma SAFE_{jt} + \beta STATION_{jhdmt} + \epsilon_{jhdmt} \end{aligned} \tag{2}$$

The outcome variable is $CONG_{jhdmt}$, which represents the average congestion among all roads with sensors in census block (group) j during the hour h at day d in month m and year t. The coefficients of interest are β and γ. First, β represents the effect of an additional bike station in a census block (group) on traffic congestion. $STATION_{jhdmt}$ is the count of bike stations in a census block (group) (j) of an hour (h) of a day (d) of a month (m) of a year (t). γ represents the effect of an additional protected bike lane in a census block (group) on traffic congestion. Second, $SAFE_{jt}$ is a dummy variable indicating if a census block (group) (j) is protected for a given year (t). We start by finding the causal effect of bike station counts on the census block level. Afterwards, we find the causal effect of bike station counts on the census block group level. Having regressions at these two different levels will allow for a robustness check of our results (if they are similar, that is). We control for unfavourable weather conditions that may affect cycling and traffic congestion. $TEMP_{dmt}$ represents the maximum and minimum temperature for a day. $AWND_{dmt}$ represents the average wind speed for a day. The regular cyclist who commutes to Manhattan is likely to switch to other forms of transportation when there are adverse weather conditions. Hence, increasing traffic congestion. Further, we have fixed effects for census block (group) (δ_j), hour (v_h), month (μ_m), and year (υ_t). First, we expect congestion to be correlated in neighbouring census blocks (groups). Having fixed effects by census block allows controlling the distinct congestion levels specific to a road. Second, there is a lot of variation in congestion over time units due to patterns in years, months, and day hours. The fixed effects o the time dimensions (hour, month, and year) controls for these variations. Lastly, we assume that congestion is correlated across time, and therefore, cluster the standard error by day (d).

5 Results

Table 1: Effect of bike infrastructure on traffic congestion in Manhattan on census block level

	(1) Basic	(2) Add census block fixed effects	(3) Add year, month, and hour fixed effects	(4) Add weather controls
Bike station count by census block	-0.20156*** (0.007308)	-0.02523** (0.011971)	-0.01449 (0.013724)	-0.00097 (0.019182)
Protected Lane	-0.15204*** (0.006139)	-0.23136*** (0.035025)	-0.06428** (0.029583)	-0.04499 (0.040788)
Average wind speed	-	-	-	-0.0027 (0.007623)
Maximum temperature	-	-	-	-0.00066 (0.00265)
Minimum temperature	-	-	-	0.000179 (0.003555)
Observations	476,811	476,811	476,811	293,879
***	P < 0.01			
**	P < 0.05			
*	P < 0.10			

The results produced by our baseline model are displayed in Table 1 for census blocks and Table 2 for census block groups. Our results suggestthat congestion is reduced by -0.76 percent by the presence of bike stations within a Census block group and -0.097 per census block level. Census block group level coefficient is significant at 5 percent level while census block level is not significant at 10 percent level. Our results also suggest that congestion is reduced by -4.6 percent by the presence of protected bike roads on the census block level group and -4.5 on the census block level. -0.76 reduction in congestion in census block group level and -0.097 congestion reduction in census block level are understandable as the presence of bike stations are not enough to reduce congestion in census block groups. The congestion is indeed reduced, but the magnitude of this decrease is relatively low compared to the presence of protected bike roads. The intuition behind

Table 2: Effect of bike infrastructure on traffic congestion in Manhattan on census block group level

	(1) Basic	(2) Add census block fixed effects	(3) Add year, month, and hour fixed effects	(4) Add weather controls
Bike station count by census block	-0.05929*** (0.002273)	-0.01242*** (0.003153)	-0.00704* (0.003532)	-0.00761** (0.003665)
Protected Lane	-0.15368*** (0.006144)	-0.23136*** (0.035025)	-0.06457** (0.029621)	-0.04597 (0.040866)
Average wind speed	-	-	-	-0.00269 (0.007622)
Maximum temperature	-	-	-	-0.00066 (0.002649)
Minimum temperature	-	-	-	0.000178 (0.003553)
Observations	476,811	476,811	476,811	293,879
***	P < 0.01			
**	P < 0.05			
*	P < 0.10			

this might be that just increasing bike-sharing stations in Manhattan does not imply there will be more bike commuters compared to car commuters. Daily commuters are more likely to own their bike and not be affected by the increased rental bike stations. On the other hand, our results for protected bike lanes suggest a larger decrease in congestion, which is consistent with the results by Hamilton and Wichman (2018). They found that the effect of bike stations on congestion ranges from -3.04% to -4.8%. These results make sense as more protected roads might induce commuters to take their bikesinstead of their cars leading to a congestion decrease in the Manhattan area. We should also consider the effect of making protected bike roads and their effect on car roads, but as bikes are smaller than cars, it is safe to assume that having protected bike roads on streets should not decrease the number of cars that use the street at the same time.

6 Discussion

Before talking about the plan of NYC and the change of protected bike lanes, we must talk about the difference between different categories of bike lanes. We must first talk about is protected bike lanes, which physically separates cyclists from traffic with vertical elements such as a lane of parked cars, concrete medians, or other treatments (NYC DOT, n.d.). The second type of bike lane is called conventional bike lane, and it provides a dedicated travel lane for cyclists delineated with traditional street markings. Some might have painted buffer to further separate cyclists (NYC DOT, n.d.). The third type is called shared lanes, which cyclist and motorists use alike, and they are marked by bike symbols with chevrons. The last type of bike lane is called signed routes, which are unmarked streets designated by "Bike Route", and following these signs helps guide cyclists along a pre-established route (NYC DOT, n.d.).

Over the past two decades, the City of New York more than quadrupled the size of the bike network, growing it from less than 250 lane miles in 1996 to over 1,100 lane miles in 2016 (NYC DOT, n.d.). They had a goal of adding 50 bike lane miles and 10 protected bike lane miles every year. In 2015, they added 13.3 protected bike lane miles and in 2016, they added 18.5 protected bike lane miles (NYC DOT, n.d.).

From 2015 to 2019, the city added many protected bike lane miles. Figures 9 and 10 show Manhattan’s census blocks.

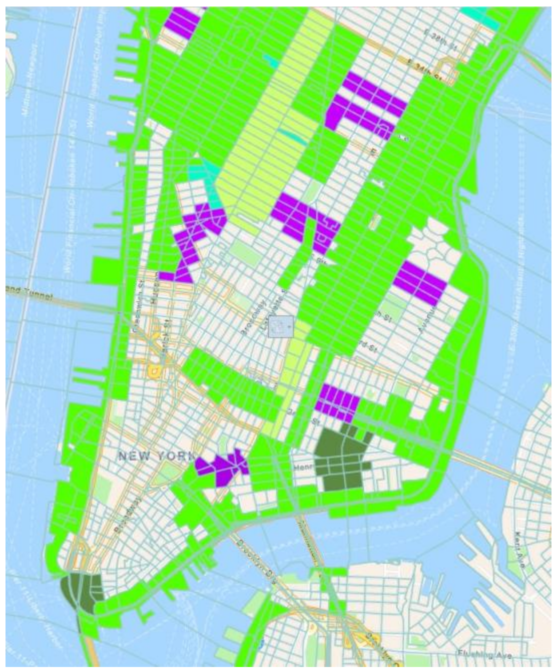

Figure 9: Protected census blocks lower Manhattan 2015-2019

To understand which census blocks are protected, we first looked at the change in protected bike lanes between 2015 to 2019. We considered a census block protected if that census block intersected with at least one protected

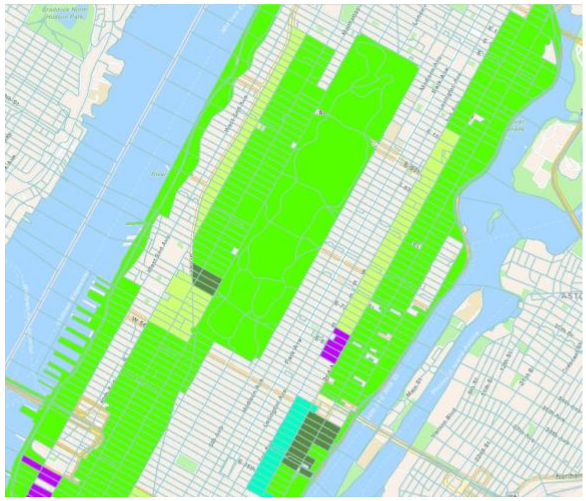

Figure 10: Protected census blocks upper Manhattan 2015-2019

bike lane. The emerald color represents the protected census blocks in 2015, the lime color represents the protected census blocks added in 2016, the dark green color represents the additions in 2017, the teal color represents the additions in 2018, and the purple color represents the additions in 2019. As we can see, the number of protected census blocks increased substantially from 2015 to 2019.

7 Conclusion

Our empirical analysis explores the causal effect of bike-sharing programs on traffic congestion and the change when these bike-sharing stations are in protected Census blocks. Our results suggest that having bike-sharing reduces the congestion but only by a small percentage. On the other hand, having protected bike roads reduces congestion by 4.6 and 4.5 percent on census block group level and census block levels, respectively, which could translate into considerable welfare gains. This can deliver meaningful insights for policymakers to optimally allocate public funding across different types of public transportation.

To extend our research, we would require a more extensive data set. If possible, we would like to expand this research beyond Manhattan to all parts of the city where bike-sharing stations are located. Identifying all the protected bike roads might be difficult, but it is one way to extend this research to see the real effect of biking on congestion.

A further interesting aspect to study would be the relationship between the availability of parking spaces on the use of bike-share programs. For example, the increasing lack of parking spaces may induce commuters to use public transportation or bikes, further reducing congestion. Also, adding bike counter data as an explanatory variable might be an extension that can be studied in the future.

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