# Evaluating the Impact of Subsidies and Bike Lane Expansions on CitiBike Ridership

Brooke McCarthy
Professor: Jonathan Hanke
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**Abstract**

In this paper, I study the impact of two distinct interventions that might help increase access to bike share programs – membership subsidies and bike lane expansions. Empirical evaluations of such policy approaches can help city officials understand the extent to which they are actually achieving their overarching goals and encourage them to take additional actions if necessary. For my analysis, I examine the impact of an affordable membership program and the NYC Streets Plan on the CitiBike bike-share program in New York City. Ultimately, I find that there is not a statistically significant relationship between the percentage of people eligible for the subsidy program and the number of bike trips in each community district, suggesting that this intervention might not be sufficient to achieve the goal of increasing ridership among under-served populations. I also do not find indications that the construction of bike lanes has driven higher bike-share usage in their proximity. Both results are robust to various specifications of the treatment variables.

## 1 Introduction

As of July 2024, the U.S. Department of Transportation reports that there are 53 bike-share programs currently in operation across the country, with more than 8,500 stations in total. Each system consists of a fleet of low-maintenance bicycles that can be rented for short periods of time and returned to docking stations after use. Bike-sharing eliminates many barriers to bike ownership such as high upfront costs, a lack of safe parking spaces, vandalism, and theft. The programs can also act as a "last-mile" complement to other public transportation systems and help reduce traffic congestion and vehicular emissions.[1] Motorized vehicles are among the major sources of environmental pollution in urban areas, and

[1] https://data.bts.gov/stories/s/Bikeshare-and-e-scooters-in-the-U-S-/fwcs-jprj/ (1)

the implementation of bike-sharing systems has been touted by several international organizations as an effective policy intervention to combat climate change. Finally, the programs have been found to provide key health benefits for users by promoting physical activity.[2]

Despite these benefits, previous studies have found that use of the programs varies widely across groups. Lower-income and people of color in the U.S. tend to participate in bike shares far less than individuals who maintain a higher socioeconomic status.[3] Therefore, cities should have a vested interest in expanding access among those who are currently excluded. In this paper, I investigate the impact of two distinct interventions that might help achieve this objective – subsidy programs and bike lane expansions. To do so, I leverage a dataset that contains detailed information about the New York City CitiBike program and analyze ridership rates before and after each intervention was put into effect. To examine the impact of subsidies, I focus on an affordable membership program that began in July of 2018. The program offers low-cost $5 per month memberships for all NYC residents who receive SNAP benefits. Over 1.6 million New Yorkers are currently eligible for the program.[4] To investigate bike lane expansions, I focus the NYC Streets Plan. This initiative was announced in 2019 and mandates that the government build 250 miles of protected bike lanes between 2022 and 2026, 61 miles of which have currently been completed.[5]

## 1.1 Research Question and Hypothesis

The specific question I intend to study is as follows. How do subsidy programs and bike lane expansions affect bike-share usage rates and patterns? I hypothesize that the subsidy program will result in a higher overall number of bike-share trips in lower-income areas (H1), and that the construction of bike lanes will drive higher bike-share usage in their proximity (H2). Ultimately, however, I find that there is not a statistically significant relationship between the percentage of people eligible for the subsidy program and the number of bike-trips in each community district, suggesting that this intervention might not be sufficient to achieve the goal of increasing program access among under-served populations. I also do not find statistical support for H2, indicating that NYC Streets Plan might also be falling short of expectations. Both results are robust to various specifications of the treatment variables.

The following section will provide background on the policy interventions used for the

[2] https://www.sciencedirect.com/science/article/abs/pii/S0160412017321566. (2)

[3] https://www.sciencedirect.com/science/article/pii/S1361920922002978?via%3Dihub#b0305. (3)

[4] http://www.nyc.gov/office-of-the-mayor/news/359-18/mayor-low-cost-citi-bike-membership-will-be-available-all-snap-recipients (4)

[5] https://projects.transalt.org/bikelanes. (5)

analysis. Next, I will outline the existing literature on to the factors that influence bike share usage. Section four will discuss my variables of interest and how I constructed my datasets. Sections five and six will outline the methods and results for my empirical analysis. Finally, sections seven and eight will interpret my findings, discuss relevant policy implications, note the limitations of my study, and suggest areas for future research.

# 2 Background

## 2.1 Subsidy Program

In July of 2018, former NYC mayor Bill de Blasio announced a new program that would enable all New Yorkers receiving Supplemental Nutrition Assistance Program (SNAP) benefits to purchase a low-cost membership to CitiBike. Unlike traditional memberships that require an annual commitment, eligible individuals would have the option to pay just $5 per month - a rate representing a 66% discount off the regular price. To apply for the discount, SNAP recipients would be able to either visit the CitiBike website or sign up in-person at SNAP enrollment centers, New York City Housing Association (NYCHA) developments, and community centers. The program was poised to benefit a significant portion of the city's population, as over 1.6 million New Yorkers are reliant on SNAP. Additionally, survey studies have found that membership costs are commonly cited as a barrier to participation by low-income respondents.[6] De Blasio and other city officials expressed great optimism about the subsidy's potential to support broader goals. He explained, "affordable bike share for more New Yorkers helps us build a fairer and more equitable city. Improving mobility for SNAP recipients will help them make ends meet by giving them greater access to jobs, services and educational opportunities."[7]

## 2.2 Bike Lane Expansion Initiative

In 2019, legislation to implement the NYC Streets Plan became law, and in 2022 Mayor Adams and the NYC City Council agreed to a $904 million dollar investment to carry it out. The legally-mandated plan requires the construction of 250 miles of protected bike lanes, with at least 30 miles in 2022 and at least 50 miles in each of the following years. Protected

[6] https://www.sciencedirect.com/science/article/pii/S1361920922002978?via%3Dihub#b0305. (3)

[7] https://www.nyc.gov/office-of-the-mayor/news/359-18/mayor-low-cost-citi-bike-membership-will-be-available-all-snap-recipients. (4)

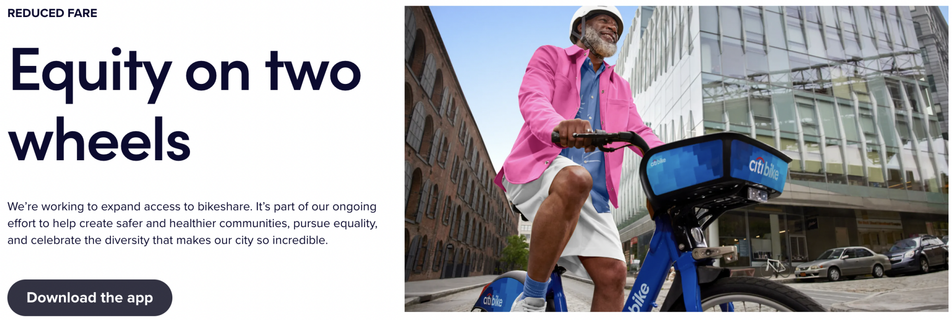


Figure 1: Advertisement for subsidy program on CitiBike website

bike lanes can be defined as those with "a physical separation from motorized vehicle traffic by a parking lane or barrier. Separation can take the form of floating parking, a curb or raised median, or other vertical elements preventing motor vehicles from accessing the bikeway."[8] While there is no open data set or tracker hosted by the city to document the completion of these lanes, the independent advocacy group Transportation Alternatives has developed a monitoring system with the assistance of city residents. According to the group, 61 miles of protected bike lanes have been completed to date.[9] A graph of the progress can be seen below in Figure 2.

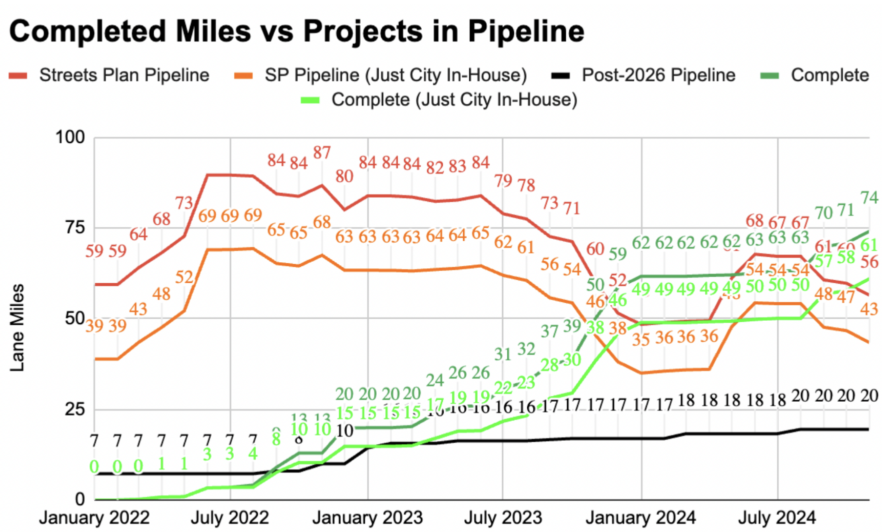


Figure 2: Bike Lane Expansion Initiative Progress

[8] https://www.nycstreetdesign.info/geometry/protected-bike-lane. (6)
[9] https://projects.transalt.org/bikelanes#smp (5)

# 3 Related Work

A number of studies have leveraged CitiBike data to attempt to explain usage rates and predict demand for various applications. These studies have tended to focus on factors such as weather (Bean, 2021), station accessibility, bike availability (Kabra, 2020), and traffic patterns (Singhvi, 2015). Despite the fact that qualitative studies often cite safety and affordability concerns as barriers to program usage (Bateman, 2021), there has been relatively little research on the impact of policies designed to address these issues. Studies that do touch on policy typically limit their analysis to that pertaining solely to infrastructure and have yielded mixed results (Mateo-Babiano, 2016; Scott, 2019). Through my project, I intend to address this salient gap in the literature.

# 4 Data

To complete my analysis, I combined data from several sources, including the CitiBike website, the NYC Department of City Planning (geospatial data), weather services, Borough Community District Reports (SNAP enrollment data), the U.S. Census (population data), and the Transportation Alternatives advocacy group (bike lane expansion data). The following paragraphs describe each data source and how it was used in the analysis.

## 4.1 CitiBike Data

The main source for this project is the CitiBike dataset, which contains information about trip dates, times, durations, and starting and ending station coordinates from February 2013 through the present. The data is comprehensive, and each row represents one trip.[10] I used the following variables from this source:

- **'starttime'**: Includes the date, month, year, and time of the trip. I extracted the months and used this variable to plot trends over time and create a column indicating whether each observation was pre- or post-intervention.
- **'start station latitude'**: Latitude of the location where the trip started. I used this in conjunction with the 'start station longitude' variable and the geospatial data to determine which community district each trip originated in.

[10] https://citibikenyc.com/system-data. (13)

- **‘start station longitude’**: Longitude of the location where the trip started.
- **‘usertype’**: Indicates whether each rider held a membership (subscriber) or a 24-hour or 3-day pass (customer). I used this variable to filter for trips made by subscribers, as the subsidy only impacted this type of ridership.

## 4.2 NYC Department of City Planning

I decided to conduct my analysis by community districts, of which there are 59 across the 5 boroughs.[11] Districts provide me with a convenient way to distinguish between my treatment and control groups, as there are vast differences between them in terms of the degree to which they were impacted by each intervention. Because the CitiBike data only contained start station coordinates, I also had to utilize geospatial data from the NYC Department of City Planning. The Boundaries of Community Districts dataset includes the names and geometry for each district, so I was able to merge this with the CitiBike data such that the resulting dataframe included the community district that each trip originated in.[12]

## 4.3 Weather Data

Temperature has been found to significantly impact bikeshare ridership in other studies, with lower temperatures being associated with a decrease in trip counts.[13] Therefore, I sourced weather data from TimeandDate.com to control for average monthly temperature in my analysis of both interventions.[14]

## 4.4 Borough Community District Reports

Borough Community District Reports are compiled by the NYC Human Resources Administration (HRA) and made available online through NYC Open Data. They contain information about enrollment in various social services programs, including SNAP, by each NYC community district.[15] I filtered the report for the time period around the implementation of the subsidy and used the following variables:

[11] https://www.nyc.gov/site/planning/community/community-portal.page (14)
[12] https://data.cityofnewyork.us/City-Government/Community-Districts/yfnk-k7r4 (15)
[13] https://www.sciencedirect.com/science/article/abs/pii/S0966692321002088. (7)
[14] https://www.timeanddate.com/weather/usa/new-york/historic?month=7&year=2018. (16)
[15] https://data.cityofnewyork.us/Social-Services/Borough-Community-District-Report/5awp-wfkt/about_data. (17)

- **'community_district'**: Indicates the community district number for the entry. I used this information to merge the SNAP enrollment data with my data for trip counts.
- **'bc_snap_recipients'**: Indicates the number of individuals receiving SNAP benefits in each community district.

## 4.5 U.S. Census Data

I obtained data from the 2010 U.S. Census on population by community districts – available through NYC Open Data – to estimate the number of people residing in each NYC community district at the time of the subsidy intervention. I used this in conjunction with the SNAP enrollment data to estimate the percentage of people eligible for the subsidy program in each community district.[16] These percentages were then used to establish my treatment and control groups.

## 4.6 Transportation Alternatives Data

Finally, to test the impact of the bike lane expansions, I also included data sourced from the Transportation Alternatives advocacy group that tracks progress on protected bike lanes associated with the NYC Streets Initiative. I filtered the dataset for bike lanes completed during my time period of interested (January 2022 - December 2023) and used the following variables:

- **'Street' & 'Extent'**: Together these variables indicate the location of the new protected bike lanes. Once again, I intended to conduct my analysis by community district, so I ran the pairs for all entries through ChatGPT-40 and requested that it provide me with the district for each new bike lane. There were just over 80 entries in the data, and I randomly selected 10 to manually confirm by locating each lane on Google Maps and cross referencing with a map of the community districts. I found that the chatbot's classifications were 100% accurate for this group. Therefore, I have a high degree of confidence in this method. I merged this data with that for the CitiBike trip counts and added a treatment variable that was 1 if the counts were for a community district where a bike lane was completed during the time period of interest and 0 otherwise.

[16] https://data.cityofnewyork.us/City-Government/New-York-City-Population-By-Community-Districts/xi7c-iiu2/data. (18)

- **'lane miles'**: Indicates the length of the lanes installed. I used this variable as another specification of the treatment variable on which I ran my regressions.

### 4.7 Structure of Final Datasets

After combining my various data sources to test the effect of the subsidy, I produced a dataset that contains variables for the number of CitiBike trips grouped by community district ('trip_count') and month ('month'), a variable indicating whether or not the month was before or after the subsidy program went into effect ('post'), and three different specifications of the treatment variable. The first treatment variable is continuous and indicates the percentage of people eligible for the subsidy in the community district ('percent_eligible'). The second is categorical and breaks the continuous 'percent_eligible' variable into 5 bins ('snap_category'). Finally, the third treatment variable is binary. It takes a value of 0 for community districts in the low 'snap_category' and a value of 1 for community districts in all other categories.

My final dataset for testing the effects of the bike lane expansions was very similar. It contains variables for the number of CitiBike trips grouped by community district ('trip_count') and month ('month'), a variable indicating whether or not the month was before or after the NYC Streets Plan went into effect ('post'), and two different specifications of the treatment variable. The first treatment variable is continuous and indicates the number of lane miles constructed in each community district during the period of interest ('lane miles'). The second variable is binary and takes a value of 0 for community districts where no lanes were built during the period, and a value of 1 for community districts where any amount of lanes were built ('lane expansion').

## 5 Analysis

In this section, I will discuss some of the exploratory data analysis I performed before testing each intervention, followed by a discussion of the various regression models I examined.

### 5.1 Exploratory Data Analysis for Subsidy

I will begin with my exploration of the data for the subsidy intervention. First, I examined how the total trip counts changed between April and October of 2018 – the period encompassing three months before and after the subsidy went into effect. This relationship can be seen below in Figure 3. On this figure, we see a large spike in ridership between April and July that is likely due to weather. Following this time period, we see that ridership appears relatively more constant but maintains some variation month to month.

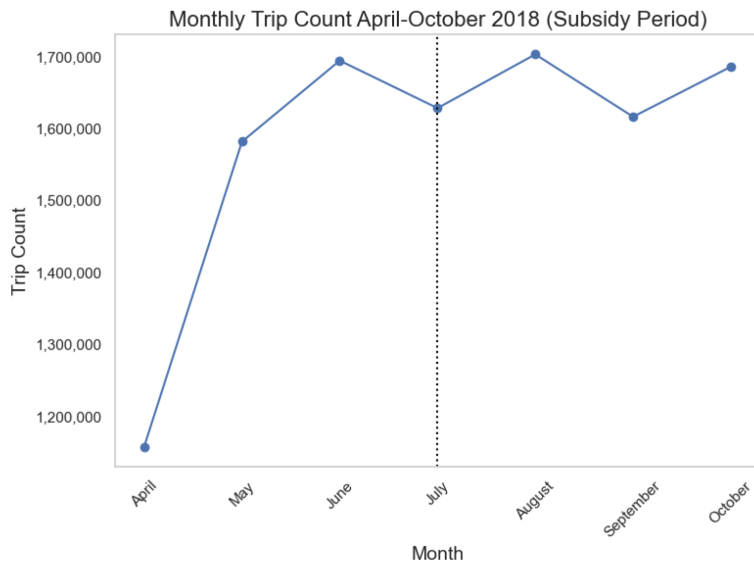


Figure 3: Monthly total trip counts during period of analysis for the subsidy. The intervention went into effect in July.

Next, I want to start gaining an idea of how subsidy eligibility might be related to changes in ridership across the treatment period. To do so, I plot a heatmap that indicates the difference in ridership before and after the subsidy for each community district. Darker values correspond to greater increases following its implementation. I compare this to a heatmap that indicates the percentage of people in each district who are eligible for the subsidy program, with darker values corresponding to higher percentages of eligibility. Heatmaps can be seen below in Figures 4 and 5. If there was a relationship between increased ridership and subsidy eligibility, we might expect to see similarities in these two maps. There does not seem to be any sort of clear visual relationship, but we are not yet controlling for various factors that could be influencing it.

Finally, I want to examine the counts for the treatment variables. The breakdown for the categorical treatment variable can be seen below in Table 1. The dataset does not encompass all 59 community districts, as several did not have any bikeshare activity during this time period due to a lack of infrastructure. The counts for the binary treatment variable can also be seen in Table 2.

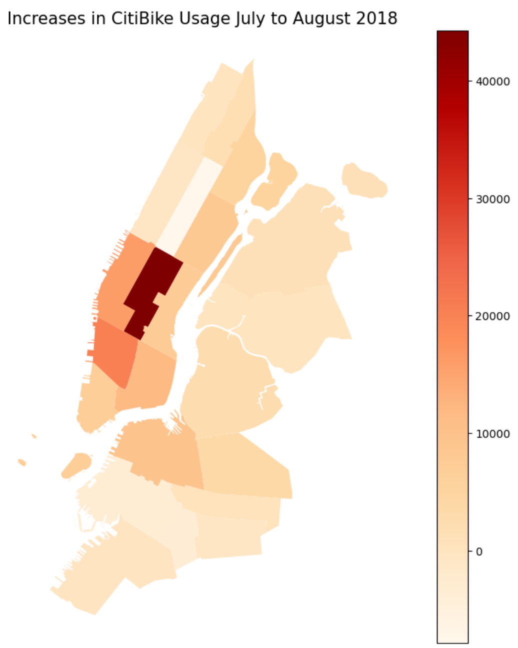


Figure 4: Increases in total trip counts before and after the subsidy went into effect

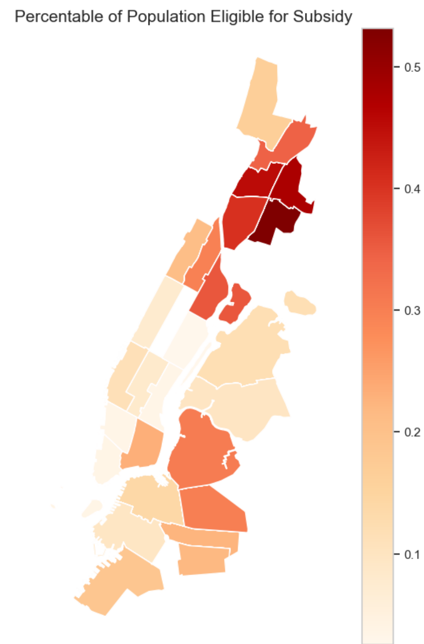


Figure 5: Percentage of population eligible for subsidy in each community district

Table 1: Number of CDs in Each Category and Percent Eligible

| ‘snap_category’ | Number of CDs | Percent Eligible |
|---|---|---|
| Low | 8 | 2-10 |
| Medium-Low | 5 | 10-20 |
| Medium | 5 | 20-30 |
| Medium-High | 4 | 30-40 |
| High | 4 | 40-54 |

Table 2: Number of CDs in Each Category and Percent Eligible

| ‘Subsidy’ | Number of CDs | Percent Eligible |
|---|---|---|
| 0 | 8 | 2-10 |
| 1 | 28 | 10-54 |

## 5.2 Exploratory Data Analysis for Bike Lane Expansion

To examine the data for the bike lane expansion, I take a similar approach. First, I plot a heatmap that indicates the difference in ridership in each community district before and after the time period during which a majority of the bike lanes were completed (Janary 2022-December 2023). Darker values correspond to greater increases following the construction. I compare this to a heatmap that indicates the miles of bike lanes completed in each district, with darker values corresponding to higher mileages. Heatmaps can be seen below in Figures 6 and 7. Once again, if there was a relationship between increased ridership and subsidy eligibility, we might expect to see similarities in these two maps. However, there does not seem to be any sort of clear visual relationship for this intervention either.

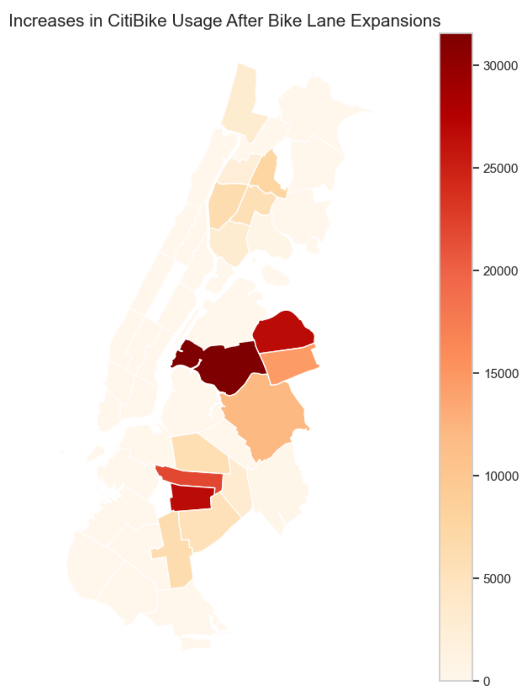


Figure 6: Increases in total trip counts before and after bike lanes were built.

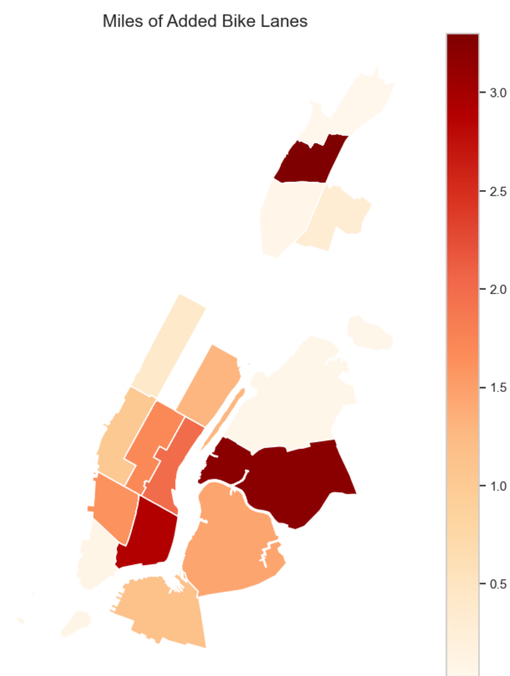


Figure 7: Miles of bike lanes built in each community district.

Next, I examine the distributions for my treatment variables. The counts for the binary treatment variable can be seen below in Table 3, and the distribution of the 'lane miles' variable can be seen in Figure 8.

Table 3: Number of CDs With Added Bike Lanes

| ‘lane_expansion’ | Number of CDs |
|---|---|
| 0 | 16 |
| 1 | 28 |

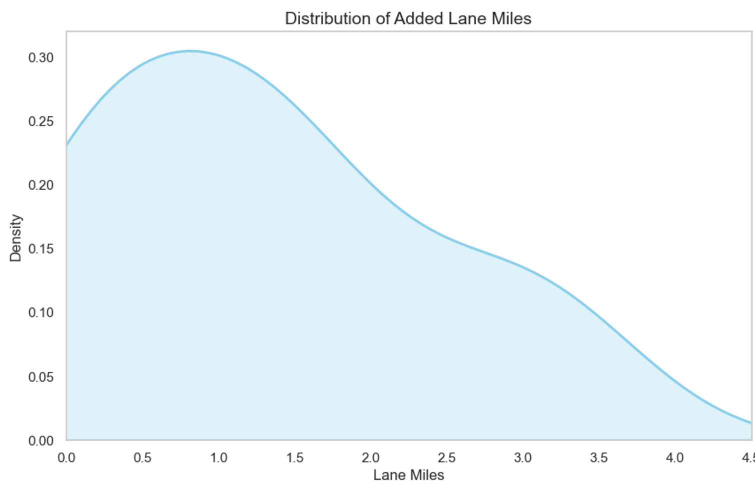


Figure 8: Distribution of ‘lane miles’ variable.

### 5.3 Regression Analysis for Subsidy

To test H1, I opted to use a difference-in-differences approach in order to isolate the causal effect of the subsidy intervention. To do so, I ran regressions on three different models, each with a different specification of the treatment variable for robustness. For Model 1, I include a variable for pre- and post- subsidy (Post), as well as a binary indicator for whether or not each community district was treated to a certain extent (Subsidy). For Model 2, I include the temporal indicator, as well as a continuous treatment variable for the percentage of people eligible for the subsidy in each district (Percent Eligible). Finally, for Model 3, I include the Post variable and coefficients for 5 different levels of subsidy eligibility. All models also contain a variable to control for changes in average temperature over time. The equations for these models can be seen below:

**Model 1 (Binary Treatment Variable):**

$$\text{Trip\_Count}_{it} = \beta_0 + \beta_1(\text{Post}_t) + \beta_2(\text{Subsidy}_i) + \beta_3(\text{Post}_t \times \text{Subsidy}_i) + \beta_4(\text{Average Temperature}_{it}) + \varepsilon_{it}$$

**Model 2 (Continuous Treatment Variable):**

$$\text{Trip\_Count}_{it} = \beta_0 + \beta_1(\text{Post}_t) + \beta_2(\text{Percent Eligible}_i) + \beta_3(\text{Post}_t \times \text{Percent Eligible}_i) + \beta_4(\text{Average Temperature}_{it}) + \varepsilon_{it}$$

**Model 3 (Categorical Treatment Variable):**

$$\text{Trip\_Count}_{it} = \beta_0 + \beta_1(\text{Low}_i) + \beta_2(\text{Medium-Low}_i) + \beta_3(\text{Medium}_i) + \beta_4(\text{Medium-High}_i) + \beta_5(\text{High}_i) + \beta_6(\text{Post}_t) + \beta_7(\text{Post}_t \times \text{Low}_i) + \beta_8(\text{Post}_t \times \text{Medium-Low}_i) + \beta_9(\text{Post}_t \times \text{Medium}_i) + \beta_{10}(\text{Post}_t \times \text{Medium-High}_i) + \beta_{11}(\text{Post}_t \times \text{High}_i) + \beta_{12}(\text{Average Temperature}_{it}) + \varepsilon_{it}$$

### 5.4 Regression Analysis for Bike Lane Expansion

I also employ a difference-in-differences approach to test H2. To do so, I ran regressions with two different specifications of the treatment variable. For Model 1, I include a variable for pre- and post- subsidy (Post), as well as a binary indicator for whether or not any amount of bike lanes were constructed in each district during the period (Lane Expansion). For Model 2, I include the temporal indicator, as well as a continuous treatment variable for the miles of new bike lanes (Lane Miles). Once again, both models also contain a variable to control for changes in average temperature. The equations for these models can be seen below:

**Model 4 (Binary Treatment Variable):**

$$\text{Trip\_Count}_{it} = \beta_0 + \beta_1(\text{Post}_t) + \beta_2(\text{Lane Expansion}_i) + \beta_3(\text{Post}_t \times \text{Lane Expansion}_i) + \beta_4(\text{Average Temperature}_{it}) + \varepsilon_{it}$$

**Model 5 (Continuous Treatment Variable):**

$$\text{Trip\_Count}_{it} = \beta_0 + \beta_1(\text{Post}_t) + \beta_2(\text{Lane Miles}_i) + \beta_3(\text{Post}_t \times \text{Lane Miles}_i) + \beta_4(\text{Average Temperature}_{it}) + \varepsilon_{it}$$

## 6 Results

### 6.1 Regression Results for Subsidy

Overall, the results fail to provide support for H1 – CitiBike ridership counts do not appear to have a statistically significant relationship with the implementation of the subsidy program. For all models, the differential effect on the treatment group relative to the control group is captured by the coefficients for the interaction terms between 'Post' and the intervention variables. For Model 1, we examine the coefficient $\beta_3$, the interaction between 'Post' and the binary treatment variable 'Subsidy', which has a value of -15,290. This finding seems to suggest that the subsidy program is actually associated with a minor decrease in ridership. However, the corresponding p-value indicates that the relationship is not statistically significant at the 0.1 level. For Model 2, we also look to the coefficient for $\beta_3$, the interaction between 'Post' and the continuous treatment variable 'Percent Eligible', which has a value of -59,130. Once again this seems to suggest that a one percent increase in subsidy eligibility is associated with a decrease in ridership, but it fails to achieve statistical significance. Finally, for Model 3, we examine coefficients $\beta_7$ - $\beta_{11}$. Each indicates the interaction between 'Post' and a distinct level of subsidy eligibility ranging from Low to High. All of these coefficients suggest a minor decrease in ridership following the treatment, but none are statistically significant. The results for all models are summarized below in Table 4.

Table 4: PanelOLS Estimation Results for Subsidy Intervention

| | **Model 1** | **Model 2** | **Model 3** |
|---|---|---|---|
| **Variable** | | **Trip Counts** | |
| **Post** | 6,726.7 | 8,255.7 | 6,787.2 |
| **Average Temperature** | 1,550.3$^{***}$ | 1,639.0$^{***}$ | 458.4 |
| **Subsidy** | -62,480$^{***}$ | | |
| **Post × Subsidy** | -15,290 | | |
| **Percent Eligible** | | -228,800$^{***}$ | |
| **Percent Eligible × Post** | | -59,130 | |
| **Low SNAP** | | | 76,920$^{**}$ |
| **Medium-Low SNAP** | | | 29,500 |
| **Medium SNAP** | | | 9,157.9 |
| **Medium-High SNAP** | | | 1,798.8 |
| **High SNAP** | | | -28,270 |
| **Low SNAP × Post** | | | -2,559.4 |
| **Medium SNAP × Post** | | | -5,194.0 |
| **Medium-High SNAP × Post** | | | -5,192.4 |
| **High SNAP × Post** | | | -10,770 |
| **R-squared** | 0.5526 | 0.5986 | 0.3218 |
| **Num. obs.** | 182 | 182 | 182 |

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

The relationships captured by the regressions can also be examined visually below in

Figure 9. On this chart, I plot the trends of the trip counts for community districts in each subsidy eligibility category over the period of interest. The vertical line indicates the time at which the intervention went into effect. If the subsidy was effective at increasing ridership, we would expect to see a greater upward trend in the higher categories relative to the Low category. However, we only see a minor increase in the Low category and relatively constant counts for the higher categories after July.

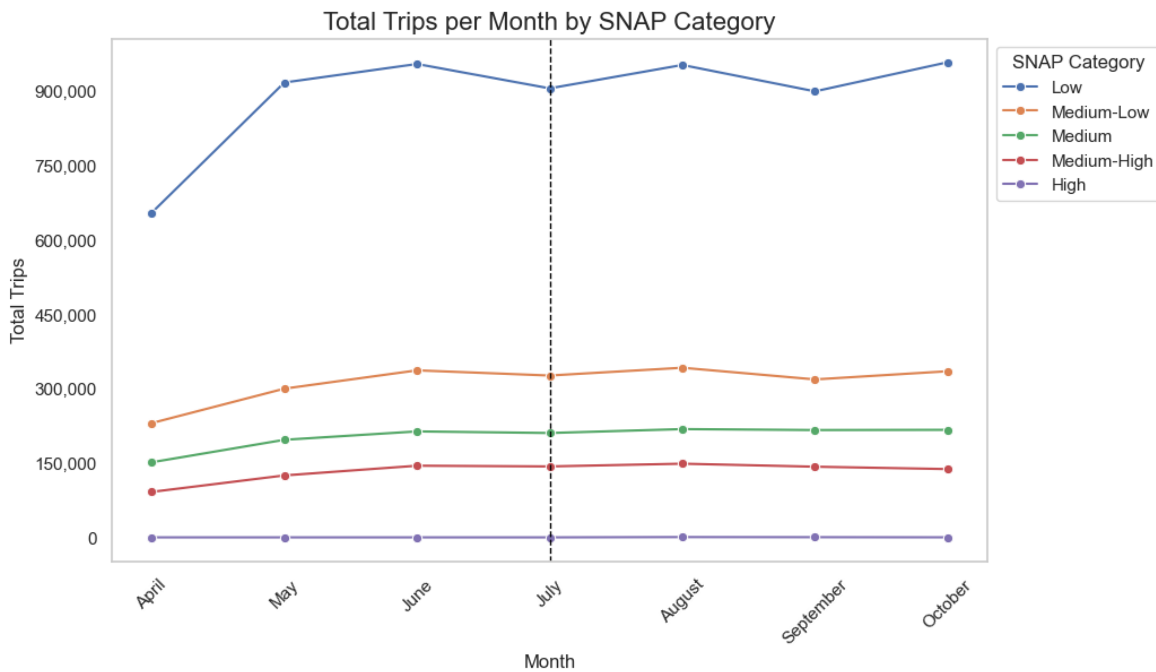


Figure 9: Visual Summary of Results

## 6.2 Regression Results for Lane Expansions

The results also do not provide support for H2 – the construction of bike lanes do not appear to drive higher bike-share usage in their proximity. For Model 1, we examine the coefficient $\beta_3$, the interaction between 'Post' and the binary treatment variable 'Lane Expansion', which has a value of -10,300. This finding seems to suggest that the bike lane expansion program is associated with a minor decrease in ridership. However, the corresponding p-value indicates that the relationship is not statistically significant at the 0.1 level. For Model 2, we also look at the coefficient for $\beta_3$, the interaction between 'Post' and the continuous treatment variable 'Lane Miles', which has a value of 897.68. This time, the coefficient suggests that each additional mile of protected bike lanes might be associated with a very minor increase in ridership, but it fails to achieve statistical significance. The results for these models are summarized below in Table 5.

Table 5: PanelOLS Estimation Results for Bike Lane Expansion Intervention

| | Trip Count | |
|---|---|---|
| | **Model 1 (Lane Expansion)** | **Model 2 (Lane Miles)** |
| **Lane Expansion** | 48,040$^{***}$ | |
| **Lane Miles** | | -3,043.2 |
| **Post** | 1,843.5 | -2,245.3 |
| **Average Temperature** | 486.06$^{*}$ | 1,660.0$^{***}$ |
| **Lane Expansion × Post** | -10,300 | |
| **Lane Miles × Post** | | 897.68 |
| **R-squared** | 0.3781 | 0.3787 |
| **Num. obs.** | 176 | 112 |

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

# 7 Discussion

The analysis suggests that neither the affordable membership program nor the NYC Streets Plan bike lane expansion initiative had a statistically significant impact on CitiBike ridership over the study period. However, the absence of significant effects does not necessarily mean that the initiatives should not be considered worthwhile investments and replicated in other cities with similar ambitions for their bike share programs. Both provide many benefits to existing users by decreasing the financial burden on SNAP recipients and increasing convenience and safety for all. It is also possible that they will yield more significant results in the long-term that could not be adequately captured by this study.

However, the findings still offer a number of key takeaways for policymakers. To achieve more immediate results, city officials might want to consider revising the design and implementation of the subsidy program. For instance, the marketing strategy might not have been sufficiently targeted to reach the intended audience. If potential beneficiaries were not adequately informed about the program, its impact would likely remain minimal. Additionally, the subsidy rate may not have been high enough for SNAP recipients to view bike share memberships as a worthwhile investment.

Similar insights can be drawn from the findings for bike lane expansions. So far, the initiative might not be sufficient in terms of scale and scope to meaningfully impact ridership. As shown in Figure 8, most lane expansions to date have been relatively small, with the majority being one mile or less in length. Once again, only 61 miles of the the 250 promised in the NYC Streets Plan have been completed to date, meaning that the full impact may only become evident as more lanes are built. However, the findings might provide an early indication that other types of interventions might need to accompany bike lane expansions in order to achieve the desired results. For instance, they might need to be paired with other infrastructural improvements like the construction of more bike share stations in districts where they are currently more sparse.

### 7.1 Areas for Future Research

Future research might seek to explore how to increase the effectiveness of subsidy programs by tailoring the outreach to specific demographics and adjusting the pricing mechanisms. Bike lane expansion programs could also be helped by studies that elucidate other factors that might influence their impact, such as an increased number of stations or proximity to other forms of public transportation. Finally, researchers should continue to monitor how ridership changes over time as a greater percentage of the promised NYC Streets Plan bike lanes are completed to gain an idea of the necessary extent of this intervention to bring about the desired impact.

## 8 Conclusion

If officials are truly committed to building a more equitable city by expanding access to a cleaner, healthier mode of transportation, they should seek to understand how different policy interventions might impact bike share usage.[17] The results of this study indicate that the current design and implementation of subsidy programs for low-income residents, as well as the ongoing bike lane expansion efforts, may not be sufficient to drive significant increases in ridership. Policymakers should, therefore, invest in further research to identify the adjustments needed to improve these initiatives. This could involve refining the subsidy pricing mechanisms, enhancing outreach efforts, and scaling up infrastructure improvements.

[17] https://www.nyc.gov/office-of-the-mayor/news/359-18/mayor-low-cost-citi-bike-membership-will-be-available-all-snap-recipients. (4)

## References

[1] "Bikeshare and e-scooters in the U.S." [Online]. Available: https://data.bts.gov/stories/s/Bikeshare-and-e-scooters-in-the-U-S-/fwcs-jprj/

[2] I. Otero, M. J. Nieuwenhuijsen, and D. Rojas-Rueda, "Health impacts of bike sharing systems in Europe," *Environment International*, vol. 115, pp. 387–394, Jun. 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0160412017321566

[3] J. Dill, J. Ma, N. McNeil, J. Broach, and J. MacArthur, "Factors influencing bike share among underserved populations: Evidence from three U.S. cities," *Transportation Research Part D: Transport and Environment*, vol. 112, p. 103471, Nov. 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1361920922002978

[4] "Mayor Announces Low-Cost Citi Bike Membership Will Be Available to All SNAP Recipients," Jul. 2018. [Online]. Available: http://www.nyc.gov/office-of-the-mayor/news/359-18/mayor-low-cost-citi-bike-membership-will-be-available-all-snap-recipients

[5] "Protected Bike Lane Tracker," Sep. 2022. [Online]. Available: https://projects.transalt.org/bikelanes

[6] "Protected Bike Lane | NYC Street Design Manual." [Online]. Available: https://www.nycstreetdesign.info/geometry/protected-bike-lane

[7] R. Bean, D. Pojani, and J. Corcoran, "How does weather affect bikeshare use? A comparative analysis of forty cities across climate zones," *Journal of Transport Geography*, vol. 95, p. 103155, Jul. 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0966692321002088

[8] A. Kabra, E. Belavina, and K. Girotra, "Bike-Share Systems: Accessibility and Availability," *Management Science*, vol. 66, no. 9, pp. 3803–3824, Sep. 2020, publisher: INFORMS. [Online]. Available: https://pubsonline.informs.org/doi/10.1287/mnsc.2019.3407

[9] D. Singhvi, S. Singhvi, P. Frazier, S. Henderson, E. O'Mahony, D. Shmoys, and D. Woodard, "Predicting Bike Usage for New York City's Bike Sharing System," 2015. [Online]. Available: https://www.semanticscholar.org/paper/Predicting-Bik

e-Usage-for-New-York-City%27s-Bike-Singhvi-Singhvi/322af5fd9610b533089b0031e4df8cdc1b7103af

[10] L. B. Bateman, M. N. Fouad, A. Sullivan, L. Heider, and G. R. Oates, "Barriers and Facilitators to Bikeshare Programs: A Qualitative Study in an Urban Environment," *Journal of transport & health*, vol. 21, p. 101062, Jun. 2021. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8104309/

[11] I. Mateo-Babiano, R. Bean, J. Corcoran, and D. Pojani, "How does our natural and built environment affect the use of bicycle sharing?" *Transportation Research Part A: Policy and Practice*, vol. 94, pp. 295–307, Dec. 2016. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0965856415301531

[12] D. M. Scott and C. Ciuro, "What factors influence bike share ridership? An investigation of Hamilton, Ontario's bike share hubs," *Travel Behaviour and Society*, vol. 16, pp. 50–58, Jul. 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2214367X18300188

[13] "Citi Bike System Data | Citi Bike NYC." [Online]. Available: https://citibikenyc.com/system-data

[14] "Community Portal." [Online]. Available: https://www.nyc.gov/site/planning/community/community-portal.page

[15] "Community Districts." [Online]. Available: https://data.cityofnewyork.us/City-Government/Community-Districts/yfnk-k7r4

[16] "Weather in July 2018 in New York, New York, USA." [Online]. Available: https://www.timeanddate.com/weather/usa/new-york/historic?month=7&year=2018

[17] "Borough/Community District Report | NYC Open Data." [Online]. Available: https://data.cityofnewyork.us/Social-Services/Borough-Community-District-Report/5awp-wfkt/about_data

[18] "New York City Population By Community Districts." [Online]. Available: https://data.cityofnewyork.us/City-Government/New-York-City-Population-By-Community-Districts/xi7c-iiu2