Summer 8-2-2021

The Impact of Select Buses on Taxi Ridership in NYC

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by

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Submitted in partial fulfillment
of the requirements for the degree of
Master of Arts in Economics, Hunter College
The City University of New York

2021

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Abstract

The objective of this research is to measure the impact of select buses on taxi ridership in NYC. Due to the phased implementation of select buses in NYC, a difference-in-differences model was used. Taxi ridership on the M14A/M14D, M34, M79, and M15 bus routes was examined as the treatment group. The control group is the M100/M101 non-select bus route that runs along Lexington and Amsterdam Avenue. The results from this model show that the M14A/M14D, M34, and M79 select buses had a negative statistically significant impact on taxi ridership. The M15 select bus had a positive statistically insignificant impact on taxi ridership. It is evident through the literature that a transition to select buses would have a positive effect on the environment.

Acknowledgments

A special thank you to my thesis advisor Professor Partha Deb for guiding me and advising me throughout the thesis writing process, and Professor Matthew Baker for taking the time to read my thesis and provide feedback. Thank you to my colleague Sunniyatul Quaderin for assisting me with the geocoding process. And finally, I would like to thank my friends and family for being a solid support system for me throughout this journey.

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1. Introduction

Consumers take taxis for convenience. Privacy, comfort, and speed deter commuters from taking; public transportation or shared vehicle services (Schaller 2021). If public transportation was faster, more comfortable, and convenient, private vehicle riders might substitute taxis or car services for public transportation (Beira, Cabral 2007). This would positively impact the environment as shared vehicles reduce miles traveled which leads to less traffic and fewer emissions (Schaller 2021).

The *Bus Rapid Transit* (BRT) system was designed for consumers to have faster and more comfortable commutes. BRT systems are especially efficient at transporting large numbers of people in urban areas (Wan et al. 2016). The first BRT began in England in 1971 as, of today, 166 cities in the world have a BRT system. BRTs have particular elements that make them more efficient and faster for travel than a regular bus (Levinson et al. 2002). These elements can be divided into two categories: speed and comfort. Speed is an important aspect that attracts passengers (Wan et al. 2016). One factor that contributes to speed is the dedicated bus lanes. These bus lanes help buses bypass traffic or congestion. Another factor is bus drivers have access to *Traffic Signal Priority* (TSP). TSP allows drivers to request extended green light time or reduced red light time at intersections.

In addition, passengers pay fare before bus arrival, making boarding time faster. Comfort and capacity are also important. Consumers see BRTs as more comfortable and spacious than a normal bus (Beirao, Cabral 2017). The aesthetic and design can attract new consumers. Many BRTs have several doors so passengers can enter and leave faster. These features might cause consumers who take taxis to take select buses instead, as they are cheaper and have the comfort and speed features that consumers value. NYC select buses are considered a “light” BRT as they include some, but not all, features of the original BRT system (Wan et al. 2016). In NYC, bus lanes are only used at certain hours, unlike the original BRT system. In addition, NYC select buses are missing important BRT infrastructure elements such as platform-level boarding and bus lanes that are located at the center of the street rather than next to parking lanes. These factors differentiate NYC select bus service (SBS) from the original BRT.

If consumers transition from taking taxis to select buses, this can positively impact the environment. Buses hold many passengers while taxis usually carry 1-4 passengers. Pooled services decrease vehicle miles traveled (VMT), which leads to a decrease in emissions (Schaller 2021). We can think of select buses as a large, pooled service. A few buses can transport many people, and more people taking the bus means fewer taxi trips and therefore less VMT. An overall increase in select bus ridership would decrease the negative; environmental effects of many taxis carrying a small number of people.

The purpose of this paper is to measure the impact of select buses on taxi ridership in NYC. This is important to study because of the policy and environmental implications this may have on different groups of people. Various studies show that BRTs and BRT features such as Traffic Signal Priority (TSP) and dedicated bus lanes can decrease emissions and help the environment (Alam and Hatzopoulou 2014, Lin et al. 2015, Rogat & Dhar 2015). If a city wants to be more sustainable, implementing select buses might be a good way to encourage residents to use public transportation. From a driver's perspective, the implementation of select buses can have a negative impact on their business. Medallion prices have plummeted due to factors such as the increase in competition and the lack of freedom for drivers to price taxi fare dynamically (Steint 2020). Since 2009 taxi drivers have had to pay a 50 cent MTA tax for every trip that took place in NYC. In 2019 an MTA congestion surcharge of $2.50 used to support MTAs operational costs was added to each trip. This surcharge was added at a time of distress for taxi drivers who are in a significant amount of debt. These fare increases lead to an initial dip in taxi ridership (Schaller 1999), where the driver ultimately gains nothing. Although it's important for a city to find new and innovative ways of improving transportation, we need to make sure that by doing so, we aren't increasing inequality (Steint 2020). If select buses are playing a role in decreasing taxi ridership during a time of great economic distress for taxi drivers, then this is something to consider when regulating the taxi industry.

2. Literature Review

Many studies have explored the impact of different types of BRTs on the environment and efficiency. A study found that BRTs in Mexico emit 23% less PM2.5 micro-particles than a conventional bus and reduced travel time by about 50%. The same study found a similar pattern in India, where emission was reduced by 17% (Rogat, Dhar 2015). Another study found that TSP decreases delays by about 3-17%, and both TSP and jumper lanes decrease overall emissions of PM2.5 (Alam & Hatzopoulou 2014). Additionally, a study done in Mexico City shows that BRT's decrease emissions of other greenhouse gases such as carbon monoxide, nitrogen oxides, and sulfur dioxide (Bel & Holst 2018).

Some studies focus on the demand for BRTs and how commuters perceive them. One study found that reliability and frequency is the most important factor for people when choosing to take the BRT (Wan et al. 2016). The same study found from a NYC survey that 26% of people taking select buses are new riders who were attracted to its improvements. In another study, the researchers conducted a survey to see which factors influenced light rail use. They found that commuters viewed the light rail “as more reliable, comfortable, frequent, faster and spacious than bus service” (Beirão and Cabral 2007).

However, few studies have focused on the relationship of BRTs as a substitute for ride-hail services such as taxis. A study by Schaller (2021) found that shared vehicle services such as Uber pool were ineffective in helping the environment. He found that consumers had a tendency to opt for private vehicles rather than shared vehicles due to privacy and comfort reasons. An earlier study by Schaller (1999) found that commuters in NYC are more elastic to taxi fare than to train or bus fare. Another study found that commuters in Pittsburg substitute transportation network companies for buses and BRTs depending on cost, location, and time (Grahn et al. 2020). This research aims to build on this by studying the relationship between select bus services in NYC and taxi ridership.

3. Data

Taxi trip record data provided by the NYC Taxi & Limousine Commission that is available on the nyc.gov website was used for this research. These data sets had millions of observations and were divided by month. The data sets reflect every taxi trip that took place in NYC. I used data from 2010, 2011, January- April 2012, November-December 2016, 2017, and 2019 to reflect the before and after periods for the M79, M34, M14A/D, and M15 select buses in the treatment group.

The data provided specific details such as the time and date of each trip, where the passengers were picked up and dropped off, trip distance, fare amount, tip amount, and payment type. All data sets before 2016 show the exact latitude and longitude of taxi drop-off and pick-up locations. All data sets during and after 2016 use taxi zones to detail pick-up and drop-off locations. According to the NYC Open Data website, these taxi zones are based on the NYC

Department of City Planning's Neighborhood Tabulation Areas (NTAs) and allows one to see which specific areas and neighborhoods passengers are taking taxis from and to. In order to use the data before 2016, it had to be geocoded from latitude and longitude to taxi zone, since information on which neighborhoods passengers are being picked up and dropped off at is required to analyze the different select bus routes. I used a python function to acquire this data using libraries and packages such as GeoPandas, Pandas, NumPy, and Shapely. The function read a CSV file containing Manhattan taxi zones' location id and their corresponding multi-polygon coordinates. It then read into the data set with all the NYC taxi trips and converted the coordinates in that file to the matching location id in the Manhattan taxi zone file. The converted taxi zones were then merged into the original data set.

To clean the data observations that had zero or negative total amounts, trip distances, and passenger counts were dropped. Dates that took place outside of each monthly data set were also dropped. Using the NYC Taxi Zones map on the data.cityofnewyork.us website provided by NYC Open Data, I determined which taxi zones fell within the M79, M34, M14A/D, M15, and M100/M101 bus routes. I then dropped all irrelevant taxi zones from the data and collapsed it to reflect trip count and the mean of trip distance, fare amount, tip amount, and passenger count for each bus. For the M15, the month of July was an outlier where the number of trips decreased dramatically. This month was dropped to remove noise from the data set. After collapsing all the data sets, the M34 data set had 95,321 observations, the M79 data set had 175,773 observations, the M15 data set had 178,080 observations, and the M14/M14D data set had 290,863 observations.

4. Methodology

A Differences-in-Differences (DiD) model allows for a "natural experiment" since it allows us to see what would have happened if the intervention never took place. An essential assumption of the DiD model is the parallel trends assumption. We must assume that the treatment would behave the same as the control if the intervention never occurred. If the control and treatment groups follow similar trends prior to the intervention, then any changes to the treatment post intervention are without bias. There aren't any statistical tests that can be used to determine whether the parallel trends assumption is being fulfilled; however, visualizations (refer to figures 1,2,3, & 4) can be used to see whether the treatment and control group are following similar trends prior to the intervention.

$$log(taxi\ trips)_{it} = \beta_0 + \beta_1 treat_i + \beta_2 time_t + \delta_3(treat_i * time_t) + \varepsilon_i + \sigma_{\bar{x}}$$

Due to the phased implementation of select buses, a DiD model was plausible. Four Manhattan select buses were used for the treatment group: the M14A/M14D, M15, M79, and M34. I chose buses in Manhattan since this is the center of business and where people commute the most in NYC. In addition, the M15 and M34 select buses were a part of the phase 1 implementation of select buses in NYC and are the most similar to the original BRT (Wan et al. 2016). The control group used for all select bus lines is the M100/M101 bus route that travels along Lexington and Amsterdam Avenue. This bus was chosen as the control group because there are plans to create a bus way for the M100/M101 due to a high volume of complaints regarding delays and congestion. Dedicated bus lanes are a select bus feature. I made this the control group since this bus follows similar trends of a high level of ridership and delays which other select bus routes experienced prior to the intervention.

The equation above illustrates how a DiD model works. A dummy "treatment" variable represents whether taxi zones belong to the control or treatment group. Essentially, the variable is equal to 0 if pickup and drop-off taxi zones occur within the control group bus route (M100/M100) and is equal to one if the taxi zones fall within the treatment group select bus routes. The second dummy variable is a time dummy ("time") to differentiate the time period before and after the treatment. This variable is equal to 0 before the bus becomes a select bus and is equal to 1 in the period the bus is converted to a select bus. The third variable in the regression is an interaction term between the time and treatment dummy. The coefficient for this variable represents the DiD coefficient. This model takes the difference between the treatment and control group pre and post-intervention and then uses the difference of these differences to determine the impact of select buses on ridership. This way, we can control for any changes that didn't occur due to the intervention. Additionally, Poisson regression was used since the outcome variable is count data.

It's important to note that there are limitations to using a DiD model. We can't control for all other events or unobservable factors that took place during the intervention. We assume that the only reason that taxi ridership decreases is due to the implementation of select buses. Realistically, there could be other unobservable factors that explain a decrease in taxi ridership. Since we can't control for these unobservable trends, they go to the error term. If a variable in the error term is correlated to the outcome variable, this can cause endogeneity issues. Endogeneity problems can create bias in the estimate. Another limitation is the difficulty of fulfilling the parallel trends assumption. It's difficult to find a control group that follows a very similar trend to the treatment prior to the intervention. NYC buses can have different trends of ridership depending on location and other socio-economic factors. DiD models can be more accurate when using shorter time frames, and visualizations help determine if the control and treatment groups are following similar trends. However, if the parallel trends assumption is violated, then the results of the DiD estimation are biased.

5. Results

The results of this study can be seen in table 5. Regressions 1, 2, 3, and 4 show the impact of the M34, M14A/M14D, M15, and M79 select buses on taxi ridership. For each regression, I controlled for months and weekday fixed effects. Cluster robust standard errors were added on pick-up and drop-off locations. The dependent variable that measured the number of taxi trips was logged to get percent change effects. On the M79 bus route, taxi ridership decreased by 4.37%, and on the M14A/M14D bus route, ridership decreased by 3.83%. These results were statistically significant at the 1%, 5%, and 10% significance levels. On the M34 taxi, ridership decreased by 2.26%, which was statistically significant at the 10% level. On the M15 bus route, taxi ridership increased by 3.8%; however, this result was statistically insignificant.

The graphs show two trend lines for the control and treatment groups. The y-axis shows the average trip count for each period, and the x-axis specifies the month each trip took place. The line in the middle of each graph represents when each bus became a select bus to show which months belong in the before and after period. These results show that on the M14A/M14D M79, M34 bus routes, select buses had a significant negative causal relationship to taxi ridership. The M15 is the only bus route that shows a positive statistically insignificant impact on taxi ridership. This unexpected result could be due to the M15 stopping in areas in lower Manhattan where commuters tend to have a higher income and could see transportation as an inferior good.

Note that average taxi ridership shows an overall decreasing trend from 2010 to 2019. This could be explained by Uber and Lyft entering the market in 2011and growing in popularity over the recent years. In this case, an increase in consumers use of TNC's could have played an additional role in decreasing overall taxi ridership.

6. Conclusion

NYC is a highly populated city where transportation is a challenge. With high levels of delays and traffic, the city needs to find ways to make transportation faster and safer. Understanding the causal relationship between select buses and taxi ridership can give policymakers insight on how to regulate transportation and plan for the future. The results of this study show that taxi ridership does decrease as a result of select buses. The literature around this topic suggests that this decrease in taxi ridership will have a positive impact on the environment. Commuters making the change to select buses may help decrease emissions and lead to less congestion in the city.

The limitations of this study are that only four Manhattan select buses were used to measure the impact on taxi ridership. All though, the results show a negative impact on taxi ridership. It's not clear whether the buses selected in this study are an accurate reflection of other areas in NYC. There might be areas where taxi ridership remains constant regardless of the intervention. Boroughs like Queens, where commuters rely more on public transportation than taxis, might show little impact on taxi ridership. Currently, in NYC, there are 20 select bus routes; further, research is needed to study the impact of select buses on NYC as a whole. In addition, this study does not account for other types of car services such as green cars and transportation network companies like Uber or Lyft. More research needs to be completed in order to have a better understanding of transportation in NYC.

7. Tables

Table 1

Summary Statistics: M15

Control = 1

	Count	Mean	Min	Max
Taxi Zone	173828	193.797	41	263
Trips	173828	116.892	1	4088
Fare Amount	173828	12.104	2.5	200
Tip Amount	173828	.909	0	60
Trip Distance	173828	7.275	.01	423612.09

Treated = 1

	Count	Mean	Min	Max
Taxi Zone	4643	245.082	140	263
Trips	4643	528.954	35	2957
Fare Amount	4643	5.874	3.82	11.791
Tip Amount	4643	.402	.112	1.376
Trip Distance	4643	1.182	.522	4.977

Table 2

Summary statistics: M34

Control=0

	Count	Mean	Min	max
Taxi Zones	83554	199.432	41	263
Trips	83554	152.08	1	3153
Fare Amount	83554	12.181	2.5	251
Tip Amount	83554	1.083	0	50.2
Trip Distance	83554	3.803	.02	92.1

Treat=1

	Count	Mean	Min	max
Taxi Zones	11955	203.425	100	246
Trips	11955	323.733	1	1142
Fare Amount	11955	7.333	4.292	50
Tip Amount	11955	.744	0	10
Trip Distance	11955	1.557	.262	4.436

Table 3

Summary Statistics: M79

Control = 0

	Count	Mean	Min	Max
Taxi Zone	160867	152.278	41	263
Trips	160867	101.896	1	2791
Fare Amount	160867	14.592	.01	821.892
Tip Amount	160867	1.825	0	80
Trip Distance	160867	3.606	.02	38.18
Treat = 1				
Taxi Zone	15336	197.167	43	263
Trips	15336	307.82	8	2604
Fare Amount	15336	7.606	4.023	526.512
Tip Amount	15336	1.078	.365	4.328
Trip Distance	15336	1.258	.459	3.427

Table 4

Summary Statistics: M14A/M14D

Control = 0	Count	Mean	Min	Max
Taxi Zone	230266	160.33	4	263
Trips	230266	61.248	1	2572
Fare Amount	230266	17.208	.01	10949.349
Tip Amount	230266	2.431	0	120
Trip Distance	230266	4.409	.01	37.72
Treat = 1				
Taxi Zone	61381	150.004	4	249
Trips	61381	97.771	1	1046
Fare Amount	61381	9.01	1.733	52
Tip Amount	61381	1.653	0	20
Trip Distance	61381	1.547	.007	1595.482

Table 5

Difference-in-Differences Estimates for Taxi Ridership

	(1) M34	(2) M14A/D	(3) M15	(4) M79
Time	-0.08***	-0.10***	0.19***	-0.16***
	(0.00)	(0.00)	(0.00)	(0.00)
Treat	0.77***	0.48***	1.50***	1.13***
	(0.00)	(0.00)	(0.00)	(0.00)
Interaction	-0.02	-0.04***	0.04	-0.04***
	(0.05)	(0.00)	(0.16)	(0.00)
_cons	4.77***	4.05***	4.65***	4.46***
	(0.00)	(0.00)	(0.00)	(0.00)
Weekday Effects	Yes	Yes	Yes	Yes
Monthly Effects	Yes	Yes	Yes	Yes
N	95321	290863	178080	175773

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

8. Figures

Figure 1

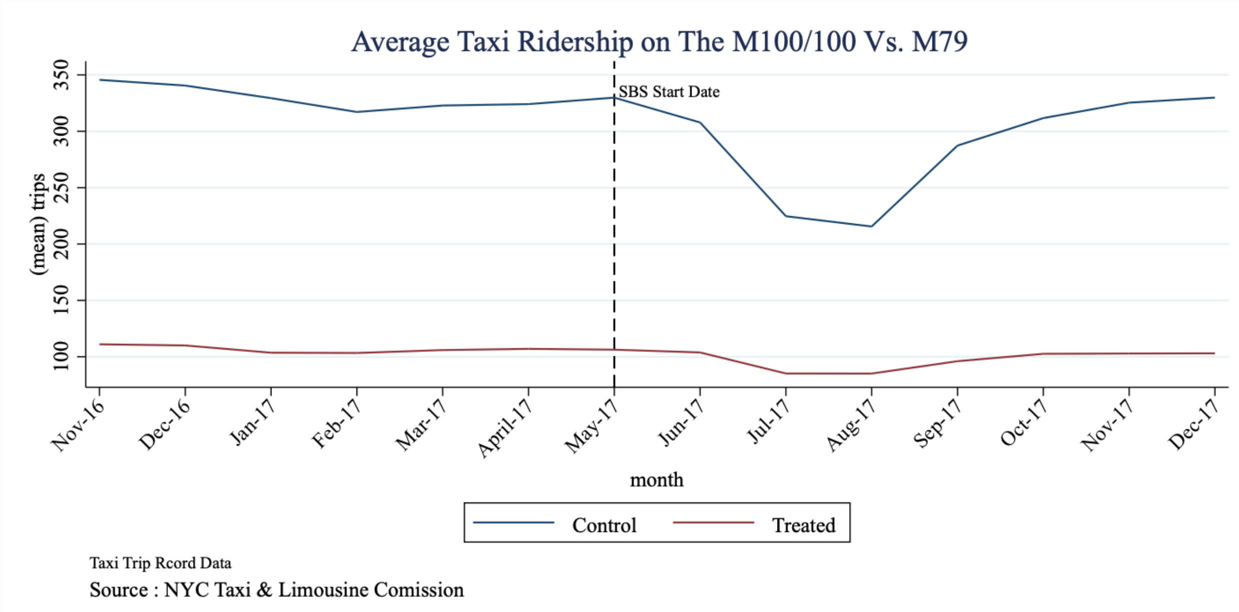


Figure 2

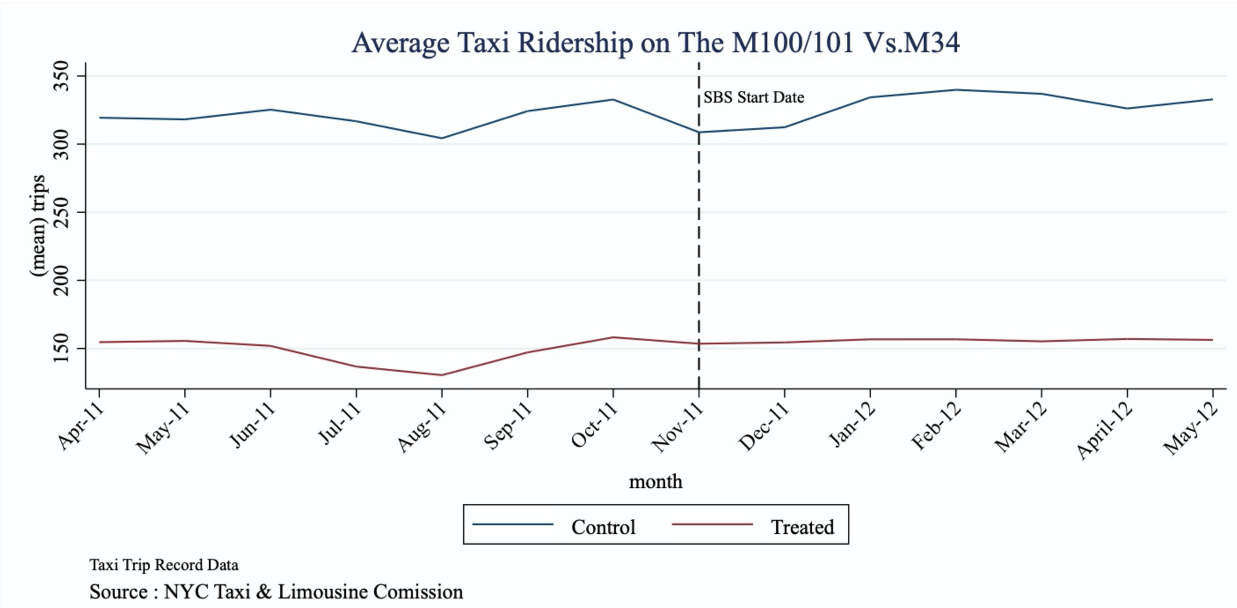

Average Taxi Ridership on The M100/101 Vs.M34
(mean) trips
350
300
250
200
150
SBS Start Date
Apr-11
May-11
Jun-11
Jul-11
Aug-11
Sep-11
Oct-11
Nov-11
Dec-11
Jan-12
Feb-12
Mar-12
April-12
May-12
month
Control
Treated
Taxi Trip Record Data
Source : NYC Taxi & Limousine Comission

Figure 3

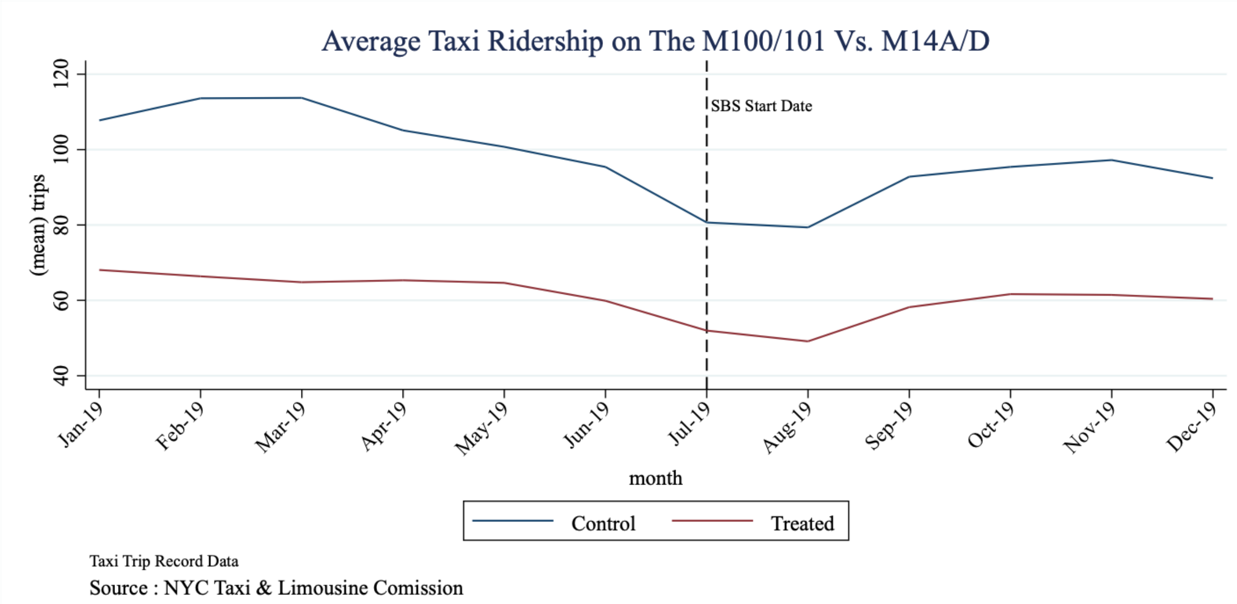
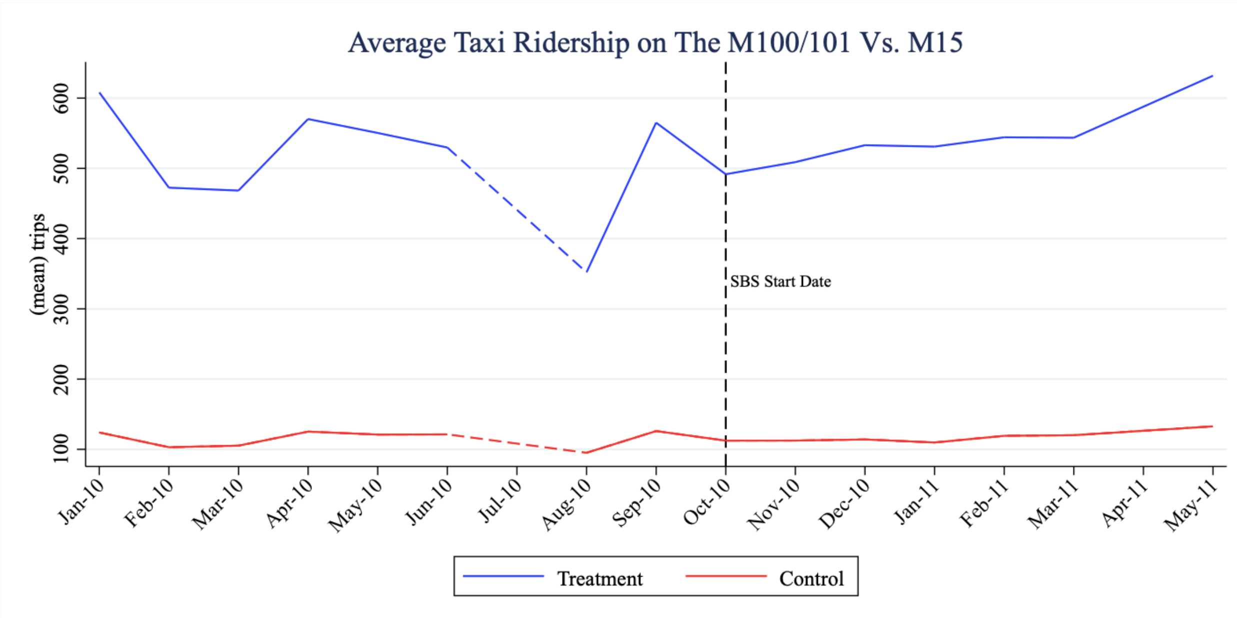

Average Taxi Ridership on The M100/101 Vs. M14A/D
SBS Start Date
(mean) trips
40
60
80
100
120
Jan-19
Feb-19
Mar-19
Apr-19
May-19
Jun-19
Jul-19
Aug-19
Sep-19
Oct-19
Nov-19
Dec-19
month
Control
Treated
Taxi Trip Record Data
Source : NYC Taxi & Limousine Comission

Figure 4


Average Taxi Ridership on The M100/101 Vs. M15
(mean) trips
100
200
300
400
500
600
SBS Start Date
Jan-10
Feb-10
Mar-10
Apr-10
May-10
Jun-10
Jul-10
Aug-10
Sep-10
Oct-10
Nov-10
Dec-10
Jan-11
Feb-11
Mar-11
Apr-11
May-11
Treatment
Control

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