Difference-in-Differences Analysis of Subway Ridership in NYC's Traffic Congestion Zone

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Abstract

On January 5th, 2025, New York City implemented a Congestion Relief Zone that tolls drivers entering Manhattan south of 60th Street. The policy decision was intended to reduce traffic and offer new revenue streams for the MTA to improve subways; as of FQ2025, the policy has brought in nearly $160 million in revenue.[1] While the status of the policy—in just three months—seems precarious with the Trump administration calling the tolls illegal, there are already valuable implications about the effects of this policy, namely on subway ridership. This research project explores the change in subway ridership for stations inside and outside the zone, before and after congestion pricing went into effect. Accordingly, we chose a difference-in-differences design to analyze subway ridership across stations in Manhattan. The State of New York offers data on MTA subway ridership in both 2024 and 2025, all of which was cleaned into a daily, by-station panel structure. Our first model utilizes simple OLS with both dummy variables (time and treatment) as well as the interaction term; our second model clusters the stations by standard error; and our third model, arguably the most improved and actionable, controls for time-invariant characteristics like holidays or construction as well as station-invariant characteristics like location and inherent busyness. From our fixed-effects model—the strongest of the three—there indicates a predicted increase in 641 daily riders for stations inside the congestion zone compared to stations outside the zone.

Introduction

On January 5th, 2025, New York implemented a congestion pricing zone in Manhattan. Vehicles that drive south of 60th Street (into the central business district) have to pay a toll of $9 (slightly more for large vehicles). This method of congestion pricing has been done in other cities around the world such as London or Singapore. The intended effects of this toll are to reduce the traffic on the busy streets, reduce the CO2 emissions from the excessive traffic, and to raise support and revenue for the subway system. However, there are also arguments that this congestion pricing can have no impact or even a negative impact in the long run. Some argue that the pricing will have no impact on traffic control in the long run. Also, it has been argued that congestion pricing can have unfair economic consequences for those who are struggling financially. The current presidential administration believes that congestion pricing is unconstitutional. Looking into the impact of congestion pricing in NYC city can be important to understand if the positive intended effects are indeed fulfilled as well as to make predictions about the impacts congestion pricing could have on other US cities if indeed implemented elsewhere. In regards to the congestion pricing in New York, in a working paper called The Short-Run Effects of Congestion Pricing in New York City (Cook, Kreidieh, Vasserman, Allcott, Arora, Sambeek, Tomkins and Turkel, 2025), researchers look at how vehicle's speeds are affected by the congestion pricing as well as how CO2 emissions are influenced. In their study, which was found using data from Google Maps Traffic Trends, it was found that vehicles speeds on both the congestion priced areas and non-congestion priced areas increased, which implies a decrease in traffic both inside and outside the zone after the pricing. It also found that the CO2 emissions from vehicles have decreased in a significant way due to there being less vehicles on the road. Another paper, Effective and Equitable Congestion Pricing: New York and Beyond (Ostrovsky and Yand, November 12, 2024) was actually written before the congestion pricing went into effect in Manhattan. It served as a warning that the congestion pricing would not be impactful, as it would have a far more severe impact on drivers of personal vehicles than taxis and other ride-hailing vehicles. Since one of the major purposes of congestion pricing is to reduce the traffic on the streets, this once-a-day type of pricing would seem counter intuitive because many taxis enter the zone more than once a day as opposed to most personal vehicles. And taxis and other hailing vehicles taking up the majority of the streets anyways. The paper offers an alternative solution in which vehicles are taxed every time they go into the congestion zone during a single day, instead of just being tolled once a day. A final paper that was looked over was called "The London Congestion Charge" (Leape, 2006). This paper did research on the congestion pricing that has been legislated in London. The paper concluded that the congestion pricing found a decrease in traffic delays, similar to what has been seen before, and it also said that the congestion pricing policy has seen very little opposition from the public. Directly relevant to our research question, the study also found that there was an increase in bus ridership into central London (where there is congestion pricing to get in) that was over 50% more than what was expected. This leads to our research question regarding the implementation of congestion pricing in New York City. Our specific research question is: how has the congestion pricing in NYC affected the ridership of the subway system? We hypothesis that the congestion pricing policy will affect the subway ridership differently between subway stations that are inside and outside of the zone.

Data Description

The data we used to answer the research question was found on the United State Government's open data site. Here we found the data for the MTA subway hourly ridership from the beginning of 2025 up until April 3rd as well as the MTA subway hourly ridership for 2024. For 2024 we only looked at the data from January 5th to April 3rd to keep it consistent when we compared it with 2025. Also created, with help from the Government open data site, was a map of New York City that could be used to plot down the locations of the subway stations in Manhattan and see whether or not they were inside the congestion zone or not. All the elements of the data and can be found at https://github.com/vaughnmitchell13/econ308-proj . Since the data set has ridership for many stations every day for 3 months, there was a lot of data to look through and it was very messy. The data was cleaned up using ArchPro and stored on GitHub to be looked over and finalized before entering into Stata. ArcGIS Pro was used to create the map showing the Congestion Relief Zone.

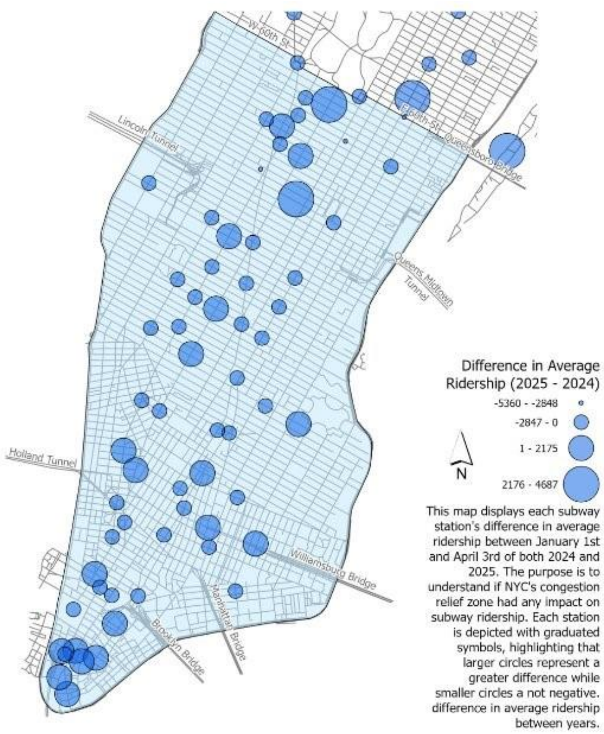

Figure 1: Map displaying the difference in average ridership (2025 – 2024).

Inside the shaded area is the congestion zone. The circles show where each subway station is. The size of the circle indicates how large the difference in ridership was between 2025 and 2024. After adding dummy variables to the data, we had our fully cleaned out data set to create models and find some results. The following is a sample of what that data set looked like.

manhattan_subways

	transit_date	station_complex_id	station_ridership	inside_zone	in_2025	day
0	1/1/2024	157	2171	0	0	0
1	1/1/2024	614	29653	1	0	0
2	1/1/2024	438	2811	0	0	0
3	1/1/2024	223	2965	0	0	0
4	1/1/2024	399	4407	0	0	0
5	1/1/2024	155	2076	0	0	0

Figure 2: Header for our final dataset

On the far left is the date for what day that particular set of data represents. Next to it. the station_complex_id simply distinguishes the different stations from one another. The variable station_ridership gives us the daily ridership per station on that particular day. The variable inside_zone is a dummy variable that tells us if the stations were inside the congestion relief zone or not. If the variable is 1 that means that station is inside the congestion relief zone, and if it is 0 that means it is not inside the relief zone. The variable in_2025 is another dummy variable that tells us whether or not that the data was taken from 2025 or from 2024 (1 for 2025 and 0 for 2024). In our experiment, the dependent variable that we are looking for is the stations ridership.

Since this is a difference in differences analysis, the independent variable is the interaction term between the inside_zone dummy variable and the in_2025 dummy variable. Some of the things we want to look to control for are location within the zone, busyness, and holidays. With regards to some of the summary statistics, the maximum value of ridership on any given day within the data set was 160,067. The minimum value was 1 (will be discussed later). The average daily ridership of individual stations was 15,631.26 with a standard deviation of 18,685.17. Since our other values are dummy variables, they are all a 0 or a 1 and there aren't any interesting or notable statistics regarding them.

Theory and Model Specification

To test our hypothesis that New York City congestion pricing would affect subway stations within the pricing zone differently than stations outside the zone, we used this baseline difference-in-differences model to test the treatment effect.

$$Ridership_{ts} = \beta_0 + \beta_1(Treatment_s) + \beta_2(Post_t) + \beta_3(Treatment_s \times Post_t) + \varepsilon_{ts}$$

In this baseline model, *Ridership* is our unit of analysis, measuring the number of riders on a given day (t), at a given station (s). *Treatment* is a dummy variable, taking a value of 1 if the station is in the congestion pricing zone (treatment group), and a value of 0 if the station is not in the zone (control group). *Post* is our time dummy variable, taking a value of 1 if the day is after the enactment of the congestion pricing policy (January 5, 2025), and 0 otherwise. *Treatment* × *Post* is our interaction term, equalling 1 only for observations inside the congestion pricing zone after the date of policy enactment. This term estimates the average treatment effect, that is that β_3 will estimate the predicted difference in subway ridership between the treatment and control groups that occurs as a result of the policy. The error term ε captures influences in our model that may differ between the treatment and control groups, such as baseline ridership and station size.

By using our model to estimate the effect of the interaction term, we can test the significance of this interaction term estimate to capture whether the enactment of this policy created differences between in vs out of congestion zone station ridership. This baseline model does not control for station or time fixed effects, however, we did generate 2 other models to control for natural differences in stations, one being a model that clustered standard errors, and another including station fixed effects. By generating multiple models in addition to this basic difference-in-differences model we were able to measure how the significance of our estimates changed among them and see how these controls would affect our conclusions.

In order to draw conclusions on the effect of the congestion pricing policy on subway ridership we made the following assumptions for inference. We assume parallel trends between the control and treatment groups prior to the enactment of the policy. By assuming the two groups have parallel trends in ridership in the dates prior to the policy data, we are able to isolate the effect of the policy to draw conclusions on how the policy differently affected the two groups.

We plotted the trends of the two groups over the entire time frame of interest and were able to verify that the two groups did in fact follow parallel trends up until the policy enactment. The two groups appear to only differ at their baseline ridership level, however, their ridership numbers both decreased at approximately the same rate over the time frame of interest.

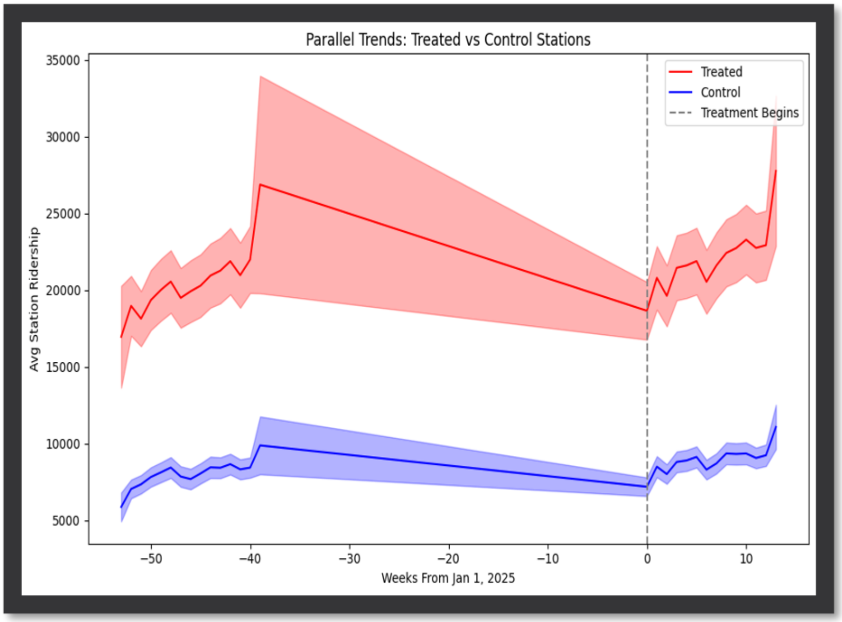

Figure 3: Visualization of parallel trends for subway ridership, treatment versus control stations

Another key identifying assumption in our model is that there were no spillover effects from the policy to the stations in the control group, meaning that we assume that control stations are not indirectly effected by the implementation of the policy. It's possible that individuals made behavioral changes in anticipation of the policy, such as switching from a subway station in the zone to just outside the zone, and this possible indirect effect would hinder our inference on the effect of the policy.

We also assume there are no confounding simultaneous policies that would create differing effects between the treatment and control groups. The no spillover assumption will be elaborated on in our challenges section, as with further research this effect could be controlled for.

When working with this model we faced the challenge of natural, time-invariant differences that exist between stations, such as baseline ridership, planned construction, and location. We were able to address this challenge in our third model by adding a control variable that captures fixed effects of station differences, this fixed effect controls for characteristics like stations being in business or school zones, which would bias our results when not controlled for. In our research, we were unable to address the challenges of spillover effects. As mentioned above, individuals its likely that individuals changed their behavior in the weeks leading up to the policy enactment. It is possible that individuals who commute in and out of the congestion pricing zone for work or school altered their driving behavior (e.g. driving to right outside the pricing zone and then walking to point of interest), or changed their means of transportation. These types of behavior changes would likely cause changes in ridership within the control group, and therefore bias our estimates of the true effect of policy. In follow up research it may be possible to test whether there is a relationship between the change in ridership in the time leading up to the policy and the spatial distance from the construction zone. By measuring the correlation of this relationship it is possible to see if there was significant change in subway ridership behavior, therefore observing whether this effect truly biased our estimates. Another potential solution would be to exclude stations just inside our outside the congestion pricing zone from our analysis, to reduce the potential effect that subway station substitution had on our model.

Results and Discussion

```
. reg station_ridership inside_zone in_2025 inter

      Source |       SS           df       MS      Number of obs   =    22,614
-------------+----------------------------------   F(3, 22610)     =   1022.52
       Model |  8.9682e+11         3  2.9894e+11   Prob > F        =    0.0000
    Residual |  6.6102e+12    22,610   292356479   R-squared       =    0.1195
-------------+----------------------------------   Adj R-squared   =    0.1193
       Total |  7.5070e+12    22,613   331977289   Root MSE        =     17098

------------------------------------------------------------------------------
station_ri~p | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
 inside_zone |   12255.84   321.2814    38.15   0.000      11626.1    12885.57
     in_2025 |   785.2321   331.3586     2.37   0.018     135.7464    1434.718
       inter |   616.9946   455.5815     1.35   0.176    -275.9765    1509.966
       _cons |   8033.623    233.634    34.39   0.000     7575.685    8491.562
------------------------------------------------------------------------------
```

Figure 4 – Model 1: DID using pooled OLS, neither fixed effects nor standard error clustering; not robust

This model uses pooled OLS, which can be problematic for a variety of reasons. For instance, residuals are assumed to be independent across observations. However, ridership at the same station on different days is likely correlated. Intuitively speaking, stations near Times Square are likely to have higher daily ridership than stations in southern Manhattan irrespective of the treatment. Because each station has its own internal pattern, p-values in this model are invalid because it assumes ridership of each station on different days are independent.

Another reason this model is problematic is that the 95% confidence interval for the interaction term includes a negative number, implying that even if the model was valid, a station inside the congestion pricing zone could lead to a *negative* change in subway ridership (which is antithetical to the whole purpose of the policy, intending to boost public transit ridership in southern Manhattan.) Further improvements to this model will be discussed.

```
. reg station_ridership inside_zone in_2025 inter, vce(cluster station_complex_id)

Linear regression                               Number of obs     =     22,614
                                                F(3, 120)         =      20.66
                                                Prob > F          =     0.0000
                                                R-squared         =     0.1195
                                                Root MSE          =      17098

                   (Std. err. adjusted for 121 clusters in station_complex_id)
------------------------------------------------------------------------------
             |               Robust
station_ri~p | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
 inside_zone |   12255.84   2702.254     4.54   0.000     6905.561    17606.11
     in_2025 |   785.2321   166.0119     4.73   0.000       456.54    1113.924
       inter |   616.9946   281.7883     2.19   0.030     59.07326    1174.916
       _cons |   8033.623    799.675    10.05   0.000     6450.323    9616.924
------------------------------------------------------------------------------
```

Figure 5 – Model 2: DID with standard error clustering; robust

This second model accounts for autocorrelated ridership counts at each station, an important factor that the first model did not account for. All terms are statistically significant at the 5% level, and the average treatment effect predicts that stations inside the congestion pricing zone experience ~616 more daily ridership than stations outside the zone. By clustering standard error, we allow for heteroskedasticity and autocorrelation to provide valid inference even when residuals are dependent. Allowing for correlation within clusters and independence between clusters, we now proceed with a model that accounts for the natural differences of the 121 stations.

```
. xtreg station_ridership in_2025##inside_zone i.date_num, fe vce(cluster station_complex_id)
note: 1.inside_zone omitted because of collinearity.
note: 23834.date_num omitted because of collinearity.

Fixed-effects (within) regression               Number of obs     =     22,614
Group variable: station_co~d                    Number of groups  =        121

R-squared:                                      Obs per group:
     Within  = 0.3634                                         min =        183
     Between = 0.1267                                         avg =      186.9
     Overall = 0.0483                                         max =        187

                                                F(120, 120)       =          .
corr(u_i, Xb) = 0.0147                          Prob > F          =          .

                          (Std. err. adjusted for 121 clusters in station_complex_id)
------------------------------------------------------------------------------------
                    |               Robust
  station_ridership | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
--------------------+---------------------------------------------------------------
          1.in_2025 |    11196.6   1109.322    10.09   0.000      9000.22    13392.98
      1.inside_zone |          0  (omitted)
                    |
in_2025#inside_zone |
               1 1  |   640.5835   287.6305     2.23   0.028      71.0952    1210.072
```

Figure 6 – Model 3: DID with standard error clustering and fixed effects

This third and final model added marginal improvements that allow for a more credible effect of congestion pricing on subway station ridership. It is a fixed effects model that controls for station-invariant characteristics like inherent busyness, station location, proximity to schools and businesses, neighborhood population as well as time-invariant characteristics like holidays or planned construction.

The interaction term is still statistically significant at a p-value of 0.028 (5%). The average treatment effect is that stations inside the congestion pricing zone are predicted to experience ~641 more daily riders than stations outside the zone.

Conclusion

To some people, the idea of congestion pricing might just feel like an easy way to squeeze out more money from the people to give to the government. Many people in NYC also have had issues with the tolls, however our models show that the congestion pricing has accomplished its intended goal of improving the subways stations in Manhattan. We used a difference in differences analysis when analyzing our data and created three different models to test our research questions. We used an interaction term between our two dummy variables, treatment and post. We tested the significance of our interaction term to identify effects of the policy. In our later models that clustered standards errors, allowing for a correlation between observations within data clusters, we found significant p values for our interaction term coefficient that gave evidence that subway ridership inside the congestion zone increases as opposed to outside of the zone. When looking at the evidence of our research and the literature review from the introduction section, there appears to be sufficient evidence that, in regard to policy implications, that the congestion pricing in New York has had the effects that the pricing intended to have. The increase in the subway ridership in both New York and the increase in the bus ridership in London from the literature review show that people will change their method of transportation to find cheaper ways to get into the city. With there being more ridership on the subway, that allows for there to be less traffic on the streets and less CO_2 emissions on the road, which is also a very positive effect. This shows that the policy of congestion pricing should continue to be implemented in Manhattan despite some of the pushback that has come from President Trump and his administration. As the policy continues in the future it seems likely that the trends will continue to move in the direction that they is already heading in, making the street even cleaner and the subway stations more prosperous. There are a few limitations that come from a study like this. Since we only have about three months' worth of data, there is only so much time that has passed, and while it seems likely that the current trend in data would continue, it is entirely possible that the data could trend in a different direction in the future if individuals decide to change their methods of transportation. Another potential limitation in the data comes from the late fees that weren't enacted until March 6th. From January 5th until March 6th there was no late penalty if an individual didn't pay their fee on time. This wasn't something that was considered in the data and it could have had a bigger impact than expected on the data that was collected. There were also some outliers in the data in which it was reported that a single digit amount of people rode a subway at a particular station that day. Obviously, that is basically impossible in such a populated city and could only have been due to the fact that there was a data collection error that day or possibly that the station was down for some reason. Future research could be conducted to see directly how the congestion pricing in New York compares to other congestion pricing methods in the world, such as London or Singapore. We could also look for other potential effects that congestion pricing may have on the city such as crime or the average income of someone who lives in the congestion zone vs outside the congestion zone. We could also compare the congestion pricing method in NYC to other forms of traffic control such as parking fees in San Fransico.

References

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