NYC Traffic Congestion:
Differences-in-Differences Approach
ECON 5312

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2025-12-07

Policy background and research question

On January 5, 2025, the city of New York implemented a congestion pricing toll for all private and commercial vehicles entering Manhattan's Central Business District, delineated south of 60th Street (basically, all of Manhattan below Central Park). This policy has the stated goal of reducing gridlock and generating more funding for public transportation projects. New York City is the first city in the United States to implement this policy, and so NYC's outcomes will determine the feasibility of congestion pricing in other cities in the United States—if it proves successful.

Details on the toll pricing can be found on NYC311, but to summarize, the toll applies to all private and commercial vehicles. For passenger cars, it costs \$9 during peak time (weekdays 9am-9pm, weekends 9am-9pm) and \$2.25 off-peak. Discounts are offered for EZ-Pass holders and motorcycles, and commercial vehicles pay a higher rate.

The NYC Automated Traffic Volume Counts dataset from NYC Open contains data from 2006 through June 2025. This gives us almost two decades of before-treatment data and six months of after-treatment data. This data structure lends itself to a Differences-in-Differences approach.

My project is compiled with Quarto using RStudio. I will provide the raw .qmd file with submission if you want to see my code.

Data overview and aggregation plan

The **NYC Automated Traffic Volume Counts** dataset contains 1,838,386 observations from January 2000 through June 2025. Each observation describes the traffic count recorded during a 15 minute interval at a given street, cross-street, and direction of travel.

One caveat is that this data is comprised of NYC 311 service requests, so coverage varies by year and location. It is not a balanced panel; rather, it is many short traffic studies scattered across space and time. I therefore aggregate to hourly counts and restrict to years with consistent coverage.

Data appear consistent from 2008 through June 2025, so I filter to that window and aggregate to the hourly level.

To align the sample with the policy boundary, I next construct spatial indicators directly from the provided geometries, flagging Manhattan locations south of 60th Street. I know from a previous course that NYC Open data uses a coordinate reference system called EPSG:2263, which are similar to latitude and longitude points. I approximate the cutoff with Latitude 40.769, but this does not actually perfectly capture the treatment area. This is an area for improvement in future research.

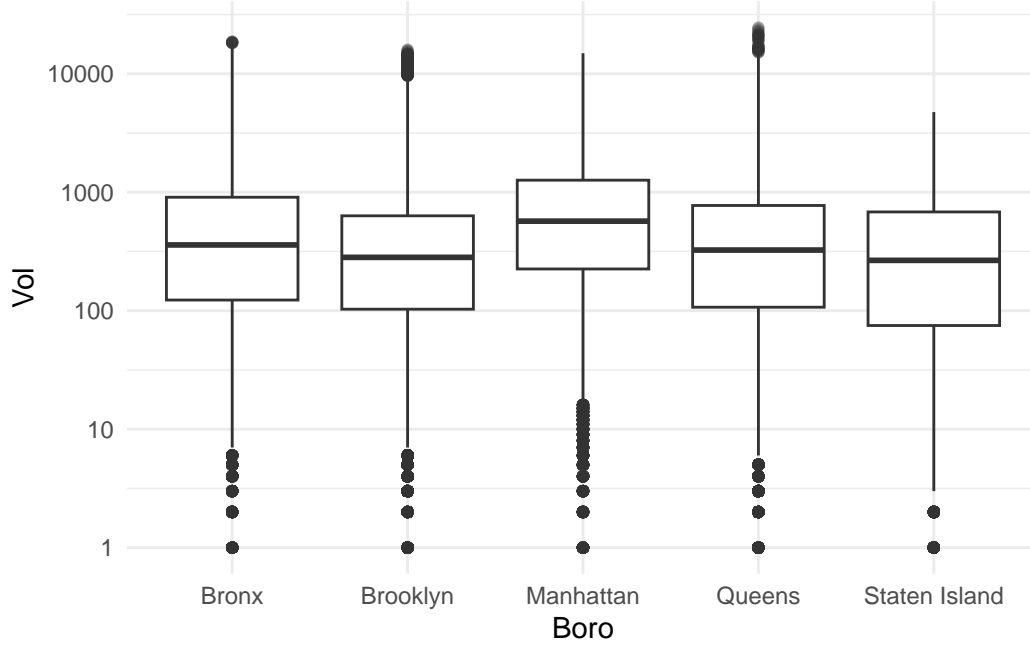|	1	2	3	4	5	6	7	8	9	10	11	12
2008	0	0	1891	3524	2871	2759	307	444	385	0	0	0
2009	2236	2488	2826	2942	2826	2835	2571	1930	2829	3004	2919	2495
2010	2860	2469	3147	2894	2719	2865	2616	2975	2879	3009	2905	2178
2011	1759	2196	3007	2909	2999	2814	2928	2976	2303	2987	2144	1315
2012	2069	1602	1465	2165	2157	1674	1455	1594	1060	1807	2308	1495
2013	1260	1324	2175	1828	1719	1560	1230	1033	1015	1847	1944	1443
2014	955	1711	1724	759	1819	1616	1272	1962	1463	2397	1344	935
2015	1184	1272	1971	1500	1659	1476	1283	1870	1561	1412	1125	866
2016	1337	1167	2365	1899	1148	2099	1359	1031	1552	1922	2054	873
2017	1165	1628	1179	1041	1221	1409	797	1435	1410	1624	1746	863
2018	720	588	2296	1000	1311	1008	647	439	771	1731	1049	455
2019	1381	1383	1474	1121	1262	890	652	840	1296	1730	1850	768
2020	336	480	192	0	0	0	0	720	624	1536	696	216
2021	457	96	1346	1056	1090	1006	592	1179	644	891	1338	58
2022	504	960	1018	843	1476	586	216	456	552	552	528	624
2023	480	288	936	385	1326	1701	288	312	456	1152	504	432
2024	984	840	2440	1229	1585	2194	0	0	576	744	840	648
2025	576	1488	1416	1008	576	1320	0	0	0	0	0	0

After data cleaning, we are left with 292,878 hours of traffic data, split between 286,494 hours and 6384 hours of pre and post data, respectively.

Table 1: Sample coverage (hours and mean volumes) by borough and period (post = 1 after 2025-01-05)

Boro	post	hours	mean_vol
Bronx	1	1032	475.3634
Bronx	0	45778	811.9038
Brooklyn	1	2712	893.8182
Brooklyn	0	84493	563.2230
Manhattan	1	600	954.2850
Manhattan	0	49635	970.7320
Queens	1	1704	726.0112
Queens	0	85694	656.8803
Staten Island	1	336	2123.8958
Staten Island	0	20894	472.1008

This table shows how the sample is distributed across boroughs before and after the policy, highlighting the limited post-period coverage.

Next I define treatment and timing indicators used in the diff-in-diff setup, along with day-of-week fixed effects for time controls. A quick boxplot shows the distribution of volumes across boroughs.

Model Implementation: Hourly Counts

I consider a differences-in-differences regression with all traffic counts in the borough of Manhattan considered the "Treat" variable. This is done for two reasons:

1. This is spatial data, so traffic studies directly next to the actual policy area south of 60th Street will also likely show declines.
2. Geocoding would be required to isolate the strict policy zone. This is possible with Python and would be interesting for future research.

Thus, the regression model is specified as:

$$\log(1 + \widehat{Volume_{it}}) = \beta_0 + \beta_1 \text{Manhattan}_i + \beta_2 Post_t + \beta_3 (\text{Manhattan}_i \times Post_t) + \text{Boro}_i + \text{Month}_t + \text{Day}_t + \text{Hour}_t. \tag{1}$$

$Post_t$ is the policy date January 5th, 2025. New York City's other four boroughs are used for parallel trends. Temporal fixed effects are included to control for seasonality, daily variation (weekday vs. weekend), and hourly variation (rush-hour spikes, etc.). A Borough-level entity fixed effect is included to account for inherent differences in traffic patterns.

Parallel Trend Checks

Before estimating the main effect, I test for pre-trend stability using event-study specifications on the pre-period, first with the full pre sample and then restricted to the last three years before the policy.

Here, `rel_month` measures months relative to the policy start (negative values are months before January 2025; -1 is December 2024). I focus on the last three pre-policy years for a readable pre-trend check.
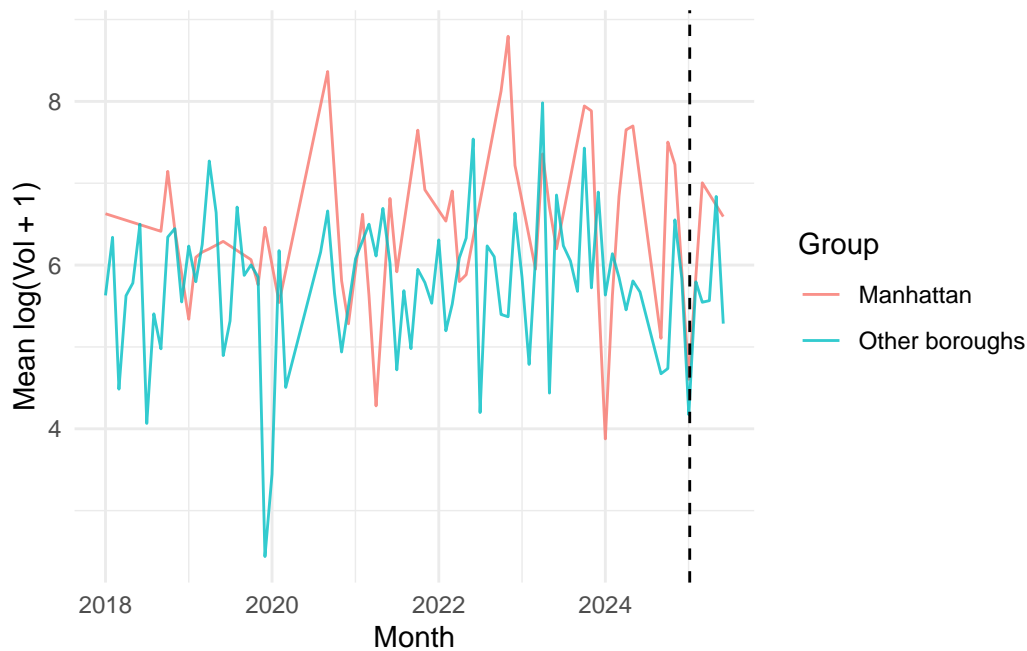
Effect on log1p(Vol)

The plot below uses the last 36 pre-policy months and shows the estimated lead coefficients for Manhattan relative to the other boroughs; confidence intervals span zero in most leads, so I don't see a visible pre-trend break before January 2025. There is very wide uncertainty however, which may be an indicator of poor data quality.

In the three years before 1/5/25, the treated group and the control boroughs do not show a clear pre-trend divergence in log traffic volumes. Parallel trends over this window look plausible, although, like said, these estimates are noisy.

With pre-trends assessed, I estimate a sequence of borough-level DIDs: (1) full sample, (2) 2015+ only, (3) 2015+ excluding Staten Island, and (4) 2015+ excluding Staten Island and the COVID years.

To visualize group trajectories around the policy date, I plot monthly average log volumes for Manhattan versus the other boroughs.

Geometry-based DID (policy zone vs. rest)

To align treatment more tightly with the policy area, I re-estimate the DID using the south-of-60th flag as treated and all other observations (north-of-60th Manhattan plus the other boroughs) as controls. This keeps the same time fixed effects as the borough model but assigns treatment only to the priced zone.

```
south60:post
   -2.357351
```

The `south60:post` coefficient captures the post-policy change in the priced zone relative to all other locations. The estimate corresponds to roughly -2.4% (95% CI: -0.654, 0.607), with the same caveat that borough-level FEs leaves very few FEs.
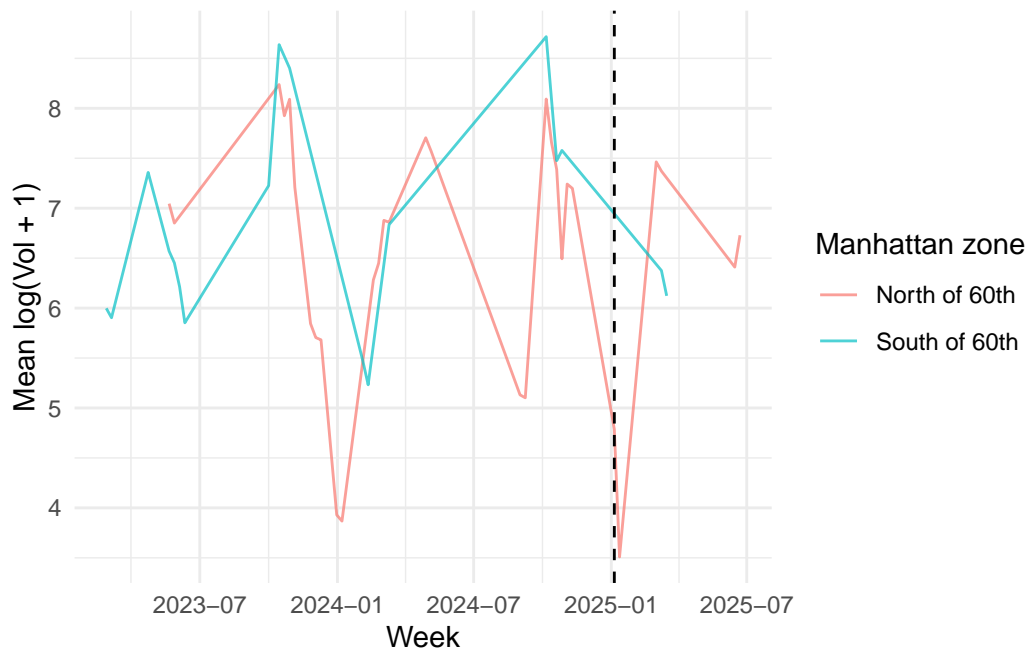
Within-Manhattan DID (south of 60th Street)

To tighten the treatment definition, I compare south-of-60th observations to north-of-60th observations within Manhattan only, controlling for week, hour, and day-of-week.
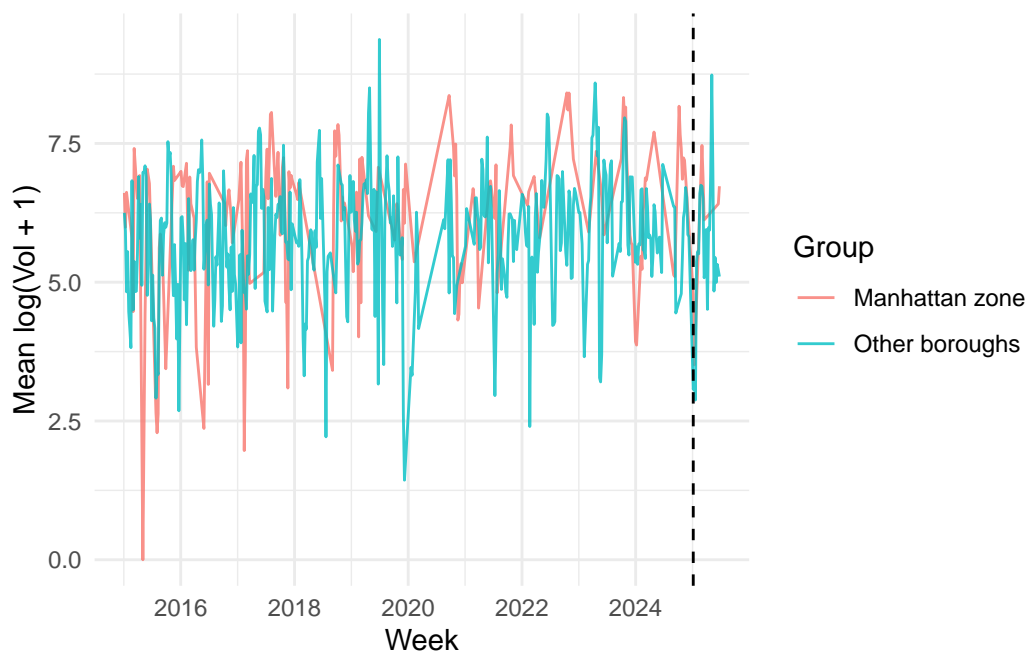
```
south60:post
   -78.56739
```

The within-Manhattan estimate indicates an approximate change of -78.6% for the priced zone relative to north-of-60th areas (95% CI: -1.956, -1.125), focusing solely on intra-Manhattan variation.

The next plot shows weekly mean log volumes for the two Manhattan zones around the policy date.
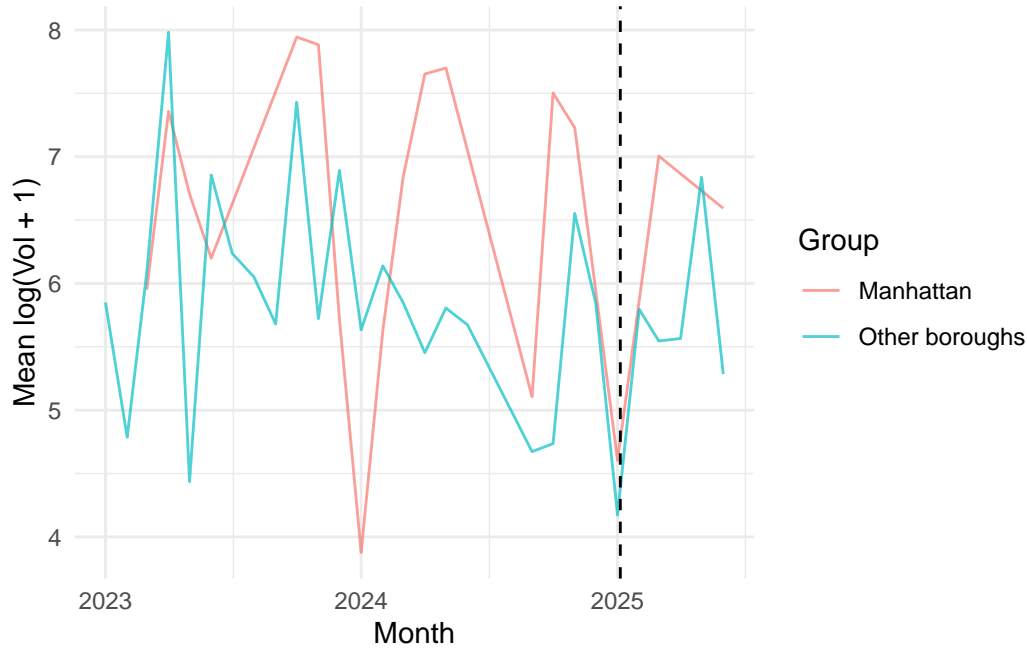

To check robustness to time aggregation and a cross-borough framing, I also collapse to borough-weeks (and later months) and re-estimate the DID.

Approach 2: Borough Weeks

Monthly aggregation provides an even smoother view of trends by group leading up to and following the policy start.

Results summary and interpretation

The table below consolidates all model estimates: four borough-level specifications (full sample, 2015+, excluding Staten Island, excluding Staten Island and COVID), the geometry-based policy-zone DID, and the within-Manhattan south-vs-north DID. Coefficients are log-point estimates; PctChange reports the implied percent change.

Table 2: Diff-in-diff estimates: coefficients, confidence intervals, and implied percent changes

Model	Coef	LowerCI	UpperCI	PctChange
Manhattan vs. other boros (all years)	-0.011	-0.658	0.637	-1.1
Manhattan vs. other boros (2015+)	0.161	-0.275	0.597	17.5
No Staten Island (2015+)	0.266	-0.160	0.692	30.5
No Staten Island, no COVID (2015+)	0.269	-0.343	0.882	30.9
Geometry-based (south of 60th vs. rest)	-0.024	-0.654	0.607	-2.4
Within-Manhattan (south vs. north)	-1.540	-1.956	-1.125	-78.6

Interpretation

- Borough-level DIDs (rows 1–4) are small, imprecise, and not statistically significant. The post-policy change for Manhattan relative to other boroughs ranges from -1% to +31% depending on sample choice, with wide CIs.
- Geometry-based DID (row 5) that treats only the priced zone as treated is also near zero and imprecise (-2%, CI includes sizable negatives and positives).
- Within-Manhattan DID (row 6) shows a large, statistically significant drop (~79%) south of 60th relative to north, but relies on week-level temporal FEs and a small set of repeat sites. I am cautious to interpret this, especially due to the lack of data found in the treatment zone.

Identification and inference

Parallel trends were checked in pre-period graphing. We don't see any clear divergence, but these estimates are noisy. The borough-level spatial FEs I used implied only 5 of them. For stronger inference, I would need finer spatial FEs, like something at the neighborhood or block-level. Currently, I believe this to be one of the biggest hinderances to this analysis. Additionally, the camera locations change over time, so the shifts in where the sites are could be biasing results. This is visible in Manhattan where post-treatment data in the policy zone is far less available than outside the policy zone. I am also just limited by only six months of post data in the first place. These effects could improve with just more data over time.Without even a full year of data, this doesn't truly employ the monthly FEs used to control for seasonality.

Conclusions

This analysis builds a set of diff-in-diff estimates to gauge the early effect of NYC's congestion pricing policy. I cleaned and aggregated the traffic data to hourly counts, defined treatment using both borough indicators and a geometry-based south-of-60th flag, checked pre-trends with event studies, and estimated effects across several samples and time aggregations. The within-Manhattan south-versus-north comparison is the tightest link to the policy zone, while the borough-wide models provide a broader citywide contrast. Further work could refine spatial precision and explore additional robustness checks, but my current pipeline offers a transparent baseline assessment. I believe it as a suitable starting point for further research.