

Do Automated Bus-Lane Cameras Change Driver Behavior?

Code-Blooded · MTA Datathon 2025

Abstract

This project investigates how Automated Camera Enforcement (ACE) bus-lane violations shifted after the launch of congestion pricing in Manhattan on January 5th, 2025. Using cleaned ACE datasets and a reproducible Python analysis pipeline, we compare multi-year pre-policy data (2019–2024) with the partial-year post-policy period (2025). To understand differences in exposure, we evaluate both CBD-only routes (M34+, M42) and Partial-CBD routes (M2, M4, M15+, M101). Our analysis shows that while average monthly violations increased after congestion pricing began, the composition of violations shifted significantly. Bus lane violations declined, while bus stop and double-parked violations rose, reflecting new challenges in curb management. Importantly, these results are complicated by the phased rollout of new cameras in 2025, which means some routes had no enforcement coverage before congestion pricing and thus show artificial increases after implementation. We conclude with targeted recommendations for MTA Bus Operations and city agencies, highlighting the need for improved curbside enforcement and careful attribution in evaluating policy impacts.

Our Question

“Some automated camera-enforced routes travel within or cross Manhattan’s Central Business District. How have violations on these routes changed alongside the implementation of congestion pricing?”

This question lies at the intersection of two major policy interventions in New York City: congestion pricing, intended to reduce vehicle volume in Manhattan’s CBD, and ACE cameras, designed to deter illegal encroachment into bus lanes and stops. By studying violation trends before and after January 5th, 2025, we hoped to determine whether congestion pricing coincided with measurable changes in driver behavior on these routes. Just as importantly, we sought to identify which types of violations remain most problematic, and whether CBD-only routes behaved differently than partial-CBD routes.

Methods

We began with the raw dataset, `violations.csv`, which contains all ACE violations on bus routes that engage with the CBD. Using Python (`pandas`, `numpy`, `matplotlib`) in VS Code, we created a data-cleaning pipeline (`cleaning.py`) to parse violation timestamps, label each record as occurring before or after January 5th, 2025, and classify bus routes into CBD-only or Partial-CBD groups. Unnecessary location fields (stop IDs, bus stop coordinates, georeferences) were removed, and the outputs were saved as structured CSV files.

Our analysis pipeline (analysis.py) added additional time-based features, such as day of week and monthly periods, and aggregated violations by period, violation type, and route. To control for uneven exposure, we computed average monthly violations for each category, rather than raw totals. This was critical, since the pre-period spanned six full years while the post-period included only eight months of 2025 data at the time of analysis. We also safeguarded percent-change calculations by excluding cases where no pre-period data existed, avoiding misleading infinite percentage increases.

An important caveat emerged during the project: ACE cameras were gradually rolled out to new routes throughout 2025, after congestion pricing began. For example, certain buses such as the M2 and M4 had no recorded violations in the pre-period simply because cameras were not installed yet. This means that their sudden appearance in the “after” dataset does not necessarily represent worse driver behavior, but rather new enforcement coverage. We explicitly acknowledge this limitation when interpreting results, especially for route-level comparisons.

All figures were generated automatically and saved into the visuals/ folder. These include trends over time, violation type breakdowns, and before-vs-after comparisons by route.

Results

Frequency of Violations Before and After Congestion Pricing

The overall frequency of ACE violations declined steadily between 2019 and 2023, with a notable uptick in 2024. Once congestion pricing began in January 2025, average monthly violations rose dramatically compared to earlier years.

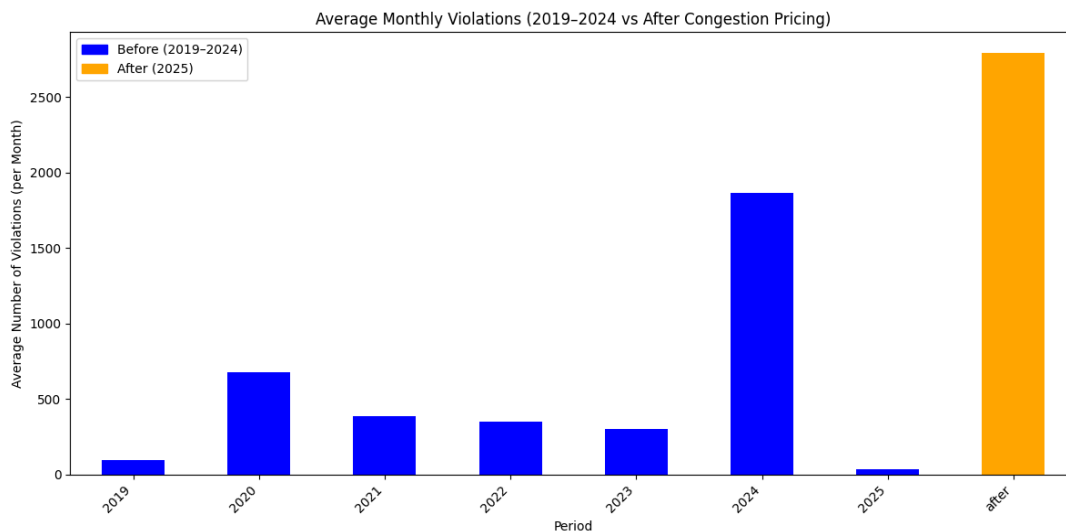


Figure 1: Average monthly violations, by period (2019–2024 vs After)

This pattern, however, must be interpreted cautiously. While the figure suggests a large increase in violations post-congestion pricing, part of that surge reflects new camera deployments in 2025. Because some buses had no cameras prior to congestion pricing, their introduction afterward inflates violation counts in the “after” period. As a result, we cannot attribute the entirety of the increase to congestion pricing itself. What we can say is that enforcement expanded in scope, and within that expanded scope, bus stop and double-parking issues became especially prominent.

Days of the Week

Day-of-week patterns show that violations consistently peak during weekdays, with Monday through Friday carrying the highest averages. In the post-congestion pricing period, however, weekend violations increased more noticeably than before.

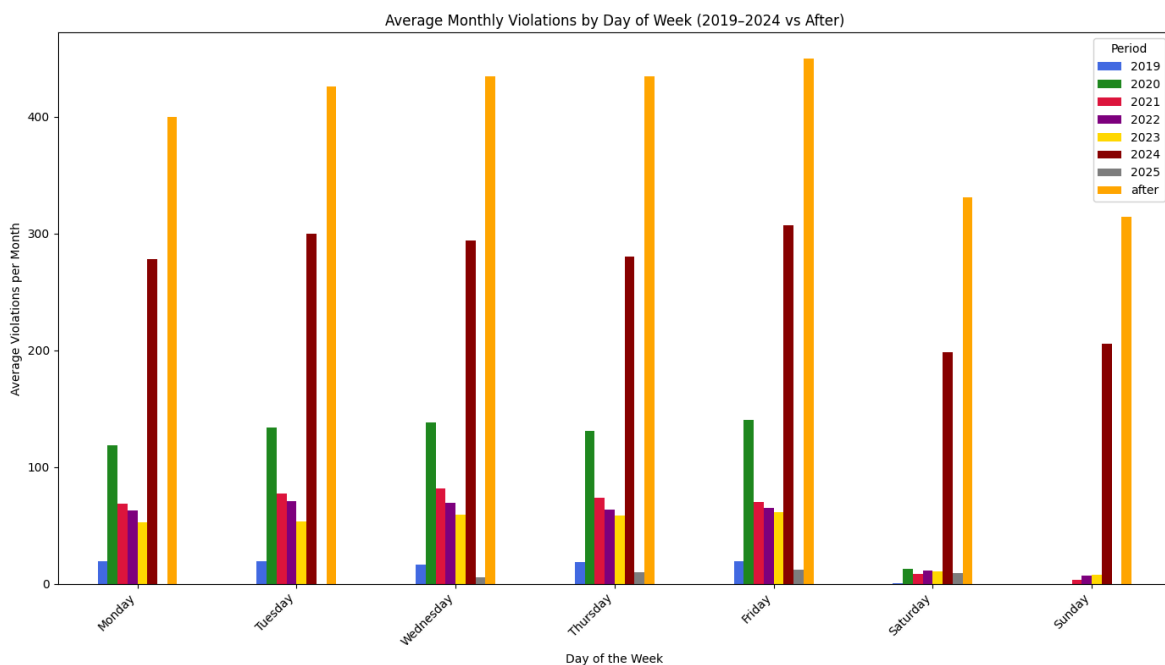


Figure 2: Average monthly violations by day of week (2019–2024 vs After)

This trend suggests that enforcement gaps or changes in traffic patterns on Saturdays and Sundays may be contributing to higher levels of illegal activity. The increase in weekend violations highlights a potential need for expanded enforcement coverage during off-peak times.

Violation Types Before and After

Violation composition shifted significantly between the pre- and post-periods. Before congestion pricing, MOBILE BUS LANE violations dominated the dataset. After congestion pricing, MOBILE BUS STOP violations became the most frequent, followed closely by DOUBLE PARKED violations.

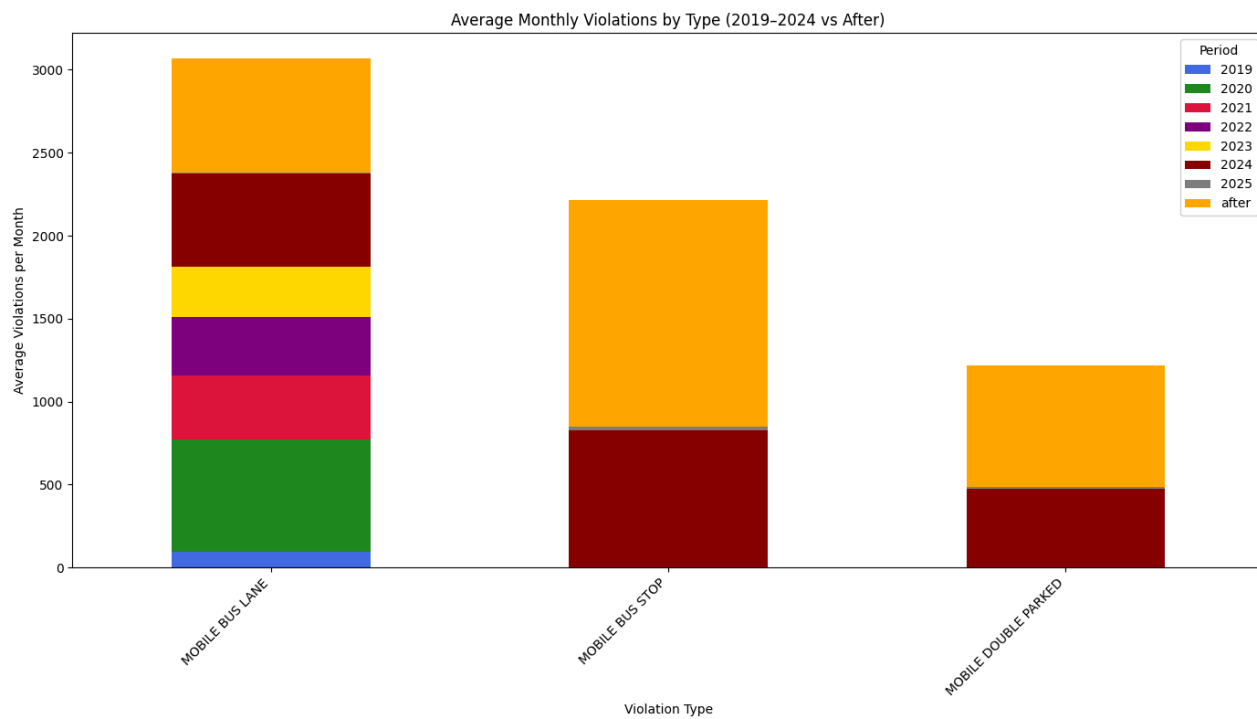


Figure 3a: Violation types over time (stacked by period)

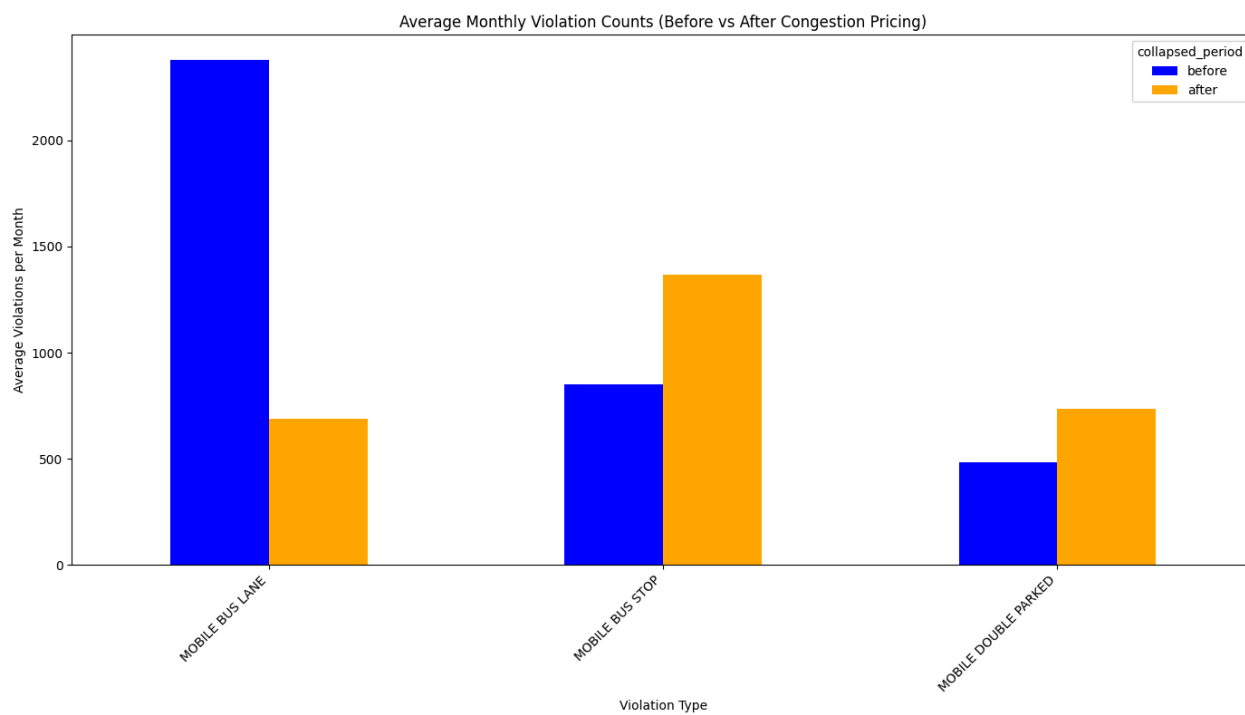


Figure 4: Before vs After by violation type (grouped)

According to the summary statistics, bus stop violations rose from approximately 849.6 to 1367.5 per month (+60.9%), while double-parked violations increased by 51.7%. In contrast, bus lane violations decreased from roughly 2378.7 to 688.5 per month (−71.1%). These results suggest that while cameras have been effective at discouraging lane intrusions, they have not deterred vehicles from blocking stops or parking illegally near bus routes.

Largest Increases and Decreases

The most significant increase was observed in bus stop violations, while the largest decrease occurred in bus lane violations. These shifts align with the idea that drivers have adapted to the presence of lane cameras but that enforcement at bus stops and adjacent curb space remains limited. This highlights a need to broaden the enforcement toolkit to address new friction points.

CBD-Only vs Partial-CBD Routes

Finally, we compared violations on routes that operate exclusively within the CBD versus those that only partially cross it.

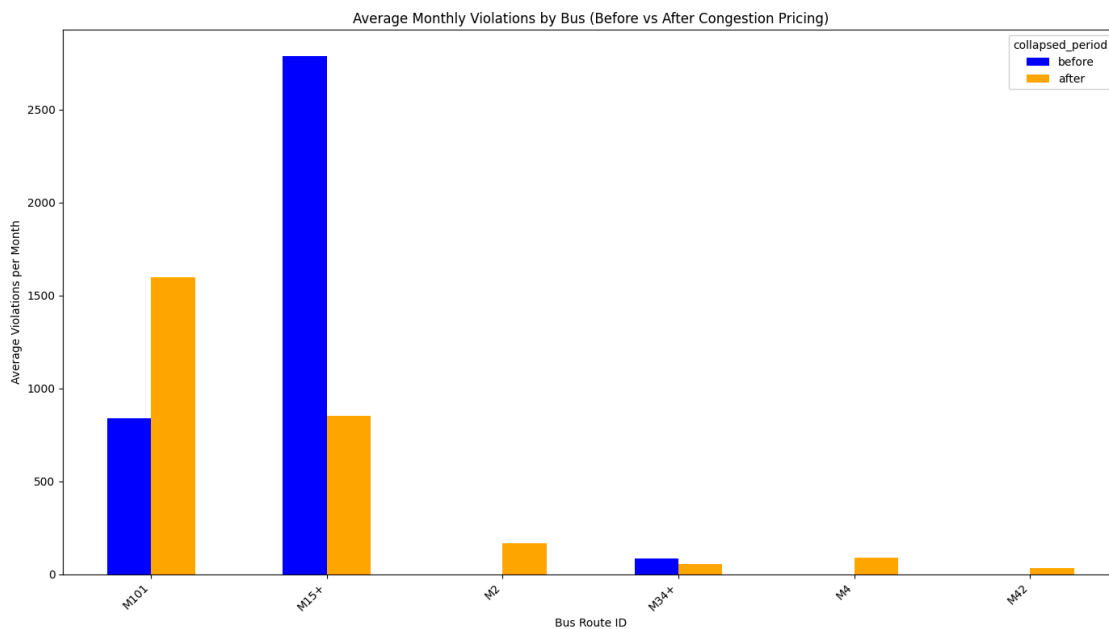


Figure 5: Average monthly violations by route (Before vs After)

On average, CBD-only buses (M34+, M42) saw a −35.7% change, while Partial-CBD buses (M2, M4, M15+, M101) increased by +10.3%. Route-level results, however, are mixed: M101 rose by 90%, while M15+ declined by nearly 70%. Importantly, the M2 and M4 had no usable pre-period baseline due to late camera installation, so their increases cannot be cleanly interpreted as behavioral shifts. Again, this underscores the importance of accounting for camera rollout when evaluating policy impact.

Recommendations

For MTA Bus Operations, the decline in bus lane violations shows that current cameras are working effectively. These should be maintained, with consideration given to optimizing placement and relocating underperforming cameras to new hotspots. At the same time, the growth in bus stop and double-parking violations indicates that more attention should be directed toward curbside management. Options include extending ACE technology to cover bus stops (installing cameras directly at bus stops so vehicles that block buses while boarding or alighting can be automatically ticketed), increasing the length of high-demand stops, and piloting timed loading zones nearby (these are designated curbside spots that are only available during certain hours so delivery drivers or ride-hail vehicles have a legal place to stop instead of blocking bus stops).

For policy makers and city agencies (NYC DOT, TLC, DSNY), we recommend several actions. Dynamic curb pricing could make it more expensive to use curb space during busy times, discouraging drivers from blocking bus stops. Weekend enforcement should be expanded since violations are rising on Saturdays and Sundays. Agencies like TLC can also tighten rules so Uber, Lyft, and taxis don't stop in bus stops. Finally, when evaluating the effect of congestion pricing, analysts should account for the fact that cameras were added gradually. Using measures like camera-days (how many cameras were active and for how long) or route-level bus hours helps ensure that higher violation counts aren't simply the result of more cameras being installed.

Reproducibility

The analysis can be replicated by running two scripts in Python:

1. `python cleaning.py` — cleans the raw dataset and generates labeled CSVs.
2. `python analysis.py` — produces figures and the `summary.txt` file summarizing results.

All work was developed in **VS Code**, with **GitHub** used for collaboration and version control.

Conclusion

Overall, the implementation of congestion pricing coincided with a measurable rise in ACE-recorded bus stop and double-parking violations, while bus lane violations declined. However, because ACE cameras were expanded during the same period, these results cannot be attributed solely to congestion pricing. They instead reflect a combination of improved enforcement coverage and shifting driver behavior. The evidence suggests that while lane intrusions are being successfully deterred, curbs and bus stops remain vulnerable points of friction, calling for new strategies in both enforcement and curbside policy.