Assessing Causality in $PM_{2.5}$ and NO_2 Changes One Year After New York City's Congestion Pricing Policy

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ABSTRACT

On January 5, 2025, New York City implemented the Central Business District Tolling Program (CBDTP), a congestion pricing policy targeting lower Manhattan. We evaluate its air quality effects after one year using ground-based and satellite observations. Using New York City Community Air Survey (NYCCAS) real-time $PM_{2.5}$ monitors, we compare $PM_{2.5}$ concentrations during the first year of CBDTP implementation with 2022-2024, finding statistically significant decreases within the congestion relief zone (CRZ). A difference-in-differences (DiD) regression approach reveals that the CBDTP drove a 13% reduction in $PM_{2.5}$ at CRZ sites ($p < 0.001$), while nearby non-CRZ sites showed statistically insignificant increases ($p = 0.056$). We also analyzed tropospheric NO_2 columns from TROPOMI, finding reductions exceeding 20% in the NYC metropolitan area in 2025 relative to a 2018-2024 baseline. Decreases are more pronounced in lower Manhattan than outer boroughs, but likely reflect broader regional trends rather than the CBDTP alone, with little to no evidence of traffic-rerouting-driven increases elsewhere. The program may nonetheless have contributed to the overall regional NO_2 decline alongside other air quality policies. These findings offer critical early evidence that congestion pricing policies can deliver measurable air quality benefits, while contextualizing local improvements within the broader landscape.

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KEYWORDS: congestion pricing, particulate matter, nitrogen dioxide

1. Introduction

Outdoor air pollution is recognized as one of the most significant global public health threats, with exposure accounting for approximately 1 in 8 deaths worldwide[1]. In urban settings, where heavy traffic is common, $PM_{2.5}$ (particles ≤ 2.5 μm in aerodynamic diameter), NO_2, and O_3 pose the greatest environmental[2,3,4] and public health burden[5,6,7]. Among internal combustion engine-powered vehicles, on-road gasoline-powered vehicles generally have the lowest $PM_{2.5}$ and NO_x emissions per vehicle-mile traveled, whereas diesel-powered vehicles emit higher levels of both;

emissions also increase with vehicle age, with older vehicles emitting more per unit of fuel consumed[8,9,10].

To mitigate urban congestion and traffic-related pollution, cities such as London[11,12,13], Stockholm[14,15,16], and Singapore[17,18] have enacted congestion pricing. Congestion pricing policies promote use of public transit and encourage drivers to adjust their routes, departure times, and destinations, thereby alleviating congestion and local air pollution[19]. However, there is also concern that congestion pricing policies may be redistributing air pollution from more affluent city centers to lower-income zones[19,20,21]. Evaluating environmental effects both within and beyond targeted zones is essential to ensure such policies do not exacerbate environmental injustice.

On January 5, 2025, New York City began its Central Business District Tolling Program (CBDTP), the first congestion pricing policy implemented in the United States. The program charges drivers a toll to enter Manhattan south of and including 60th street, though excludes roadways on the perimeter of Manhattan so long as the driver does not exit these roadways onto local streets in the congestion relief zone (CRZ)[22,23]. The CBDTP is in effect 24 hours a day, with toll amounts depending on vehicle type, time of day, whether any crossing credits apply, and the method of payment. Individuals paying with E-Zpass, which accounts for around 90% of toll transactions, receive a discount of 33% relative to toll by mail rates. During phase 1 of the program (2025-27), tolls for vehicles paying with E-Zpass are \$9, \$4.50, \$14.40, and \$21.60 for passenger vehicles, motorcycles, small buses, and large buses, respectively. These rates are in effect during peak periods (5 a.m. to 9 p.m. on weekdays, and from 9 a.m. to 9 p.m. on weekends). Overnight toll rates are 75% less than the respective rates during the peak period[23].

To date, there exists few evaluations of the CBDTP. One study integrated data from 42 monitors in NYC's core-based statistical area to analyze immediate impacts (first 6 months) of the CBDTP, finding a 22% decrease in $PM_{2.5}$ in the CRZ as well as moderate declines (~1 $\mu g/m^3$) throughout the region when compared to data from 2024[24]. The Metropolitan Transit Authority of New York (MTA), in partnership with city agencies such as the Department of Health, also published their 1-year assessment, and found an 11% reduction in vehicle entries into the CRZ, but no significant short-term impact on air quality[25]. Though previous studied across Europe and Asia[17,26,27], New York City presents a unique context due to its distinctive American vehicle fleet and traffic patterns. Few studies have addressed both direct and spillover effects at fine spatial scales, and even fewer, if any, have integrated satellite observations to capture the spatial heterogeneity of urban air pollution following congestion pricing policies.

Here we examine the short-term impacts of the CBDTP on $PM_{2.5}$ and NO_2 concentrations across New York City, using a difference-in-differences regression on ground-level monitoring data complemented by satellite-based tropospheric NO_2 measurements. This approach allows us to assess both direct, causal changes within the Manhattan congestion relief zone and potential spillover effects into surrounding boroughs. We go beyond initial assessments of the CBDTP by incorporating satellite observations and by directly addressing spillover effects. Our findings provide actionable evidence for air quality managers, policymakers, and urban planners, both for making adjustments to the CBDTP and for informing future congestion pricing implementations in other cities.

2. Results and Discussion

2.1 $PM_{2.5}$ Concentrations in 2025 Compared to Previous Years

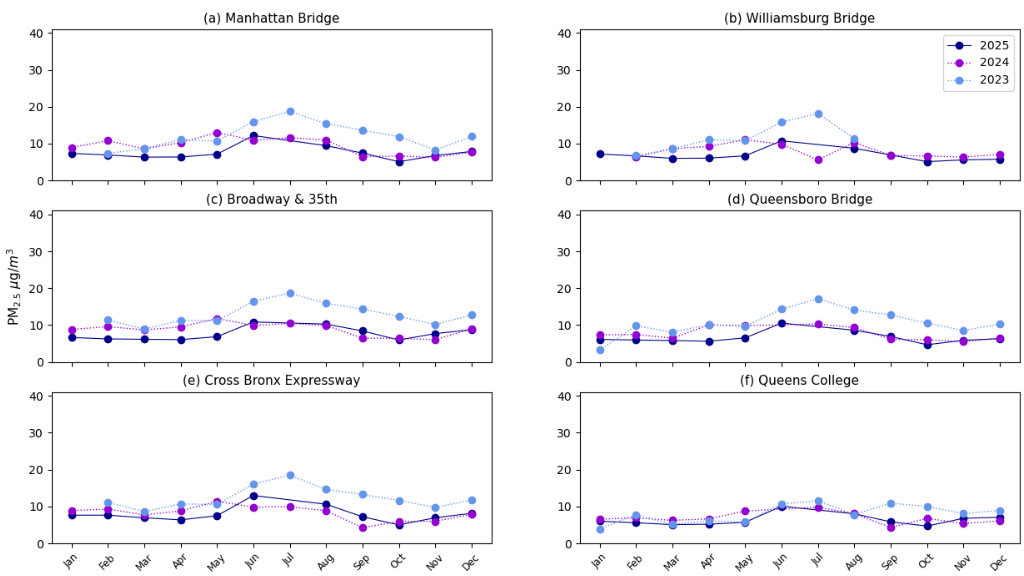

Figure 1: Time series of monthly-averaged $PM_{2.5}$ measurements at six New York City monitoring sites: (a) Manhattan Bridge, (b) Williamsburg Bridge, (c) Broadway & 35th, (d) Queensboro Bridge, (e) Cross Bronx Expressway, and (f) Queens College. 225 (solid, dark blue) vs. 2024 (purple) vs. 2023 (light blue) seasons. Observations with $PM_{2.5}$ > 40 µg/m3 are removed.

Monthly-averaged $PM_{2.5}$ concentrations at 6 (out of 15) select New York City monitoring sites, selected to be representative of both within and outside of the CRZ, are shown for the 2023 through 2025 (Figure 1). Across all locations, $PM_{2.5}$ concentrations fluctuated substantially from month to month, ranging from less than 5 to greater than 15 µg/m^3. The high late summer peak observed in 2023 is attributed to long-range $PM_{2.5}$ pollution from Canadian wildfires[28].

Across all sites, 2025 values tracked closely with the 2024 and 2023 seasons, with recorded $PM_{2.5}$ concentrations being generally lowest and least variable between late winter and early spring. The 2025 season displays dampened magnitudes throughout the year, particularly between March and June. All 6 selected monitoring sites showed lower median $PM_{2.5}$ concentrations in 2025 as opposed to 2022-2024 (Supplementary Table 1). Across the larger 15-site monitoring network, some sites show increases of $PM_{2.5}$ in 2025 compared to previous years, but each of these cases are statistically insignificant (Supplementary Table 1). The largest decrease, -2.70 µg/m^3, was observed at the Broadway & 35th site ($p < 0.001$). A smaller decrease was observed at the Queens College site (-0.76 µg/m^3, $p = 0.08$), furthest from the CRZ. Other sites had decreases between -1.74 µg/m^3 (Cross Bronx Expressway) and -2.11 µg/m^3 (Williamsburg Bridge). Citywide $PM_{2.5}$

decreases likely reflect broader efforts such as Clean Transportation Programs and regional shifts to cleaner energy, rather than the CBDTP alone[29,30].

Figure 2: Diurnal profile of $PM_{2.5}$ measurements at six New York City monitoring sites: (a) Manhattan Bridge, (b) Williamsburg Bridge, (c) Broadway & 35th, (d) Queensboro Bridge, (e) Cross Bronx Expressway, and (f) Queens College. 2024-25 (solid) vs. 2023-24 (dashed) post-intervention seasons.

Diurnal profiles of $PM_{2.5}$ concentrations during the 2025, 2024, and 2023 seasons across monitoring sites are shown in Figure 2. For all locations, the diurnal curves are relatively flat, with only modest increases during late morning and evening hours. The diurnal curves for all sites are flatter in 2025 as compared to both 2024 and 2023, often showing little to no distinguishable rush hour spikes with the exception of Broadway & 35th. These differences are most apparent at the Manhattan Bridge, Williamsburg Bridge, and Queensboro Bridge sites (Figure 2a-b, d), which are all located in the CRZ, indicative of reduced rush-hour traffic (Supplementary Information Section 1 and Supplementary Figure 1).

Consistent with the monthly time series data, diurnal $PM_{2.5}$ concentration measurements in 2024 were consistently higher than that in 2025. These differences appear to be highest for sites located in downtown Manhattan at the southernmost part of the CRZ, with maximum interannual differences of -2.40, -1.98, and -1.85 $\mu g/m^3$ for the Manhattan Bridge, Williamsburg Bridge, and Broadway & 35th monitoring sites, respectively. The Queensboro Bridge, located at the northernmost point of the CRZ, and the Cross Bronx Expressway, located in northern Manhattan, show slightly smaller decreases of -1.56 and -1.55 $\mu g/m^3$, respectively, while the Queens College site shows a much smaller change of -0.58 $\mu g/m^3$.

2.2 Difference-in-difference Regression Analysis

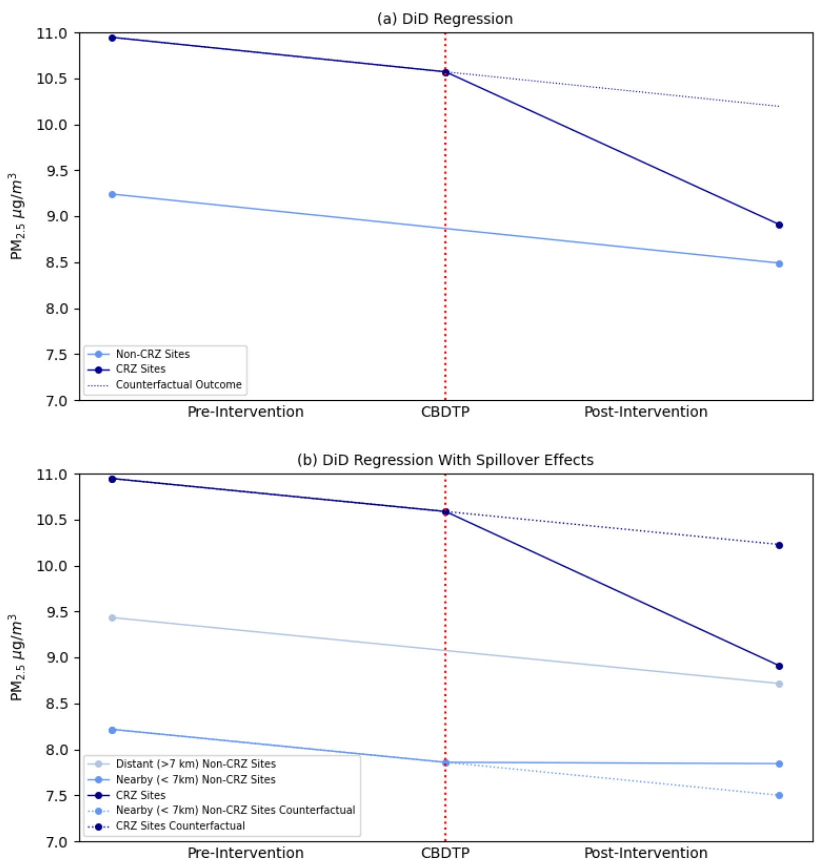

Figure 3: Difference-in-differences regression of daily-averaged $PM_{2.5}$ measurements for stagnant-wind days for New York City monitoring sites: (a) DiD regression, (b) DiD Regression with spillover effects.

Difference-in-difference regression was implemented to discern causal impacts of the CBDTP and to contextualize the $PM_{2.5}$ reductions described in Section 2.1 amidst interannual variability (Figure 3, Supplementary Tables 2, 3, and 4). Results indicate that the CBDTP was largely successful in reducing $PM_{2.5}$ concentrations in the CRZ. As seen in Figure 2a, a difference-in-difference regression comparing CRZ vs all non-CRZ sites yielded a DiD value of -1.29 ($p < 0.001$), indicating that $PM_{2.5}$ concentrations decreased by -1.29 μg/m^3 (13%) beyond that which was conferred by long-term, interannual reductions. This effectively minimized the difference in $PM_{2.5}$ pollution between CRZ and non-CRZ sites from 1.71 μg/m^3 to 0.42 μg/m^3.

Given concerns that the CBDTP may spatially redistribute pollution, we performed a DiD regression comparing CRZ vs nearby (within 7 km) non-CRZ and distant (further than 7 km) non-CRZ sites (Fig. 2b). The CBDTP was still significantly successful in reducing $PM_{2.5}$ concentrations in the CRZ by a value of -1.33 μg/m^3 ($p < 0.001$) or 13%. However, for nearby non-CRZ sites (namely, BQE and Mott Haven), the implementation of the CBDTP is associated with a causal increase of 0.33 μg/m^3 ($p = 0.056$). These increases observed are not statistically significant at the 95% confidence level, but are approaching significance, suggesting that there may also be unintended environmental consequences for surrounding neighborhoods, though more data collection is required to further establish significance.

2.3 Satellite Estimates of NO_2

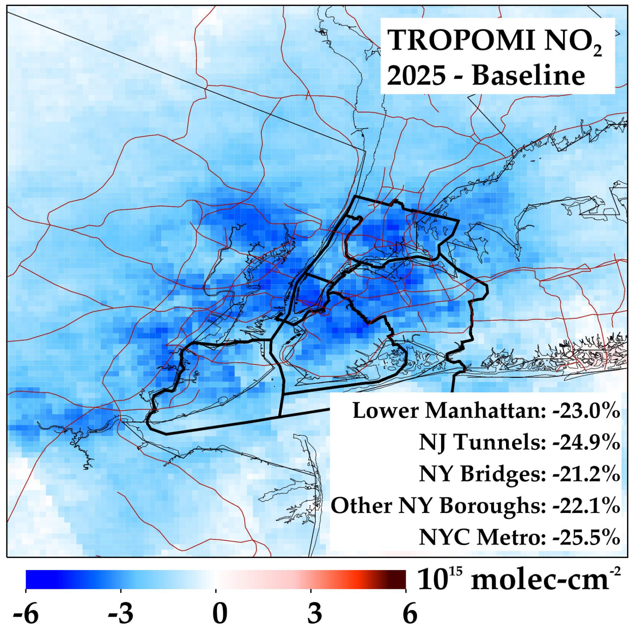

Figure 4: Spatial distribution of tropospheric NO_2 changes (10^{15} molecules/cm^2) across New York City on cloud-free stagnant-wind days, comparing 2025 with a 2018-24 baseline, excluding COVID19 lockdown period (Mar - Dec 2020). The CRZ corresponds to lower Manhattan. The NJ Tunnels and NY Bridges are a 0.03° × 0.03° box surrounding the NJ and Queens/Brooklyn entrance points respectively to the CRZ. The Other Boroughs are all NYC boroughs excluding Lower Manhattan. The NYC Metro is the average across all Counties in the Metropolitan area (all five boroughs, Fairfield CT, Westchester NY, Nassau NY, Bergen NJ, Hudson NJ, Essex NJ, and Union, NJ)

Figure 4 shows tropospheric NO_2 column concentration differences on stagnant-wind days between 2025 and a 2018-24 baseline, excluding the COVD-19 lockdown period. NO_2 following CBDTP implementation is largely decreasing in the NYC metropolitan area, though magnitudes of decrease are variable dependent on region.

Lower Manhattan shows a 23.0% drop in atmospheric NO_2, compared to a 22.1% drop in outer boroughs. This similarity suggests that there is no discernible additional amelioration of NO_2 pollution within the CRZ due to the CBDTP, nor is there discernable exacerbation of in other boroughs. In addition, NO_2 concentrations decreased by 25.5% in the NYC metropolitan area. Although the CBDTP may have contributed to this effect, the magnitude and spatial extent of this reduction suggest that NO_2 decreases in 2025 are largely driven by concurrent regionwide policies, including fleet turnover associated with the MTA 2020-24 capital program[31], as well as the ongoing electrification in the area.

3. Conclusions

This study provides detailed characterization of the short-term effects of the Central Business District Tolling Program (CBDTP) on $PM_{2.5}$ and NO_2 pollution in NYC. We first analyze ground-based $PM_{2.5}$ measurements from six NYCCAS sites both within and outside of the Congestion

Relief Zone (CRZ). Time series and diurnal data reveal that $PM_{2.5}$ concentrations in 2025 were generally lower than in 2023-2024, particularly for sites located within the CRZ, consistent with other literature[24]. Flattening diurnal curves in the 2025 season are consistent with rush-hour traffic suppression following CBDTP implementation.

We leverage a DiD regression model to assess for a causal relationship between CBDTP implementation and ambient $PM_{2.5}$ measurement. Results indicate that the CBDTP was associated with significant decreases in $PM_{2.5}$ concentrations at CRZ sites of around 1 $\mu g/m^3$. However, when accounting for spillover effects by comparing CRZ, nearby non-CRZ (within 7 km), and distant (further than 7 km) non-CRZ sites, results suggest that the CBDTP was also associated with a 0.18 $\mu g/m^3$ increase in $PM_{2.5}$ ($p = 0.056$). These ground-based results point to a possible redistribution of air pollutants that disfavorably impacts communities nearest to but not within the CRZ, but additional monitoring sites that are well-positioned and intended as control sites are needed to further establish robust statistical significance.

We find a greater than 20% reduction in atmospheric NO_2 in the NYC metropolitan area. While there is a minor difference in NO_2 changes between lower Manhattan and other boroughs, this difference is likely not large enough to represent a meaningful difference attributable to the CBDTP. Instead, the CBDTP may have contributed to larger factors, such as the MTA's transition to a zero-emission bus fleet and further electrification of vehicles and buildings.

These outcomes highlight the importance of assessing congestion pricing programs on larger spatial scales to ensure such policies do not exacerbate existent environmental and public health inequities. The MTA's mitigation efforts included in the CBDTP plan, such as the Bronx Asthma Program, Bronx Clean Trucks Program, and funds for air filtration in schools, represent a strong consideration of these unintended impacts[25].

Future research should extend the analyses by incorporating additional pollutants (e.g. O_3 and chemical components of $PM_{2.5}$) and health outcomes. Such analyses would provide a more holistic assessment of the CBDTP that would better inform policymakers and stakeholders.

4. Methodology

4.1 Ground-based $PM_{2.5}$ data

Ground-based datasets were obtained from the NYC Environment and Health Data Portal. These data represent hourly averaged measurements of $PM_{2.5}$ from the New York City Community Air Survey (NYCCAS) and the CBDTP network of continuous, real-time, TSI DustTrak Environmental Monitor 8540 sensors[25]. These monitors, which measure PM_1, $PM_{2.5}$, and PM_{10}, are located along roads on light poles 8 to 10 feet from the surface. NYCCAS applies a linear regression correction factor derived from comparisons between their Queens College monitoring site and federal reference method measurements taken every three days (Eq. 1).

$$PM_{2.5} = \beta_0 + \beta_1 \text{ TSI DustTrak } PM_{2.5} + \beta_2 \text{ RH} + \beta_3 \text{ Temp} \qquad (1)$$

Data used for analysis was taken from 15 NYCCAS monitoring sites across New York City from January 1 2022 through December 31 2025. To account for meteorological impacts on air pollution that are unrelated to the CBDTP, only stagnant wind days were considered for $PM_{2.5}$, defined as days when at least two of three nearby airports (EWR, TEB, LGA) reported average 10m wind speeds less than 3.2 m/s between 12:00 and 4:00 PM local time. Further detail is provided in Supplementary Table 5 and Supplementary Figure 2.

4.2 Satellite NO_2 data

Satellite NO_2 data was obtained from the Tropospheric Monitoring Instrument (TROPOMI), an imaging spectrometer aboard the European Copernicus Sentinel-5 Precursor (S5P) satellite. We used the Level 2 tropospheric vertical column NO_2 density product, which provides global daily measurements in mol/m^2 at a native resolution of 3.5 km x 5.5 km (13.75 km^2 per pixel). The data were filtered for clouds and quality assurance using a filter of qa_value > 0.75 from the TROPOMI NO_2 product. The data were then re-gridded to 0.01° × 0.01° resolution which allowed us to more easily combine the data over time.

The 2025 post-implementation data was limited to cloud-free stagnant-wind days (as defined in Sect. 4.1) between January and December 2025. The baseline period, representing cloud-free stagnant-wind days from 2018 to 2024, was similarly restricted to January through December excluding data from March through December 2020 due to the COVID-19 pandemic. Differences were calculated by subtracting the baseline period mean from the 2025 mean.

4.3 Statistical Analysis

The nonparametric Mann-Whitney U test was applied. The hypothesis that pollutant levels during the 2025 season were stochastically lower than those during the 2022-2024 seasons was tested at a significance level of $\alpha = 0.05$. To more rigorously assess the causal impact of the CBDTP, we first implemented a standard difference-in-differences (DiD) regression method (Eq. 2) [32,33].

$$PM_{2.5} = \beta_0 + \beta_1 CRZ + \beta_2 Policy + \beta_3 (CRZ \times Policy) \quad (2)$$

CRZ is a binary indicator distinguishing $PM_{2.5}$ monitoring sites within the CRZ from those outside the region. *Policy* is a binary indicator of if the observation was taken after the CBDTP implementation date of January 5, 2025. β_3, also known as the DiD estimator, captures the estimated effect of the CBDTP on $PM_{2.5}$ concentrations in the CRZ.

To assess $PM_{2.5}$ spillover effects to monitoring sites nearest the CRZ, we implemented an adapted DiD regression model[34] (Eq. 3).

$$PM_{2.5} = \beta_0 + \beta_1 CRZ + \beta_2 Nearby + \beta_3 Policy + \beta_4 (CRZ \times Policy) + \beta_5 (Nearby \times Policy) \quad (3)$$

Here, *Nearby* is a binary indicator for non-CRZ $PM_{2.5}$ monitoring sites that are within 7 km of the CRZ, namely the Brooklyn Queens Expressway and Mott Haven. While β_4 in this model is a DiD estimator for the effect of the CBDTP on $PM_{2.5}$ concentrations in the CRZ, β_5 is a DiD estimator for the effect of the CBDTP on $PM_{2.5}$ concentrations for sites nearest the CRZ.

The DiD estimator assumes that all sites followed a parallel trend in the absence of CBDTP. Statistical significance of the DiD estimator was tested at $\alpha = 0.05$.

Data availability statement

All ground-based $PM_{2.5}$ data is publicly available on NYC Open Data website via https://a816-dohbesp.nyc.gov/IndicatorPublic/data-features/realtime-air-quality/. MTA Bridges & Tunnels Hourly Traffic Rates are available via https://data.ny.gov/Transportation/MTA-Bridges-and-Tunnels-Hourly-Crossings-Beginning/ebfx-2m7v/about_data. Satellite data from TROPOMI is available on the NASA Earth Data (https://www.earthdata.nasa.gov/) and Google Earth Engine.

References

1. Health Effects Institute. *State of Global Air 2024*; Health Effects Institute: Boston, MA, 2024. https://www.stateofglobalair.org/resources/archived/state-global-air-report-2024

2. Wu, H.; Cao, Y.; Wang, T.; You, J.; Yang, T.; Qu, Y.; Yan, S.; Yang, H.; Mu, X.; Gao, L.; Huang, C. How does PM2.5 impact the urban vertical temperature structure? A case study in Nanjing. *Aerosol and Air Quality Research* **2024**, *24* (4), 230214. DOI: https://doi.org/10.4209/aaqr.230214

3. Khorshidian, N.; Choi, Y.; Mousavinezhad, S.; Pouyaei, A.; Park, J.; Fan, J. Comparing the interactions between particulate matter and cloud properties over two populated cities in Texas using WRF-Chem fine-resolution modeling. *Atmospheric Environment* **2024**, *338*, 120795. DOI: https://doi.org/10.1016/j.atmosenv.2024.120795

4. Westervelt, D. M.; Conley, A. J.; Fiore, A. M.; Lamarque, J.-F.; Shindell, D. T.; Previdi, M.; Mascioli, N. R.; Faluvegi, G.; Correa, G.; Horowitz, L. W. Connecting regional aerosol emissions reductions to local and remote precipitation responses. *Atmospheric Chemistry and Physics* **2018**, *18* (16), 12461–12475. DOI: https://doi.org/10.5194/acp-18-12461-2018

5. Sicard, P.; Agathokleous, E.; Anenberg, S. C.; De Marco, A.; Paoletti, E.; Calatayud, V. Trends in urban air pollution over the last two decades: A global perspective. *The Science of the Total Environment* **2022**, *858* (Pt 2), 160064. DOI: https://doi.org/10.1016/j.scitotenv.2022.160064

6. Song, X.; Hao, Y. Emission characteristics and health effects of PM2.5 from vehicles in typical areas. *Frontiers in Public Health* **2024**, *12*, 1326659. DOI: https://doi.org/10.3389/fpubh.2024.1326659

7. Zhang, K.; Batterman, S. Air pollution and health risks due to vehicle traffic. *The Science of the Total Environment* **2013**, *450–451*, 307–316. DOI: https://doi.org/10.1016/j.scitotenv.2013.01.074

8. Woo, S.-H.; Jang, H.; Lee, S.-B.; Lee, S.-B.; Lee, S.; Lee, S. Comparison of total PM emissions emitted from electric and internal combustion engine vehicles: An experimental analysis. *The Science of the Total Environment* **2022**, *842*, 156961. DOI: https://doi.org/10.1016/j.scitotenv.2022.156961

9. Shi, J.; Yao, Q.; Han, X.; Wang, Y.; Wu, X.; Tian, S.; Wang, J.; Yang, X.; Xie, H.; Xiang, F.; Ning, P. Chemical characteristics of PM2.5 emitted from motor vehicles exhaust under the plateau with low oxygen content. *Atmospheric Environment* **2023**, *314*, 120053. DOI: https://doi.org/10.1016/j.atmosenv.2023.120053

10. Brimblecombe, P.; Chu, M.; Liu, C.-H.; Fu, Y.; Wei, P.; Ning, Z. Roadside NO2/NOx and primary NO2 from individual vehicles. *Atmospheric Environment* **2022**, *295*, 119562. DOI: https://doi.org/10.1016/j.atmosenv.2022.119562

11. Tang, C. K. The Cost of Traffic: Evidence from the London Congestion Charge. *Journal of Urban Economics* **2020**, *121*, 103302. DOI: https://doi.org/10.1016/j.jue.2020.103302

12. Herzog, I. The city-wide effects of tolling downtown drivers: Evidence from London's congestion charge. *Journal of Urban Economics* **2024**, *144*, 103714. DOI: https://doi.org/10.1016/j.jue.2024.103714

13. Green, C. P.; Heywood, J. S.; Paniagua, M. N. Did the London congestion charge reduce pollution? *Regional Science and Urban Economics* **2020**, *84*, 103573. DOI: https://doi.org/10.1016/j.regsciurbeco.2020.103573

14. Eliasson, J. A cost–benefit analysis of the Stockholm congestion charging system. *Transportation Research Part a Policy and Practice* **2009**, *43* (4), 468–480. DOI: https://doi.org/10.1016/j.tra.2008.11.014

15. Simeonova, E.; Currie, J.; Nilsson, P.; Walker, R. Congestion pricing, air pollution, and children's health. *The Journal of Human Resources* **2019**, *56* (4), 971–996. DOI: https://doi.org/10.3368/jhr.56.4.0218-9363r2

16. Johansson, C.; Burman, L.; Forsberg, B. The effects of congestions tax on air quality and health. *Atmospheric Environment* **2008**, *43* (31), 4843–4854. https://doi.org/10.1016/j.atmosenv.2008.09.015

17. Watson, P.; Holland, E. Congestion pricing-the example of Singapore: One way of reducing daytime traffic problems. *Finance & Development* **1976**, *13* (1), 48. DOI: https://doi.org/10.5089/9781616353247.022

18. Phang, S.-Y.; Toh, R. S. From manual to electronic road congestion pricing: The Singapore experience and experiment. *Transportation Research Part E Logistics and Transportation Review* **1997**, *33* (2), 97–106. DOI: https://doi.org/10.1016/s1366-5545(97)00006-9

19. Jing, P.; Seshadri, R.; Sakai, T.; Shamshiripour, A.; Alho, A. R.; Lentzakis, A.; Ben-Akiva, M. E. Evaluating congestion pricing schemes using agent-based passenger and freight microsimulation. *Transportation Research Part a Policy and Practice* **2024**, *186*, 104118. DOI: https://doi.org/10.1016/j.tra.2024.104118

20. Eliasson, J.; Mattsson, L.-G. Equity effects of congestion pricing. *Transportation Research Part a Policy and Practice* **2006**, *40* (7), 602–620. DOI: https://doi.org/10.1016/j.tra.2005.11.002

21. Kaida, N.; Kaida, K. Spillover effect of congestion charging on pro-environmental behavior. *Environment Development and Sustainability* **2014**, *17* (3), 409–421. DOI: https://doi.org/10.1007/s10668-014-9550-9

22. Central business district tolling program. *The Metropolitan Transportation Authority*. https://www.mta.info/project/CBDTP

23. Congestion relief zone. *The Metropolitan Transportation Authority*. https://congestionreliefzone.mta.info/tolling

24. Fraser, T.; Park, Y. G.; Lu, D.; Tayarani, M.; Deng, H.; Gao, H. O. A first look into congestion pricing in the United States: PM2.5 impacts after six months of New York City cordon pricing. *Npj Clean Air* **2025**, *1* (1). DOI: https://doi.org/10.1038/s44407-025-00037-2

25. *Congestion relief zone tolling first evaluation report*; The Metropolitan Transportation Authority Bridges & Tunnels: 2026. https://www.mta.info/document/195631

26. Phang, S.-Y.; Toh, R. S. From manual to electronic road congestion pricing: The Singapore experience and experiment. *Transportation Research Part E Logistics and Transportation Review* **1997**, *33* (2), 97–106. DOI: https://doi.org/10.1016/s1366-5545(97)00006-9

27. Son, B.; Hwang, K. Y. Four-year-old Namsan tunnel congestion pricing scheme in Seoul. *IATSS Research* **2002**, *26* (1), 28–36. https://doi.org/10.1016/s0386-1112(14)60079-0

28. Zhang, Q.; Wang, Y.; Xiao, Q.; Geng, G.; Davis, S. J.; Liu, X.; Yang, J.; Liu, J.; Huang, W.; He, C.; Luo, B.; Martin, R. V.; Brauer, M.; Randerson, J. T.; He, K. Long-range PM2.5 pollution and health impacts from the 2023 Canadian wildfires. *Nature* **2025**, *645* (8081), 672–678. DOI: https://doi.org/10.1038/s41586-025-09482-1

29. Lau, K.; Guo, J.; Miao, Y.; Ross, Z.; Riley, K. W.; Wang, S.; Herbstman, J.; Perera, F. Major air pollution and climate policies in NYC and trends in NYC air quality 1998–2021. *Frontiers in Public Health* **2024**, *12*, 1474534. DOI: https://doi.org/10.3389/fpubh.2024.1474534

30. Lovasi, G. S.; Treat, C. A.; Fry, D.; Shah, I.; Clougherty, J. E.; Berberian, A.; Perera, F. P.; Kioumourtzoglou, M.-A. Clean fleets, different streets: evaluating the effect of New York City's clean bus program on changes to estimated ambient air pollution. *Journal of Exposure Science & Environmental Epidemiology* **2022**, *33* (3), 332–338. DOI: https://doi.org/10.1038/s41370-022-00454-5

31. *MTA Capital Program 2020-2024: Rebuilding New York's Transportation System;* The Metropolitan Transportation Authority: 2019. https://www.mta.info/document/10511

32. Zhou, H.; Taber, C.; Arcona, S.; Li, Y. Difference-in-Differences Method in Comparative Effectiveness Research: Utility with Unbalanced Groups. *Applied Health Economics and Health Policy* **2016**, *14* (4), 419–429. DOI: https://doi.org/10.1007/s40258-016-0249-y

33. Wang, G.; Hamad, R.; White, J. S. Advances in difference-in-differences methods for policy evaluation research. *Epidemiology* **2024**, *35* (5), 628–637. DOI: https://doi.org/10.1097/ede.0000000000001755

34. Butts, K. Difference-in-Differences Estimation with Spatial Spillovers. *arXiv (Cornell University)* **2021**. DOI: https://doi.org/10.48550/arxiv.2105.03737

Acknowledgements

The authors acknowledge the Lamont-Doherty Earth Observatory summer internship program for providing funding for this work.

Author Contributions

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Daniel M. Westervelt: data curation, methodology, validation, supervision, funding acquisition, conceptualization, project administration, resources, writing – review and editing

Abhishek Anand: writing – review and editing, formal analysis, supervision, validation, resources

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Competing Interests

The authors declare no conflicts of interest.

Supplementary Information for

Assessing Causality in $PM_{2.5}$ and NO_2 Changes One Year After New York City's Congestion Pricing Policy

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1. Traffic Volume in 2025 Compared to 2024

Traffic analysis was based on the Metropolitan Transportation Authority's (MTA) Bridges & Tunnels Hourly Traffic Rates dataset, which represents the number of vehicles that pass through each tunnel or bridge's toll plaza. The Queens Midtown Tunnel, which connects Queens to Manhattan's east side at 42nd street, and the Hugh L. Carey Tunnel, which connects Brooklyn to the southern tip of Manhattan (Supplementary Table 6, Supplementary Figure 3), were selected for further analysis by virtue of their direct entry into the CRZ. Data was restricted to vehicles traveling northbound or westward to Manhattan for the Hugh L. Carey Tunnel and Queens Midtown Tunnel, respectively, from January 5th through December 31st for both 2024 and 2025. Daily-averaged data at these sites was used to create interrupted time series and diurnal visualizations.

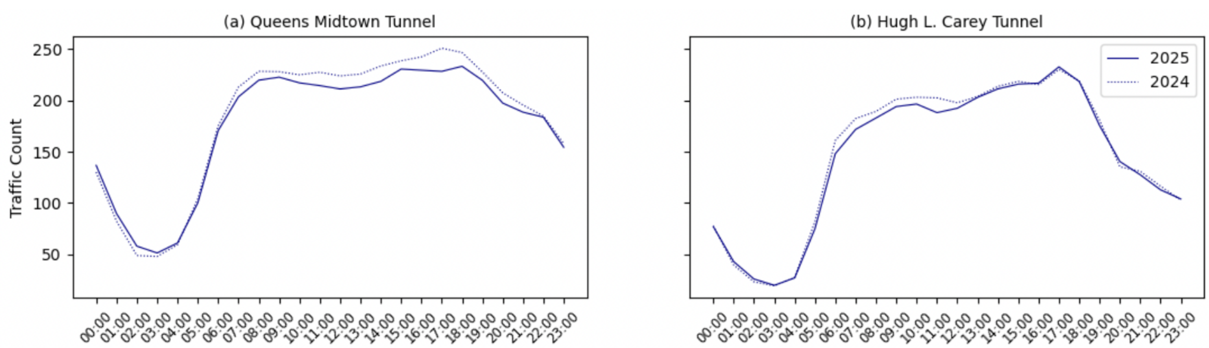

Figure 1: Diurnal profile of vehicle counts at two New York City monitoring sites: (a) Queens Midtown Tunnel, (b) Hugh L. Carey Tunnel. 2025 (solid) vs. 2024 (dashed) seasons.

Diurnal trends of vehicle counts at two New York City monitoring sites are shown for the years 2024 and 2025. The Queens Midtown tunnel connects Queens to Manhattan's east side at 42nd street, and is one of the roads covered by the CBDTP. The Hugh L. Carey Tunnel, which enters Manhattan at the southernmost tip from Brooklyn, is not directly covered by the CBDTP; it is only when the vehicle exits the tunnel onto streets that congestion pricing is applied. However, these data represent the number of vehicles that pass through each tunnel's toll plaza when entering Manhattan, and so are representative of traffic entering into the CRZ. It is important to note that these traffic sites do not correspond to the aforementioned $PM_{2.5}$ monitoring sites.

The above diurnal trends point to moderate decreases in traffic volume for both monitoring sites. The Queens Midtown Tunnel and Hugh L. Carey Tunnel both show a characteristic curve corresponding to peak traffic hours in the late morning and early evening. While the shape of these curves does not change drastically between 2024 and 2025, the peaks appear dampened.

For the Queens Midtown Tunnel, decreases in 2025 relative to 2024 are noted between 05:00 and 23:00, with differences ranging from -1 vehicle at 22:00 to -23 vehicles at 17:00. In 2024, for instance, maximum average vehicle counts were observed at 17:00, with a value of 251 vehicles. In 2025, the vehicle count average at 17:00 dropped to 228. Observed increases in 2025 are slight, ranging from +2 at 04:00 to +9 at 02:00. These slight increases likely reflect the overnight toll rate being 75% less than the respective rates in the standard peak period for all drivers. For the Hugh L. Carey Tunnel, 2025 trends track closely with that of 2024. Notable decreases are observed between 05:00 and 12:00, ranging from -5 vehicles at 12:00 and -14 vehicles at 11:00. It is unclear why decreases are not observed for end-of-work-day hours. Nonetheless, the results at both tunnel sites are generally consistent with the expectations for the program.

Table 1: Descriptive Statistics and Mann-Whitney U (MWU) Test Results of Ground-Based $PM_{2.5}$ ($\mu g/m^3$) by Monitoring Site for Stagnant-Wind Days

	2022-24			**2025**				**MWU**
	Mean	**St. Dev**	**Median**	**Mean**	**St. Dev**	**Median**	**Δ**	**p-value**
Manhattan Bridge	11.86	6.19	10.50	9.27	4.37	8.41	-2.09	< 0.01
Williamsburg Bridge	10.69	5.61	9.37	8.27	3.91	7.26	-2.11	< 0.001
Broadway & 35th	11.96	5.62	10.87	9.27	4.25	8.17	-2.70	< 0.001
Queensboro Bridge	10.17	4.92	9.00	8.10	4.05	7.15	-1.85	< 0.01
Cross Bronx Expy.	11.39	5.56	10.37	9.67	4.84	8.63	-1.74	0.02
Queens College	8.61	4.67	7.40	7.52	4.08	6.64	-0.76	0.08
Mott Haven	7.77	3.68	6.12	8.45	4.43	6.98	0.86	0.84
Hunt's Point	11.61	5.90	9.29	8.72	5.28	7.21	-2.08	< 0.01

BQE	8.71	5.29	6.86	7.56	3.51	6.76	-0.10	0.30
FDR Drive	8.88	4.79	7.92	7.81	3.22	7.04	-0.88	0.21
Midtown West	12.39	6.13	10.04	11.46	4.44	10.31	0.27	0.39
Hamilton Bridge	7.00	3.18	6.16	10.25	4.75	9.24	3.08	0.99
Van Wyck Expy.	7.80	3.53	6.50	7.32	3.54	6.64	0.14	0.26
Glendale	9.83	5.11	8.11	8.89	5.43	8.28	0.17	0.26
Staten Island Expy.	8.18	4.35	7.03	9.83	4.89	8.63	1.60	0.98

Table 2: Descriptive Statistics of Ground-Based $PM_{2.5}$ ($\mu g/m^3$) by Monitoring Site Region

	Pre-Implementation			**Post-Implementation**		
	Mean	**St. Dev**	**Median**	**Mean**	**St. Dev**	**Median**
Non-CRZ	9.24	5.93	7.41	8.49	5.15	6.98
CRZ	10.95	6.55	9.00	8.91	5.02	7.72
Nearby Non-CRZ	8.22	5.23	6.42	7.84	4.58	6.59
Distant Non-CRZ	9.43	6.03	7.59	8.72	5.31	7.09

Table 3: $PM_{2.5}$ Difference-in-Differences Regression Results

	Pre-Implementation	**Post-Implementation**	**Difference**
Non-CRZ	9.24	8.49	-0.75
CRZ	10.95	8.91	-2.04
Difference	1.71	0.42	DiD = -1.29***

*p < 0.05, **p < 0.01, ***p<0.001

Table 4: $PM_{2.5}$ Difference-in-Differences Regression with Spillover Results

	Pre-Implementation	**Post-Implementation**	**Difference**
Distant Non-CRZ	9.43	8.72	-0.71
CRZ	10.95	8.91	-2.04
Difference	1.52	0.19	DiD = -1.33***
Distant Non-CRZ	9.43	8.72	-0.71
Nearby Non-CRZ	8.22	7.84	-0.38
Difference	-1.21	-0.88	DiD = 0.33 (p = 0.056)

*p < 0.05, **p < 0.01, ***p<0.001

Table 5: Real-time $PM_{2.5}$ Monitoring Locations

Monitoring Location	**Latitude**	**Longitude**
Mott Haven	40.80649	-73.92249
Hunt's Point	40.81909	-73.88566
Cross Bronx Expy.	40.84517	-73.90614
Brooklyn Queens Expy. (BQE)	40.70280	-73.96082
Manhattan Bridge	40.71651	-73.99700
Williamsburg Bridge	40.71807	-73.98606
FDR Drive	40.72229	-73.97465
Broadway & 35th	40.75069	-73.98783
Midtown West	40.75508	-73.99041
Queensboro Bridge	40.76123	-73.96389

Hamilton Bridge	40.84654	-73.93302
Van Wyck Expy.	40.69015	-73.80908
Glendale	40.70574	-73.88627
Queens College	40.73711	-73.82156
Staten Island Expy.	40.60921	-74.15118

Table 6: Traffic Volume Monitoring Locations

Monitoring Location	**Latitude**	**Longitude**
Queens Midtown Tunnel	40.74721	-73.96709
Hugh L. Carey Tunnel	40.70039	-74.01512

Figure 2: Selected Real-time $PM_{2.5}$ Sensor Locations Relative to Congestion Relief Zone (CRZ). Nearby (<7 km) sites include Mott Haven and BQE.

Figure 3: Selected Tunnel Entry Point Locations Into the CRZ