A first look into congestion pricing in the United States: PM$_{2.5}$ impacts after six months of New York City cordon pricing

Check for updates

Timothy Fraser [1], Yeonkyeong Gina Park [2], Danni Lu [1], Mohammad Tayarani[2], Haiyan Deng[1] & H. Oliver Gao [1,2] ✉

In January 2025, New York City became the first U.S. metropolis to implement cordon-based congestion pricing, establishing a toll zone in Manhattan's core. The zone, which covers all local streets and avenues at or below 60th Street, is designated the Congestion Relief Zone (CRZ). While cordon pricing is theorized to reduce traffic and improve health, rigorous causal evidence in the U.S., particularly with environmental justice considerations, has been limited. To address this gap, we evaluate short-term impacts using daily PM$_{2.5}$ data from 42 air quality monitors across the New York City metropolitan area, spanning 518 days and 17,758 observations. For the analysis, we divide the study area into three spatial units: the broader metropolitan area (Core-Based Statistical Area, CBSA), the five boroughs of New York City, and the CRZ itself. Using predictive models that incorporate meteorology, baseline pollution, and neighborhood demographics, we estimate counterfactual air quality for each station-day and compute treatment effects. We find that average daily maximum PM$_{2.5}$ concentrations declined by 3.05 μg/m^3 (SE = 0.022) within the CRZ during the first six months. This represents a 22% reduction from a projected average of 13.8 μg/m^3 without the policy. Effects extend beyond Manhattan: average declines across New York City's five boroughs were 1.07 μg/m^3 (SE = 0.006), and the broader CBSA saw reductions of 0.70 μg/m^3 (SE = 0.004). Moreover, treatment effects in the CRZ grew over time, rising from 0.8 μg/m^3 in Week 1 to 4.9 μg/m^3 by Week 20, indicating accumulating behavioral adaptation. These results provide the first zone-specific, quasi-experimental evidence of air-quality improvements following congestion pricing in the United States. As other American cities consider similar policies, our findings demonstrate that cordon pricing can deliver rapid, geographically broad environmental benefits.

As communities worldwide increasingly experience the severe consequences of climate change, the transportation sector remains a significant and growing contributor to global greenhouse gas (GHG) emissions[1]. The transportation sector is also a major contributor to toxic air pollution, particularly in densely populated urban areas[2].

Congestion pricing has been used for years in global cities like London, Stockholm, Milan, and Singapore as a policy tool to reduce traffic demand and alleviate congestion[3,4]. In addition to reducing congestion, it is widely understood that congestion pricing should likely generate environmental and health co-benefits by reducing GHG emissions and ambient air pollution from on-road transportation sources like passenger cars and trucks[5–8].

While previous studies have estimated substantial environmental gains from international congestion pricing schemes, most U.S. evidence remains theoretical or limited in scope[9]. Moreover, existing cordon zones have typically been implemented at a smaller scale[4]. Compared to prior international cases, New York City (henceforth NYC) stands out with >600,000 daily trips entering its relief zone, ambitious revenue goals to support public transportation, and a policy design that anticipates health co-benefits.

In this study, we evaluate the policy's short-term impacts using daily PM$_{2.5}$ data from 42 monitoring stations across the New York metropolitan area, spanning 546 days (January 1, 2024–June 30, 2025), including 178 days under the new pricing policy. Our dataset includes 17,758 valid monitor-day

[1]Systems Engineering Program, Cornell University, Ithaca, USA. [2]School of Civil and Environmental Engineering, Cornell University, Ithaca, USA. ✉e-mail: hg55@cornell.edu

Fig. 1 | Policy effects on NYC air quality. Statistical significance: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, $p < 0.10$. Bars and text show average treatment effects on the treated (ATT) with 95% confidence intervals, estimated by models each with successively more controls. Statistical model tables for Models M1-M9 are shown in Table 1.


Results and discussion

We evaluated changes in ambient air quality in the New York metropolitan area by analyzing $PM_{2.5}$ concentrations across a three-tiered monitor sample: 13 monitors in the broader New York City Core-Based Statistical Area (CBSA), which includes suburban counties in upstate New York and New Jersey; 23 monitors within the five boroughs of New York City; and 6 monitors within the CRZ.

Overall effect

In Figs. 1 and 2, we show the average treatment effect on the treated monitors as well as policy effects on air quality per monitors during the congestion policy, repeated for each model, to show how estimates change from lightweight to the most robust model specifications. We find that the congestion pricing policy substantially reduced ambient air pollution, particularly within the toll zone. Average daily maximum $PM_{2.5}$ concentrations within the CRZ decreased by 3.05 µg/m³ (SE = 0.022). For context, background levels in the New York City metropolitan area during the study period averaged ~8–9 µg/m³, meaning the observed reduction represents ~22% decline from the counterfactual mean of 13.8 µg/m³ that would have occurred in the absence of the policy. Figure 1 displays the estimated average treatment effects from these models, showing statistically significant and sizable reductions in $PM_{2.5}$ levels following the introduction of congestion pricing. Effects were also observed outside Manhattan. Across the five boroughs of New York City, average concentrations declined by 1.07 µg/m³ (SE = 0.006), while the broader CBSA region saw a more modest but statistically significant decrease of 0.70 µg/m³ (SE = 0.004). These reductions

observations, measuring max daily $PM_{2.5}$ concentrations in micrograms per cubic meter (henceforth µg/m³). We estimate treatment effects by comparing actual air-quality readings to counterfactual predictions generated by a series of predictive models incorporating baseline pollution levels, meteorology, and neighborhood demographics.

Here we show that New York City's congestion pricing policy significantly reduced ambient air pollution across the broader New York metropolitan area, with especially pronounced effects inside the new Congestion Relief Zone (CRZ). As a preview of our results, we estimate that average daily maximum $PM_{2.5}$ concentrations declined by 3.05 µg/m³ (SE = 0.022) within the CRZ during the first six months of implementation. This marks an estimated 22% reduction from a projected counterfactual average of 13.8 µg/m³ had the policy not been adopted.

Effects extend beyond Manhattan: average reductions across the five boroughs of New York City were 1.07 µg/m³ (SE = 0.006), while sites across the broader New York Metropolitan area (specifically, the NYC core-based statistical area, henceforth CBSA) saw more modest reductions of 0.70 µg/m³ (SE = 0.004). Notably, these effects grew over time, from a 0.8 µg/m³ decline in Week 1 to 4.9 µg/m³ in Week 20, suggesting that air-quality improvements may continue to compound with longer-term implementation.

This study provides the first zone-specific, quasi-experimental evidence of air-quality benefits following congestion pricing in the United States. As other American cities consider similar policies, our findings indicate that cordon pricing can yield rapid, spatially broad environmental improvements.

Fig. 2 | Policy Effects on NYC PM$_{2.5}$ by Monitor.
A shows air-quality monitor locations (points) in the NYC Metropolitan Core-Based Statistical Area (CBSA). Points are shaded from white to blue by the size of the estimated decrease in PM$_{2.5}$ during the Congestion Pricing policy from 6 January 2025 to 1 June 2025. Monitors outside the CBSA are shaded gray. **B** narrows into the extent of the Congestion Relief Zone (CRZ) in Manhattan. Estimates reflect monitor average treatment effects for fully specified models for the CBSA in **A** (Model 3) and for the CRZ in **B** (Model 9). Roads are shown in white. Block groups are shaded by population density in yellow, where gray indicates unavailable data. Mapped in R with the ggplot2 and sf packages[30,31].
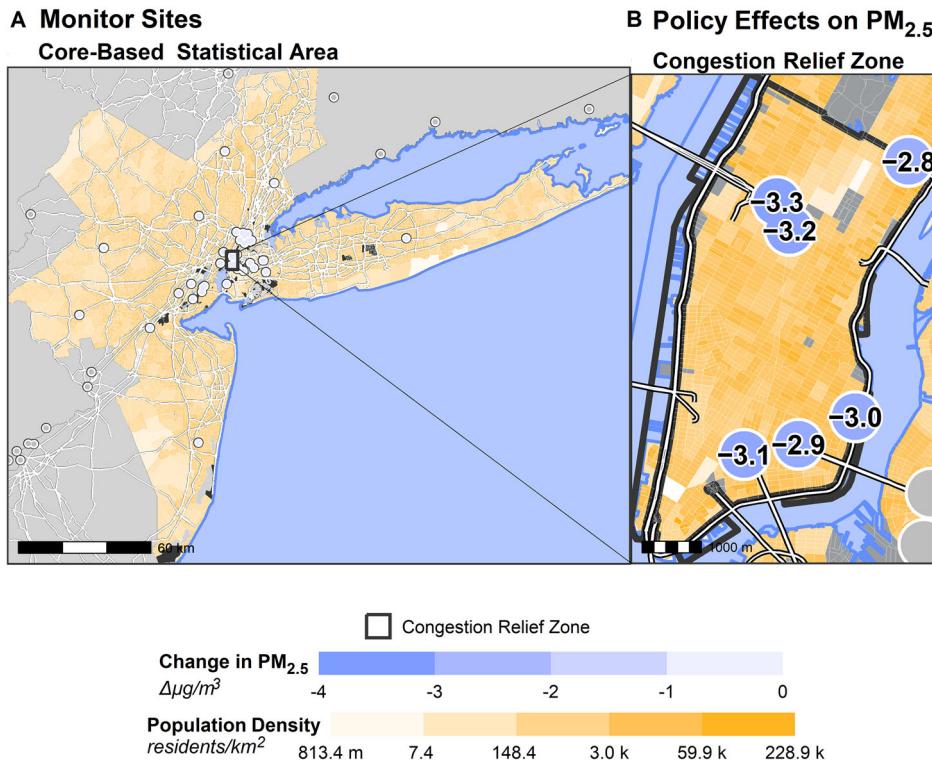
suggest that the policy's effects radiated beyond the tolled area, likely due to spillover changes in traffic volume and behavior.

Robustness across zones

The magnitude of pollution reductions varied by geographic zone but remained directionally consistent, indicating overall decreases across regions, though not uniformly across all locations or road types. Within all three regions—the CRZ, the five boroughs, and the CBSA—models showed statistically significant decreases in PM$_{2.5}$ levels across all specifications, with results robust to additional environmental and socio-demographic controls (for details, see Models 1–9 in Table 1). This consistent pattern across spatial zones and model types strengthens confidence in the policy's effectiveness in improving air quality, particularly in dense urban centers.

Descriptive evidence

Figure 3 illustrates the annual distributions of the wind direction, speed, and net PM$_{2.5}$ concentration in NYC, before and after the implementation of congestion pricing. Figure 3A presents wind rose plots for the entire year of 2024 and the first half of 2025. In both years, the prevailing winds came predominantly from the west and northwest directions, consistent with typical meteorological patterns in the region. The mean windspeed increased from 7.6 m/s in 2024 to 9.3 m/s in early 2025, while the proportion of calm wind conditions decreased from 16.4% to 12.3%. These changes suggest a better atmospheric dispersion capacity in 2025, which may influence the transport and dilution of urban air pollutants.

To isolate local emissions from regional background pollution, we selected four upwind background monitoring sites. These stations were chosen based on two criteria: (1) their persistent positioning upwind of the CRZ under dominant west and northwest wind conditions, as shown in seasonal wind rose patterns (Fig. 3A); and (2) their minimal influence from proximate traffic or industrial emission sources. consistent representation of transported background PM$_{2.5}$ levels, which were subtracted from city-wide measurements to calculate net PM$_{2.5}$, thus isolating the local-scale impact of congestion pricing on ambient air quality.

Figure 3B shows monthly net PM$_{2.5}$ concentrations within and outside the CRZ from January 2024 to June 2025. In 2024, concentrations exhibited clear seasonal variation, peaking in spring and early summer. Comparing median values for January through June, PM$_{2.5}$ declined within the CRZ from 1.143 μg/m^3 in 2024 to 0.865 μg/m^3 in 2025, but increased outside the CRZ from 0.542 μg/m^3 to 0.727 μg/m^3. A similar pattern was observed when comparing the full year of 2024 with the first half of 2025: within the CRZ, medians fell from 1.053 μg/m^3 to 0.542 μg/m^3, whereas outside the CRZ, they rose from 0.523 μg/m^3 to 0.727 μg/m^3. These temporal contrasts suggest a possible association between reduced traffic activity and improved air quality within the central urban area.

Figure 4 characterizes the temporal evolution and spatial heterogeneity of net PM$_{2.5}$ concentrations in NYC before and after the implementation of the congestion pricing policy. Figure 4A, B summarizes monthly trends in policy-hour (05:00–21:00) net PM$_{2.5}$ levels, comparing monitoring stations located within and outside the CRZ. Following policy initiation in January 2025, median net PM$_{2.5}$ concentrations consistently declined within the CRZ across most months. In contrast, outside the CRZ, net PM$_{2.5}$ concentrations exhibited a mixed pattern: initial declines were followed by increases in later months, suggesting possible redistribution or displacement of emissions linked to traffic rerouting. These temporal contrasts are further illustrated by the monthly percent changes, which show pronounced reductions within the CRZ during the early months of 2025, reaching up to a 66% decrease in May, while outside the CRZ, changes were more variable, including increases exceeding 90% in April.

Figure 4C–G further examines the spatial and temporal distribution of net PM$_{2.5}$ concentrations during policy hours across selected monitoring stations, highlighting regional contrasts inside and outside the CRZ. Stations located within the CRZ—D (Broadway) and F (Manhattan Bridge)—exhibited clear and consistent declines in PM$_{2.5}$ following policy implementation, with minor fluctuations during the early transition period (February–March) and pronounced reductions by June 2025. In contrast, E (Cross Bronx Station), situated outside the CRZ in the Bronx, showed a

**Table 1 | Linear models of air pollution in the New York City metropolitan area**

Predictor	CBSA			NYC			CRZ		
	M1 base	M2 +weather	M3 +demo	M4 base	M5 +weather	M6 +demo	M7 base	M8 +weather	M9 +demo
Daily effect	<0.01*** (0.00)	<0.01*** (0.00)	<0.01*** (0.00)	<0.01*** (0.00)	<0.01* (0.00)	<0.01*** (0.00)	< 0.01 (0.00)	<0.01*** (0.00)	<0.01*** (0.00)
Treatment	−0.39*** (0.02)	−0.20*** (0.02)	−0.20*** (0.02)	−0.47*** (0.03)	−0.22*** (0.03)	−0.22*** (0.03)	−0.49*** (0.05)	−0.21*** (0.06)	−0.19*** (0.05)
$\sqrt{\text{Background}PM_{2.5}}$	0.91*** (0.01)	0.80*** (0.01)	0.79*** (0.01)	0.91*** (0.01)	0.75*** (0.01)	0.77*** (0.01)	0.86*** (0.02)	0.67*** (0.02)	0.66*** (0.02)
ln(Distance from road)	−0.03*** (0.00)	−0.03*** (0.00)	−0.01 (0.00)	−0.03*** (0.00)	−0.03*** (0.00)	−0.02*** (0.00)			
ln(Temperature)	0.74*** (0.04)	0.72*** (0.03)	0.66*** (0.03)		0.83*** (0.04)	0.84*** (0.04)		0.76*** (0.08)	0.73*** (0.07)
% Humidity		< 0.01 (0.00)	<0.01*** (0.00)		0.01*** (0.00)	0.01*** (0.00)		0.01*** (0.00)	0.01*** (0.00)
Windspeed (m/s)		−0.02** (0.00)	−0.02*** (0.00)		−0.02*** (0.00)	−0.02*** (0.00)		−0.03* (0.01)	−0.03*** (0.00)
Precipitation		0.48 (0.40)	−0.54 (0.39)		−0.80 (0.51)	−1.01* (0.51)		−3.17** (1.01)	−2.92** (0.93)
% Cloud cover		<0.01 (0.00)	<0.01*** (0.00)		<0.01*** (0.00)	<0.01*** (0.00)		<0.01*** (0.00)	<0.01*** (0.00)
ln(Pop. density)			0.07*** (0.00)			0.07*** (0.01)			
ln(Median income)			−0.09*** (0.02)			0.13*** (0.03)			−1.21*** (0.06)
% Non-White			−0.03 (0.03)			0.07 (0.05)			0.10** (0.03)
% Hispanic/Latino			−0.36*** (0.03)			−0.14** (0.04)			
Constant	0.74*** (0.04)	−1.36*** (0.12)	−0.89*** (0.28)	0.80*** (0.05)	−1.76*** (0.15)	−4.10*** (0.39)	0.82*** (0.08)	−1.70*** (0.28)	10.01*** (0.78)
R^2	0.54	0.56	0.58	0.54	0.57	0.58	0.58	0.62	0.68
Max VIF	6.5	7.0	7.0	6.8	7.4	7.4	7.3	7.9	8.0
F (df)	336.4*** (62)	335.1*** (67)	338.7*** (71)	207.3*** (62)	218.3*** (67)	214.0*** (71)	59.1*** (61)	64.8*** (66)	79.2*** (68)
RMSE (μg/m³)	0.55	0.54	0.53	0.56	0.54	0.53	0.50	0.48	0.44
MAE (μg/m³)	0.42	0.41	0.41	0.43	0.42	0.41	0.39	0.37	0.34
%MAE/Range	9%	9%	9%	10%	9%	9%	12%	11%	10%
Range (μg/m³)	0.3–5.0	0.3–5.0	0.3–5.0	0.5–5.0	0.5–5.0	0.5–5.0	1.8–5.0	1.8–5.0	1.8–5.0
N obs	17,758	17,667	17,667	11,228	11,193	11,193	2651	2651	2651
N treated	5469	5412	5412	3608	3589	3589	882	882	882
N control	12,289	12,255	12,255	7620	7604	7604	1769	1769	1769

Dependent variable: $\sqrt{PM_{2.5}}$ concentration (μg/m³).

Statistical significance: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, ⋅$p < 0.10$.

Fixed effects: day-of-week (7 levels) and week-of-year (52 levels) included in the model estimation but omitted from the table due to space constraints.

A Annual Wind Direction and Speed Patterns in New York City (2024 vs 2025)
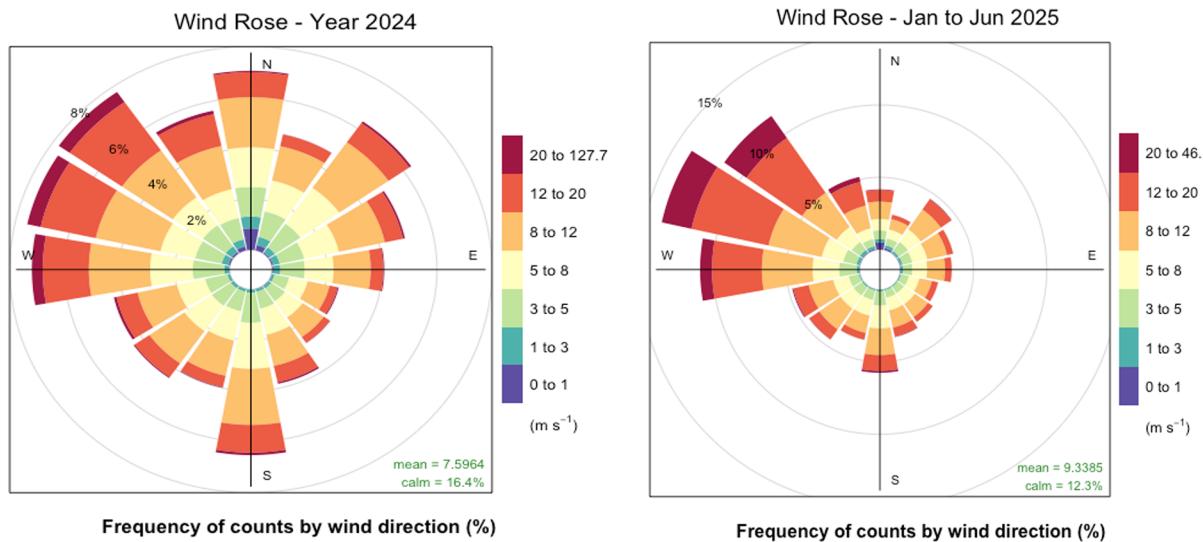
## B Trends in Net PM$_{2.5}$ Concentration Within and Outside CRZ (2024-2025)
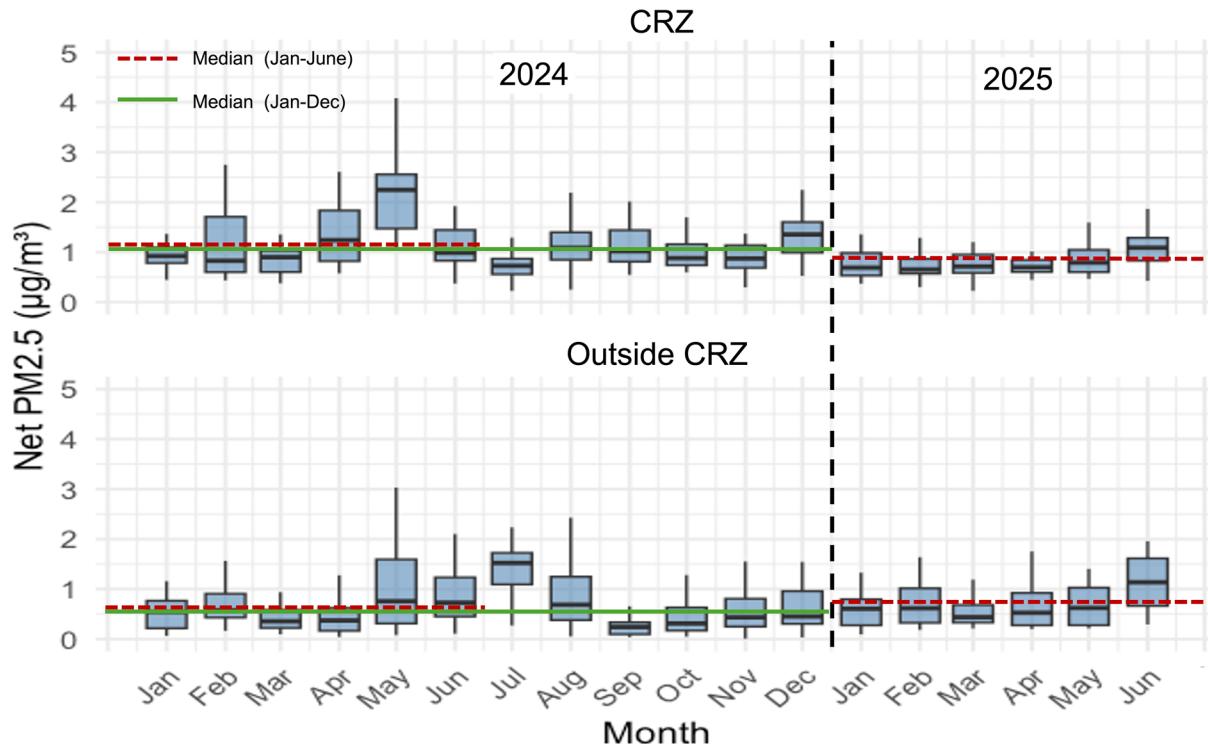
Fig. 3 | Annual wind direction and speed patterns and net PM$_{2.5}$ concentration trends in NYC pre- and post-congestion pricing (2024–2025). A Wind rose depicts direction and speed distributions for 2024 and Jan–Jun 2025. **B** Boxplots show monthly net PM$_{2.5}$ inside vs. outside the CRZ, with median lines for Jan–Jun and Jan–Dec periods.

different temporal profile: PM$_{2.5}$ levels did not decline immediately and even rose slightly in March, possibly reflecting increased traffic rerouting around the CRZ. A gradual decline emerged from April onward, suggesting a delayed response as traffic patterns adjusted. G (Van Wyck Station), located further from both the CRZ boundary and primary traffic detour corridors, displayed relatively stable PM$_{2.5}$ levels, with little year-to-year variation. This suggests that the policy's influence diminished with increasing distance from the CRZ and that Van Wyck Station was less affected by traffic redistribution.

Together, these observations underscore the heterogeneous impacts of congestion pricing: core CRZ areas experienced immediate and substantial air-quality improvements, while peripheral neighborhoods showed either delayed responses or negligible changes, depending on proximity to the CRZ and exposure to traffic spillover.

Change in effects over time

Excitingly, these effects were not static over time, but grew within the CRZ over time. Figure 5A shows average weekly treatment effects for each
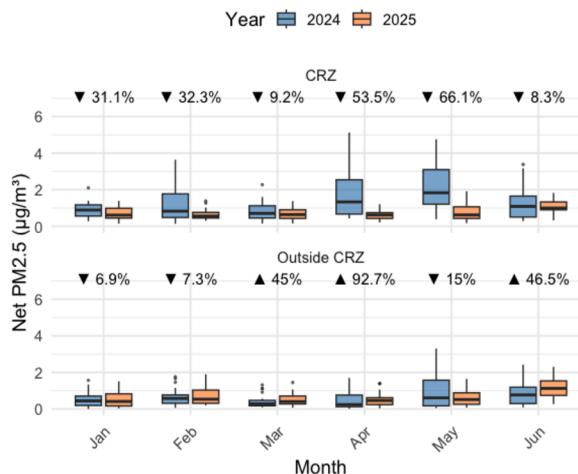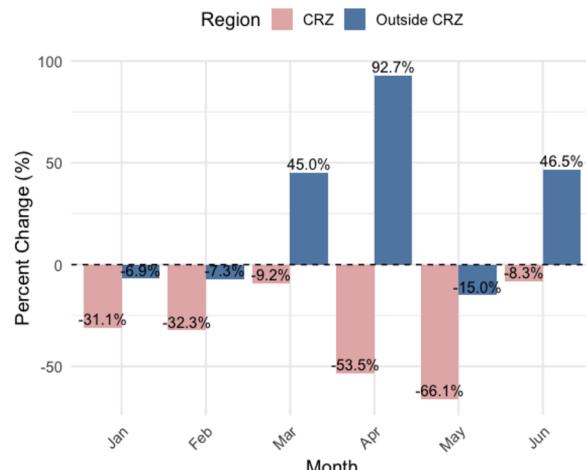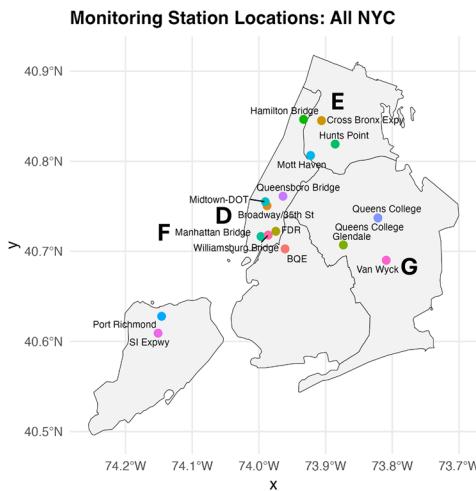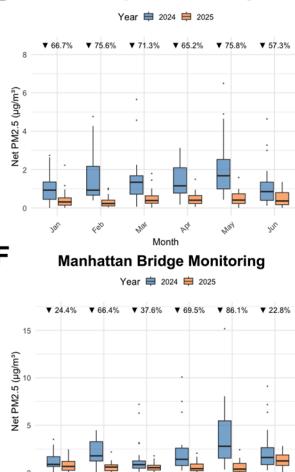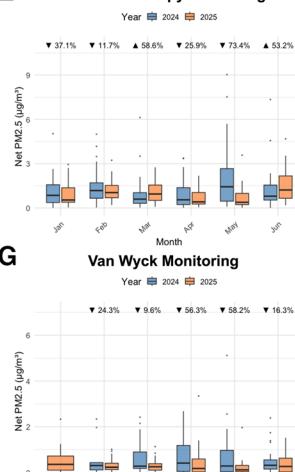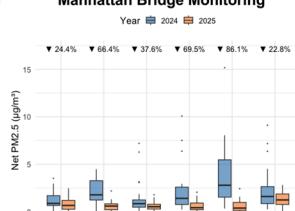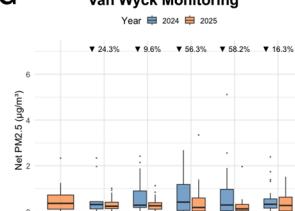
Fig. 4 | Temporal and spatial reductions in net PM$_{2.5}$ during congestion pricing hours across NYC. A, **B** Boxplots and histograms of monthly net PM$_{2.5}$ inside vs. outside the CRZ for 2024 and 2025, showing percent changes relative to the baseline. **C** Locations of hourly PM$_{2.5}$ monitoring stations in NYC. **D–G** Spatiotemporal distributions at key monitoring stations, highlighting variability across locations and months. Specifically, **D** Bowery (within CRZ), **E** Cross Bronx (outside CRZ), **F** Manhattan Bridge (within CRZ), and **G** Van Wyck (outside CRZ).

geographic zone, where bands show the range of effects most likely per week (95% confidence intervals). These dynamic weekly effects are shown for the CRZ (Model 9), NYC 5 Boroughs (Model 6), and the broader NYC Metropolitan CBSA (Model 3). During the first week of implementation, we estimate an average PM$_{2.5}$ reduction of 0.8 μg/m^3 in the CRZ. These effects steadily increased, reaching an average weekly reduction of 4.9 μg/m^3 by Week 20. This cumulative trend suggests persistent and compounding air-quality benefits within the tolled zone.

In contrast, we find that air-quality improvements in outer zones (the NYC boroughs and CBSA) were more modest and showed decreases over time. Average treatment effects in these areas were significant in the first weeks of implementation, but the rate of improvement slowed as time progressed. These diminishing returns likely reflect adaptive transportation behavior, describing the thousands of NYC metro area residents and firms who are adjusting their behavior to avoid driving through the tolling zone by rerouting trucks, mode switching, or rescheduling trips. These concurrent changes in vehicle behavior are likely responsible for the change in marginal environmental benefits outside the CRZ. However, it is worth noting that even these further-out areas still produce statistically significantly less air pollution than before congestion pricing's implementation.

To better understand the link between vehicle activity and air-quality changes, Fig. 5B shows weekly traffic entry trends within the CRZ, with a notable early drop in multi-unit truck entries. Between January and June 2025, vehicle entries into the CRZ decreased substantially: heavy-duty truck entries fell by approximately 18%, car entries by about 9%, and overall vehicle entries by around 11%. These reductions in traffic activity are of a scale that could plausibly account for the observed decreases in peak PM$_{2.5}$ levels, especially given the disproportionate contribution of heavy-duty vehicles to urban air pollution. The differing responses between trucks and passenger vehicles likely reflect their distinct decision-making dynamics, where individual drivers adjust gradually through small, trip-level changes, whereas trucking companies plan ahead to minimize operating costs, leading to larger, more coordinated adjustments such as rerouting or reducing cross-cordon entries. Figure 5C plots correlations between PM$_{2.5}$ changes and hourly vehicle entry volumes, disaggregated by vehicle type and time period. These results reinforce that reductions in heavy-duty vehicle traffic are closely associated with air-quality improvements, especially during peak daytime hours.

Taken together, these results suggest that congestion pricing produces increasingly strong environmental returns within the tolled zone while producing time-limited co-benefits in adjacent areas. Future analyses could

A | Weekly Average Treatment Effects on Air Quality
January 6, 2025 to June 1, 2025

B | Weekly Vehicle Activity in Congestion Relief Zone
January 6, 2025 to June 1, 2025

C | Impacts of Vehicle Entries to Congestion Relief Zone on Air Pollution
Janury 6, 2025 to June 1, 2025
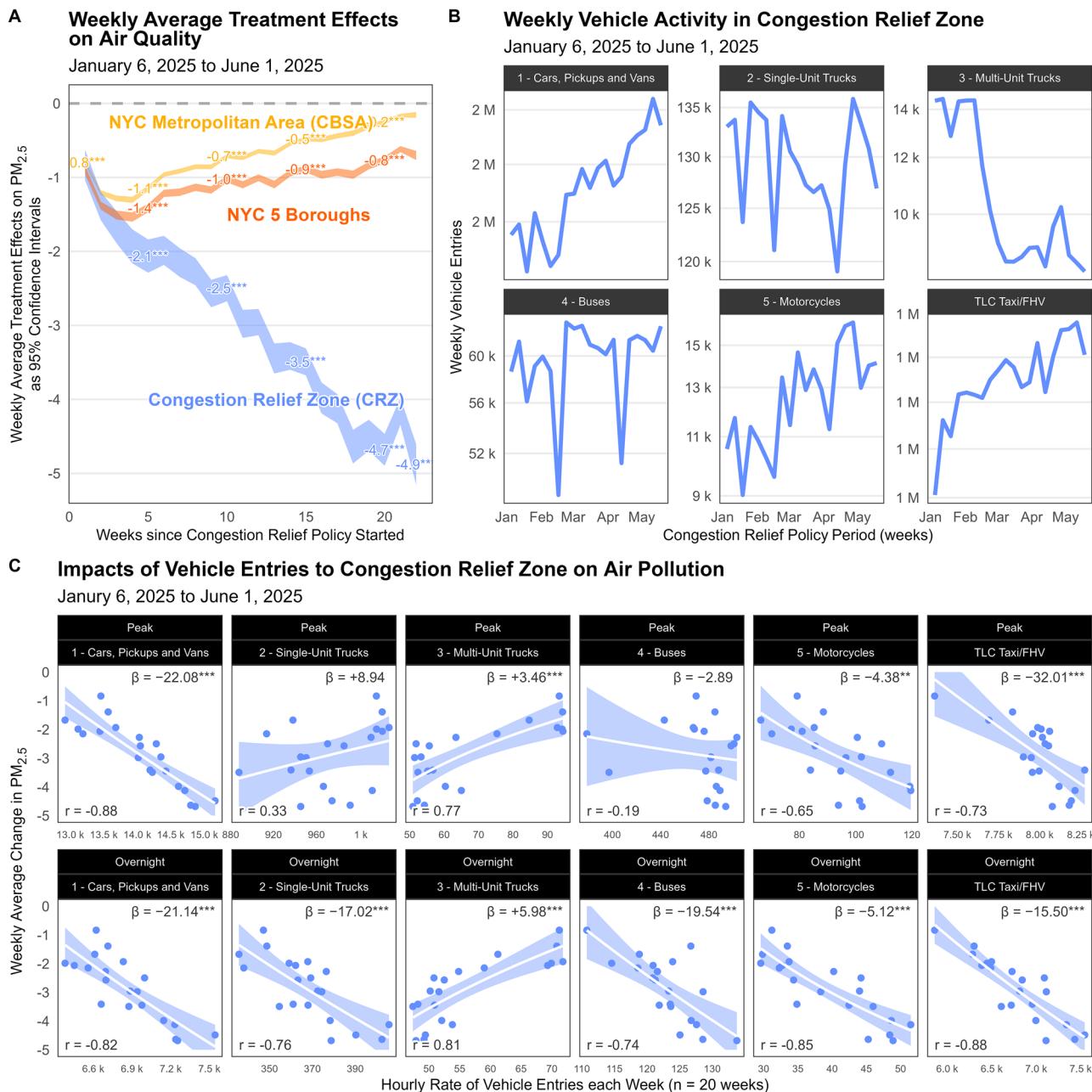
Fig. 5 | Air-quality benefits increase in the congestion relief zone over time.
A Bands show weekly average treatment effects within the CRZ (Model 9), NYC 5 Boroughs (Model 6), and NYC Metropolitan Area CBSA (Model 3), with 95% confidence intervals. **B** Lines depict weekly vehicle activity inside the CRZ, highlighting the drop in Multi-Unit Truck entries. **C** Trend lines relate changes in air pollution to hourly vehicle entry rates per week, by vehicle class and time period (Peak = 5 AM–10 PM; Overnight = 11 PM–4 AM).

evaluate whether longer-term shifts in commuting patterns sustain or reshape these trends.

NYC congestion pricing cut PM$_{2.5}$ by 22%. Our analysis provides the first quasi-experimental evidence that New York City's cordon-based congestion pricing policy produced rapid and substantial air-quality improvements. Within just six months of implementation, daily maximum PM$_{2.5}$ in the CRZ declined by 22%, controlling for background concentrations, meteorology, and neighborhood demographics. This magnitude exceeds prior evidence from Stockholm, where congestion pricing reduced air pollution by 5–15% between 2006 and 2010[5], and London's Ultra Low Emission Zone, which achieved about a 7% decline in PM$_{2.5}$ citywide between 2019 and 2022[10]. The comparatively larger effects in New York likely reflect both the intensity of travel demand and the greater modal flexibility of its commuters, supported by an extensive transit system and multi-modal system.

Importantly, the results show that air-quality improvements were not confined to the tolled zone. We find no evidence of emissions displacement to neighboring areas; instead, the analysis reveals net reductions across the broader metropolitan region. While improvements in the five boroughs and the broader CBSA were smaller (1.07 and 0.70 μg/m³, respectively), these reductions remain statistically significant across specifications. This spatial gradient reflects how pricing reshapes travel behavior beyond the tolled zone through rerouting, mode switching, and trip rescheduling, while producing both direct and indirect environmental benefits. These findings suggest that congestion pricing acts as a system-wide behavioral intervention rather than a geographically bounded one.

Behavioral adaptation drives compounding environmental gains. Temporal dynamics reinforce this interpretation. As shown in Fig. 5A, weekly treatment effects within the CRZ intensified nearly fivefold by Week 20 (rising from ~0.8 µg/m³ in Week 1 to ~4.9 µg/m³ by Week 20), while the corresponding curves for the five boroughs and the CBSA are flatter and begin to plateau earlier, indicating more modest but still negative effects outside the cordon. Read together with the spatial pattern in Fig. 2A, where monitors across the CBSA are shaded light blue, these trends indicate net reductions rather than displacement: early gains are concentrated in the core, and smaller improvements diffuse outward as travelers adapt. This pattern implies that early post-implementation evaluations may understate long-term air-quality gains, as behavioral adjustments (e.g., trip consolidation, increased transit use, and peak-hour avoidance) accumulate gradually rather than instantaneously. Conversely, smaller or slower improvements in outer zones may reflect the limits of mode substitution once key travel patterns stabilize.

Long-term success demands reinvestment, freight integration, and adaptive management. Three key takeaways emerge. First, reinvestment is critical. Allocating a portion of toll revenues to support outer-borough transit, subsidized fares, and active-mobility infrastructure would extend benefits beyond the CRZ and ensure citywide accessibility[11,12]. Second, freight management deserves explicit integration. Our results confirm that heavy-duty truck activity remains a dominant driver of localized air-quality variation. Differentiated tolls, incentives for zero-emission freight vehicles, and coordinated delivery scheduling could amplify environmental benefits while reducing concentrated burdens in communities already overexposed to truck emissions[13,14]. Third, adaptive management is essential. As weekly treatment effects grew over time, continuous air-quality monitoring, dynamic rate adjustments, and iterative policy design will be vital to sustaining gains and preventing rebound effects[15,16]. These lessons align with international evidence that successful congestion pricing programs rely on transparency, reinvestment, and continuous adaptation.

New York's experience reinforces global evidence on congestion pricing. From a broader perspective, this study contributes new empirical evidence to the global literature on pricing-based environmental policy. The results demonstrate that congestion pricing, when implemented in a high-density, transit-oriented U.S. city, can achieve emission reductions comparable to or exceeding those of long-established European cases, such as Milan's Area C program (17% decline in PM_{10}) and London's congestion charge (5–10% reduction in PM_{10})[17,18]. They also underscore that environmental and mobility benefits can coexist, positioning congestion pricing as a rare intervention that advances multiple urban sustainability goals simultaneously: reducing pollution, improving traffic efficiency, and generating revenue for infrastructure modernization[19].

Finally, while these findings are encouraging, several caveats merit discussion. The analysis covers only the first six months of implementation, limiting inferences about longer-term outcomes or potential rebound effects. Moreover, the absence of unaffected counterfactual monitors required reliance on predictive modeling rather than traditional difference-in-differences (DiD) methods[20]. Future research should assess whether the observed $PM_{2.5}$ reductions persist over time, how benefits vary across demographic and spatial contexts, and how complementary measures—such as fleet electrification, transit expansion, and active-mobility investment—can amplify these gains. Extending this framework to other pollutants, including NO_x and O_3, will also help clarify the full atmospheric and health implications of congestion pricing[21–24].

Methods
Our objective is to estimate the causal effect of congestion pricing on air quality. We apply a modified DiD framework, widely used in environmental epidemiology, to evaluate policy impacts under observational conditions[13,25,26]. This design compares air-quality trends in the treated group (CRZ) with those in control groups (the five NYC boroughs and the CBSA), under the assumption that, absent the policy, concentrations would have followed business-as-usual trajectories. Controls for meteorology, baseline concentrations, and neighborhood demographics are explicitly included.

In a dense metropolitan area like New York City, identifying a truly unaffected control group is infeasible because regional background pollution and traffic redistribution influence monitors across the region. Unlike pharmaceutical trials, where distinct treated and untreated groups can be maintained, air-quality studies typically adopt modified DiD designs that rely on internal benchmarks rather than perfectly unaffected controls. Accordingly, we incorporate upwind monitors as benchmarks for regional variation, consistent with established practice[27,28]. These stations, located outside the CRZ and in areas less likely to be influenced by traffic rerouting, provide reference levels for meteorology and regional background. Roadside studies further show that incremental $PM_{2.5}$ declines by 75% between 5 m and 30 m from traffic[29], underscoring the importance of siting controls away from direct roadway influence.

While robustness could be enhanced through unaffected metropolitan comparison groups or synthetic controls, these require extensive data harmonization across cities. We are exploring synthetic control methods as part of ongoing work, but the current design reflects established practice in environmental epidemiology and provides a rigorous basis for causal inference in this early evaluation of New York City's congestion pricing.

Data
We modeled air pollution outcomes for $N = 42$ monitors throughout New York City's census-defined CBSA, spanning 518 days from January 1 2024 to June 1 2025, covering 148 days treated and 371 untreated for comparison. This integrates 24 monitors available through the AIRNOW API, plus 18 sensors from New York City's own monitor network.

For each day, we calculated each monitor's max hourly concentration of $PM_{2.5}$. To produce daily maxes, we trimmed the hourly readings to the 99% range of most common readings, from 0.1 to 25.5 micrograms per cubic meter, to exclude a handful of particularly high (or low) readings. This produces a final unbalanced panel of 17,758 valid monitor-day observations (out of a full grid of 42 monitors × 518 days = 21,798). Some monitors were offline for portions of the study period; data were available for 6216 treated days (97%) and 15582 untreated monitor-days (85%). Our final sample includes 6 monitors ($n = 3114$ monitor-days) within the CRZ, 23 more within the NYC 5-boroughs area ($n = 11,937$), and 13 more in the metropolitan CBSA ($n = 6747$). Monitor locations are mapped in Fig. 2 with R version 4.1.1, using the ggplot2 package [30] for data visualization and the sf package [31] for geospatial operations.

Because the NYC CRZ affects traffic beyond Manhattan and throughout the metropolitan area, we cannot perform a true quasi-experiment (since there are no true counterfactual monitors unaffected by the CRZ within New York City). However, we can construct an approximate model that estimates the average change in air pollution concentration for each day passed since the enactment of the CRZ.

Model estimation
To estimate the change in air pollution, we constructed a series of iterative models of the entire region, starting with (1) basic controls, then (2) adding environmental controls, followed by (3) neighborhood demographic characteristics of the monitors' neighborhoods.

Estimation strategy. We model the enactment of the congestion relief policy as a binary treatment affecting all air-quality monitors in the metro region, regardless of location, ever after January 6, 2025. We control for temporal variation in air pollution using fixed effects for each week (week 1–52) and each day of the week (Monday, Tuesday, etc.). (We avoid daily fixed effects because they are collinear with the time-based treatment variable). Finally, following the logic of DiD models, we model the average treatment effect using an interaction

between the treatment effect and a daily counter variable, describing how many days have passed since the adoption of the congestion relief policy (0, 1, 2, etc.).

Basic controls. Then, we adjusted for several necessary, basic controls. Even without on-road transportation, all cities have a certain background concentration level of $PM_{2.5}$. We estimate the background concentration level of our pollutant by calculating the mean daily maximum concentration of the pollutant averaged from 4 monitors spread across Hunterdon, Middlesex, Morris, and Passaic counties, located outside the road-dense 5-boroughs and as far away from the major thoroughfares as possible. We control for background concentration levels, square-rooted to account for slight right skew, which is a common practice in air quality and epidemiological research when dealing with right-skewed pollution data[32]. Then, we control for the logged minimum distance of each monitor from the nearest highway (classified as primary (interstate) or secondary (state) highways). This represents our basic, minimal model of air pollution, with all necessary fundamental spatial controls.

Environmental controls. Next, we constructed a second model, appending environmental controls. Using hourly estimates from the weather station nearest each monitor, sourced from VisualCrossing API, we controlled for the log-temperature, percentage of relative humidity, windspeed in miles per second, precipitation levels, and cloud cover levels[33]. (We logged temperature to avoid heat-bubble-related collinearity with population density).

Neighborhood demographic controls. Finally, we constructed a third model, appending neighborhood demographic controls. Using census block group estimates from the American Community Survey 5-year Estimates (2019–2023)[34], we took the average traits of census block groups located nearby, within a 1 km buffer of each air-quality monitor. These average traits characterize the transportation demand profile of each monitor's neighborhood. Specifically, we added controls for the population density in persons per square kilometer (logged), median income in USD (logged), the share of non-white residents, and the share of Hispanic or Latino residents. (We use the share of non-white residents, rather than a larger set of demographic groups, because more detailed breakdowns are highly collinear with median income within New York City. We drop race and ethnicity controls in our analysis of monitors within Manhattan's CRZ because of collinearity with median income spikes (median income captures their shared trend in that area).

Estimating treatment effects. We applied our trained models to estimate predicted treatment effects for the entire grid of all possible monitor-days. (Because predictor data were available for the entire grid, even during gaps in monitor readings, we were able to estimate average treatment effects for the balanced dataset.) For each monitor, we simulated the average treatment effect on the treated monitors, calculating how much air quality was predicted to change given the policy vs. if the policy were not present, predicted for each day between January 6th, 2025 and June 1st, 2025, We approximated prediction uncertainty by simulating 1000 effects per monitor using Monte Carlo simulations from distributions sized by model prediction error. Then, we calculated the range of effects experienced in this time period and these geographic zones.

Data availability
The data and code are available here: https://github.com/timothyfraser/nyc_congestion_rep.

Code availability
The data and code are available at https://github.com/timothyfraser/nyc_congestion_rep.

References
1. Speizer, S. et al. Integrated assessment modeling of a zero-emissions global transportation sector. *Nat. Commun.* **15**, 4439 (2024).
2. McDuffie, E. E. et al. Source sector and fuel contributions to ambient PM2.5 and attributable mortality across multiple spatial scales. *Nat. Commun.* **12**, 3594 (2021).
3. de Palma, A. & Lindsey, R. Traffic congestion pricing methodologies and technologies. *Transport. Res. Part C: Emerg. Technol.* **19**, 1377–1399 (2011).
4. Croci, E. Urban road pricing: a comparative study on the experiences of London, Stockholm and Milan. *Transport. Res. Proc.* **14**, 253–262 (2016).
5. Simeonova, E., Currie, J., Nilsson, P. & Walker, R. Congestion pricing, air pollution, and children's health. *J. Hum. Resour.* **56**, 971–996 (2021).
6. Tonne, C., Beevers, S., Armstrong, B., Kelly, F. & Wilkinson, P. Air pollution and mortality benefits of the london congestion charge: spatial and socioeconomic inequalities. *Occup. Environ. Med.* **65**, 620–627 (2008).
7. Johansson, C., Burman, L. & Forsberg, B. The effects of congestions tax on air quality and health. *Atmos. Environ.* **43**, 4843–4854 (2009).
8. Rotaris, L., Danielis, R., Marcucci, E. & Massiani, J. The urban road pricing scheme to curb pollution in Milan, Italy: description, impacts and preliminary cost-benefit analysis assessment. *Transport. Res. Part A: Policy Pract.* **44**, 359–375 (2010).
9. Baghestani, A., Tayarani, M., Allahviranloo, M. & Gao, H. O. Evaluating the traffic and emissions impacts of congestion pricing in New York City. *Sustainability* **12**, 3655 (2020).
10. Ellerbeck, S. London's low emissions zone has reduced pollution levels by more than a quarter, new study finds. Tech. Rep., World Economic Forum https://www.weforum.org/stories/2023/03/london-low-emissions-zone-pollution/. Accessed: 2025-07-31 (2023).
11. Mathur, S. Using tax increment financing to fund public transportation: enabling environment and equity impacts. *Public Works Manag. Policy* **22**, 201–225 (2017).
12. New York State Governor's Office. Six months in, Governor Hochul highlights the success of congestion pricing: Traffic is down, business is up, and critical investments are being made to improve transit. https://www.governor.ny.gov/news/six-months-governor-hochul-highlights-success-congestion-pricing-traffic-down-business-and (2025).
13. Park, Y. G. & Gao, H. O. Port cleaner trucks and environmental justice in the greater New York area. *Sci. Total Environ.* **979**, 179396 (2025).
14. Anciaes, P., Cheng, Y. & Watkins, S. J. Policy measures to reduce road congestion: what worked? *J. Transp. Health* **41**, 101984 (2025).
15. Isaksen, E. T. & Johansen, B. G. Congestion pricing with electric vehicle exemptions: car-ownership effects and other behavioral adjustments. *J. Environ. Econ. Manag.* **131**, 103154 (2025).
16. Greater London Authority. London-wide ultra low emission zone: one year report. https://www.london.gov.uk/programmes-strategies/environment-and-climate-change/environment-and-climate-change-publications/london-wide-ultra-low-emission-zone-one-year-report (2024).
17. Gibson, M. & Carnovale, M. The effects of road pricing on driver behavior and air pollution. *J. Urban Econ.* **89**, 62–73 (2015).
18. Green, C. P., Heywood, J. S. & Navarro, M. Did the London congestion charge reduce pollution? *Reg. Sci. Urban Econ.* **84**, 103573 (2020).
19. Yu, W. et al. The cost-effectiveness of competing congestion pricing plans in New York City. *J. Transp. Health* **14**, 100586 (2019).

20. Burns, J. et al. Interventions to reduce ambient particulate matter air pollution and their effect on health. *Cochrane Database Syst. Rev.* **5**, CD010919 (2019).
21. Zhang, K. & Batterman, S. Air pollution and health risks due to vehicle traffic. *Sci. Total Environ.* **450-451**, 307–316 (2013).
22. Yang, B. et al. On-road chemical transformation as an important mechanism of NO_2 formation. *Environ. Sci. Technol.* **52**, 4574–4582 (2018).
23. Tu, R. et al. Real-world emissions and fuel consumption of gasoline and hybrid light duty vehicles under local and regulatory drive cycles. *Sci. Total Environ.* **805**, 150407 (2022).
24. Cook, C. et al. The short-run effects of congestion pricing in New York City. *NBER Working Paper No*. w33584 (2025).
25. Yazdi, M. D. et al. The effect of long-term exposure to air pollution and seasonal temperature on hospital admissions with cardiovascular and respiratory disease in the United States: a difference-in-differences analysis. *Sci. Total Environ.* **843**, 156855 (2022).
26. Wan, Z., Zhou, X., Zhang, Q. & Chen, J. Do ship emission control areas in china reduce sulfur dioxide concentrations in local air? a study on causal effect using the difference-in-difference model. *Mar. Pollut. Bull.* **149**, 110506 (2019).
27. Collischon, M. & Patzina, A. Covid-19 and gender differences in social trust: causal evidence from the first wave of the pandemic. *Socius* **8**, 23780231221117910 (2022).
28. Karner, A. A., Eisinger, D. S. & Niemeier, D. A. Near-roadway air quality: synthesizing the findings from real-world data. *Environ. Sci. Technol.* **44**, 5334–5344 (2010).
29. Mukherjee, A. et al. Influence of roadway emissions on near-road $pm_{2.5}$: monitoring data analysis and implications. *Transport. Res. Part D: Transp. Environ.* **86**, 102442 (2020).
30. Wickham, H. *ggplot2: elegant graphics for data analysis.* https://ggplot2.tidyverse.org (Springer-Verlag New York, 2016).
31. Pebesma, E. Simple features for R: standardized support for spatial vector data. *R J.* **10**, 439–446 (2018).
32. Sampson, P. D. et al. A regionalized national universal kriging model using partial least squares regression for estimating annual $pm_{2.5}$ concentrations in epidemiology. *Atmos. Environ.* **75**, 383–392 (2013).
33. Visual Crossing. Visual crossing weather (January 2024 to June 2025). https://www.visualcrossing.com/ Timeline Weather API (2025).
34. U.S. Census Bureau. American community survey 5-year estimates (2019–2023). https://www.census.gov/programs-surveys/acs Accessed 2025 (2024).

Competing interests
The authors declare no competing interests.

Additional information
Correspondence and requests for materials should be addressed to H. Oliver Gao.

Reprints and permissions information is available at http://www.nature.com/reprints

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.