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Quantifying diurnal changes in NO_2 due to COVID-19 stay-at-home orders in New York City

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ABSTRACT

Introduction: Policy responses to the COVID-19 pandemic, such as the NY on Pause stay-at-home order (March 22 – June 8, 2020), substantially reduced traffic and traffic-related air pollution (TRAP) in New York City (NYC). We evaluated the magnitude of TRAP decreases and examined the role of modifying factors such as weekend/weekday, road proximity, location, and time-of-day.

Methods: Hourly nitrogen dioxide (NO_2) concentrations from January 1, 2018 through June 8, 2020 were obtained from the Environmental Protection Agency's Air Quality System for all six hourly monitors in the NYC area. We used an interrupted time series design to determine the impact of NY on Pause on NO_2 concentrations, using a mixed effects model with random intercepts for monitor location, adjusted for meteorology and long-term trends. We evaluated effect modification through stratification.

Results: NO_2 concentrations decreased during NY on Pause by 19% (-3.2 ppb, 95% confidence interval [CI]: -3.5, -3.0), on average, compared to pre-Pause time trends. We found no evidence for modification by weekend/weekday, but greater decreases in NO_2 at non-roadside monitors and weak evidence for modification by location. For time-of-day, we found the largest decreases for 5 am (27%, -4.5 ppb, 95% CI: -5.7, -3.3) through 7 am (24%, -4.0 ppb, 95% CI: -5.2, -2.8), followed by 6 pm and 7 pm (22%, -3.7 ppb, 95% CI: -4.8, -2.6 and 22%, -4.8, -2.5, respectively), while the smallest decreases occurred at 11 pm and 1 am (both: 11%, -1.9 ppb, 95% CI: -3.1, -0.7).

Conclusion: NY on Pause's impact on TRAP varied greatly diurnally. Decreases during early morning and evening time periods are likely due to decreases in traffic. Our results may be useful for planning traffic policies that vary by time of day, such as congestion tolling policies.

Introduction

Policy responses to the COVID-19 pandemic, such as large-scale stay-at-home orders, were implemented across the United States (US) and globally in 2020 (Brodeur et al., 2021). The pandemic and its response policies substantially disrupted daily life, with major impacts on the labor market (Brodeur et al., 2021), economies (Brodeur et al., 2021), and transportation systems (Sun et al., 2021, Yasin et al., 2021), among other systems. In New York City (NYC), the most populous city in the US and the site of an early COVID-19 outbreak (The New York Times 2021), stay-at-home orders were implemented on March 22, 2020 (Governor Cuomo Signs March 20 2020). Called NY on Pause, the policy closed all non-essential businesses, prohibited non-essential gatherings of any size, advised individuals to stay home, and required social distancing (Governor Cuomo Signs March 20 2020).

Numerous studies have shown the impact of stay-at-home orders on traffic and traffic-related air pollutants (TRAP), both in the US and globally (Yasin et al., 2021, Burns et al., 1994, Dey et al., 2021, Bauwens et al., 2020, Dutheil et al., 2020, Hudda et al., 2020, Li et al., 2020, Patel et al., 2020, 13, Siddiqui et al., 2020, Tobías et al., 2020, Pitiranggon et al., 2022, Fu et al., 2020, Bian et al., 2021, Elshorbany et al., 2021). Traffic decreased dramatically in many regions of the world (Yasin et al., 2021, Schuman, 2020, Bian et al., 2021). Pollutants that are emitted directly by traffic (primary pollutants), such as black carbon (Hudda et al., 2020, Patel et al., 2020, Tobías et al., 2020), NO_2 (Burns et al., 1994, Dey et al., 2021, Bauwens et al., 2020, Dutheil et al., 2020, Li et al., 2020, Patel et al., 2020, Siddiqui et al., 2020, Tobías et al., 2020, Pitiranggon et al., 2022, Fu et al., 2020, Elshorbany et al., 2021), and particulate matter (PM) (Hudda et al., 2020, Li et al., 2020, Patel et al., 2020, Tobías et al., 2020, Pitiranggon et al., 2022, Fu et al., 2020), tended to decrease with traffic. These findings have been more consistent for NO_2 (Dey et al., 2021, Tobías et al., 2020, Fu et al., 2020), an established tracer for TRAP (Beckerman et al., 2008) that tends to correlate strongly with traffic

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(Kendrick et al., 2015). However, not all air pollutants decreased during stay-at-home orders; studies have shown that ozone, a secondary pollutant formed from the chemical reaction of volatile organic compounds (VOCs), NO_x (NO_2 and NO), and sunlight (Jhun et al., 2015), generally increased (Li et al., 2020, Patel et al., 2020, Tobías et al., 2020, Fu et al., 2020).

Understanding decreases in primary TRAP is important, considering the negative health effects associated with TRAP. For example, epidemiologic studies have connected different primary traffic pollutants with increased risk of stroke (Shah et al., 2015, Yorifuji et al., 2013), incident myocardial infarction (Hart et al., 2013, Nawrot et al., 2011), childhood asthma development (Khreis et al., 2017), asthma exacerbation (Lai et al., 2018), certain cancers (Cohen et al., 2018), pregnancy loss (Kioumourtzoglou et al., 2019), heart failure (Carey et al., 2016), all-cause mortality (Hart et al., 2013, Hoek et al., 2013), and decreases in cognition (de Prado Bert et al., 2018). In NYC, TRAP contributes to an estimated 320 deaths and 870 hospitalizations from traffic-related particulate matter $\leq 2.5\ \mu$m ($PM_{2.5}$) every year (Kheirbek et al., 2016).

Considering the negative impact of primary traffic pollutants on health, studying changes in air pollution as a result of stay-at-home orders is important not only in the context of understanding the effects of policy responses to the pandemic but also in projecting the impact of future large-scale traffic interventions in cities. For example, NYC is in the process of implementing a congestion pricing policy, which would charge drivers a toll to enter part of Manhattan (Gold, September 29, 2021). Various congestion pricing schemes have been implemented and proposed in cities globally, but NYC is the first US city to implement such a policy (Lehe, 2019). One main goal of the policy is to decrease traffic congestion; if successful, we could expect corresponding decreases in primary traffic pollutants, such as NO_2 (Gold, September 29, 2021, United States Department of Transportation 2022, Metro Transit Authority 2022). Understanding decreases in traffic and NO_2 during the pandemic is helpful in projecting impacts of a congestion pricing policy or other traffic interventions (see, e.g., Perera et al., 2020) that may cause a similar change in traffic patterns. An effective congestion pricing policy (either in NYC or in other cities) may both decrease traffic overall and attenuate rush hour peak traffic, especially if tolls are higher during rush hours as is the case in other cities such as Stockholm (Lehe, 2019). This change in traffic patterns would be similar to what we have previously shown occurred in NYC during NY on Pause (Shearston et al., 2021), and thus we might expect similar changes in NO_2.

Previous studies in NYC have shown that traffic decreased during NY on Pause (Pitiranggon et al., 2022, Bian et al., 2021, Shearston et al., 2021), and correspondingly, primary traffic pollutants also decreased (Pitiranggon et al., 2022, Fu et al., 2020, Zangari et al., 2020, Shehzad et al., 2021). However, none of the air pollution studies describes diurnal changes in NO_2, only two investigate differences by location, and none separate changes at roadside monitors from changes at non-roadside monitors. We contribute to this body of knowledge by addressing each of these research gaps. The objectives of this analysis are to assess: (1) the overall impact of NY on Pause on NO_2 concentrations in NYC, and (2) effect modification by (a) weekday/weekend, (b) roadside versus non-roadside monitors, (c) time-of-day, and (d) geographic location. We hypothesized that (1) NO_2 would decrease overall on the order of ~25%, given that traffic decreased by approximately 48% (Bian et al., 2021) and traffic is not the only source of NO_2, (2a) decreases would be greater for weekdays rather than weekends given the larger pandemic-related traffic declines during weekdays (Shearston et al., 2021), (2b) roadside monitors would have greater decreases considering their proximity to traffic sources and the short NO_2 decay distance (~ 300 m) (Beckerman et al., 2008), (2c) greater decreases would be seen for NO_2 in morning hours when NO_2 has been found to have stronger correlations with traffic (Kendrick et al., 2015), and (2d) variation by geographic location would be observed, given that monitors represent very different traffic areas in NYC.

Methods

Study design

We used an interrupted time series (ITS) study design (Bernal et al., 2017) to evaluate the impact of NY's stay-at-home order, "NY on Pause," on TRAP, using data from January 1, 2018 through June 8, 2020. Briefly, in the ITS study design, an underlying trend in the given time series is identified, and the degree to which an intervention or policy "interrupts" the existing time trend is evaluated (Bernal et al., 2017). In this design, there is no control group, as the continuation or interruption of a pre-existing trend is instead evaluated. This study design was selected given that the intervention/policy being evaluated occurred at the population level, and so an appropriate control group does not exist. As the intervention period, we used the date NY on Pause went into effect (March 22, 2020) through the date the policy ended for NYC (June 8, 2020), when the city entered Phase 1 of the state's reopening plan (Gold and Stevens, 2020). NO_2, a primary pollutant emitted from vehicles and a well-known marker of vehicular traffic due to its moderate to high correlation with multiple traffic-related pollutants, was used to represent TRAP (Beckerman et al., 2008).

Data sources and definitions

NO_2 Data

Hourly NO_2 concentrations were obtained from the Environmental Protection Agency (EPA) Air Quality System (AQS) (United States Environmental Protection Agency 2020). We used data from all six hourly monitors maintained by the New York State Department of Environmental Conservation and New Jersey State Department of Environmental Protection in the NYC region (Fig. 1) to represent NYC. These stations collect data using continuous monitors, and report hourly averages to the EPA AQS following designated reference and equivalent methods used for air quality regulation (Table 1). Raw data accessed from the EPA AQS API was used in this analysis. No data transformation was applied. Monitor locations included two near-road sites (Queens College Near Road, Fort Lee Near Road) to capture emissions from roads. Two locations in New Jersey (NJ) were included as they are near major entrances to Manhattan from NJ, and were therefore likely impacted by NY on Pause.

Meteorological data

Hourly weather information was obtained from the National Aeronautics and Space Administration (NASA) North American Land Data Assimilation System's primary forcing data (Xia). Meteorological data included: total precipitation, short-wave radiation flux downwards, surface pressure, specific humidity, temperature, and zonal and meridional wind vectors. Wind data were then converted to continuous wind speed and an eight-category meteorological wind direction variable (N, NE, E, SE, S, SW, W, NW). Meteorological data were included in statistical models as potential confounders of the relationship between NY on Pause and NO_2 concentrations because they vary with time in a manner similar to traffic and directly impact NO_2 concentrations through atmospheric dispersion and influence on NO_x chemical reactivity.

Long-term trends

To account for long-term (greater than 3 years) and seasonal trends in NO_2 concentrations not fully captured by the ITS design, models were additionally adjusted for year and month as categorical variables.

Statistical analyses

First, descriptive statistics for all variables were conducted. Next, we constructed a linear mixed effects model with random intercepts for each monitor, serving as the main model. While the distribution of NO_2 was mildly right skewed, we chose not to scale or log transform NO_2

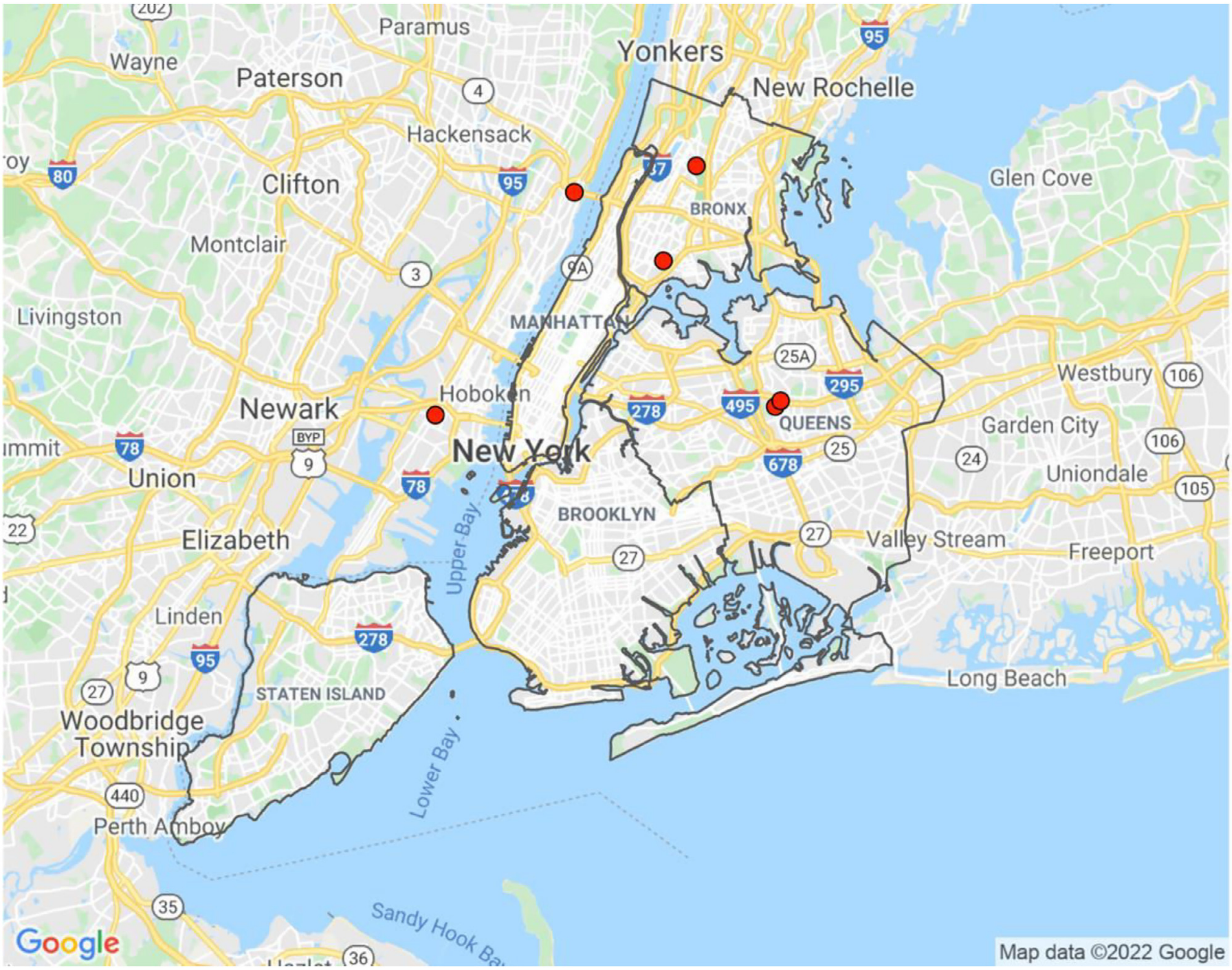

Fig. 1. Map of the six hourly NO_2 AQS monitors in the NYC area (red circles). Black lines outline the five boroughs of NYC, overlaid on a Google roadmap (Map data © 2022 Google).

Table 1
EPA AQS monitors included in the analysis.

Monitor Name	Monitor ID	EPA Measurement Scale	Description	Method Reference ID[a]
Pfizer Lab Site	36-005-0133	Urban scale	On campus of botanical garden	EQNA-0514-212
IS 52	36-005-0110	Urban scale	In the South Bronx neighborhood, an area with greater traffic	RFNA-1289-074
Queens College Near Road	36-081-0125	Middle scale	At Queens College campus near Long Island Expy	EQNA-0512-200
Queens College 2	36-081-0124	Neighborhood	At Queens College campus	RFNA-1289-074
Jersey City	34-017-1002	Neighborhood	In Journal Square neighborhood, inland from the Hudson River	RFNA-1194-099
Fort Lee Near Road	34-003-0010	Microscale	At entrance to George Washington bridge; major entrance to Manhattan from New Jersey	RFNA-1289-074

[a] More details on methods can be found here: https://www.epa.gov/system/files/documents/2021-12/designated-referene-and-equivalent-methods-12152021.pdf

or meteorological covariates in order to facilitate interpretation of the results for policymakers. We modeled all variables linearly and included all meteorological variables in the model regardless of their statistical significance. Additionally, we included year and month to account for long-term and seasonal trends, and time of day (a 24-level categorical variable) and day of week (a 7-level categorical variable) to account for potential confounding by other NO_2 sources that covaried with traffic. We assumed that NY on Pause would cause an immediate and sharp decrease in NO_2 concentrations and used the ITS study design to model a step change in NO_2 concentrations. We therefore constructed two additional variables: a binary variable to represent the intervention, NY on Pause, coded as 0 from January 1, 2018 through March 21, 2020, and 1 from March 22, 2020 through June 8, 2020; and a continuous variable representing time elapsed since the beginning of the analysis (January 1, 2018).

To assess effect modification by weekend/weekday status, we ran stratified models by weekend and weekday, which were otherwise the same as described above. Similarly, to assess differences in NO_2 concentrations measured at roadside vs. non-roadside monitors, we stratified by roadside vs non-roadside status. To assess diurnal changes in NO_2 concentrations, we ran stratified models by time of day. Short-wave radiation flux downwards was removed from the models for 8 pm to 4 am because it was always 0 W/m^2, but the model was otherwise the same. Effect estimates from stratified models were compared using the Wald test and Cochran test to determine if estimates were significantly different, using a p-value cutoff of 0.05 (Kaufman and MacLehose, 2013). To evaluate potential variation in effect estimates by monitor location, we added a random slope for monitor ID to the main model, and then compared Akaike information criterion (AIC)s between the two models (random intercepts only vs. random intercepts and slopes) and ran a likelihood ratio test to determine if the models were significantly different at $p = 0.05$.

We present model results as percent decreases in pre-NY on Pause NO_2 concentrations, calculated by dividing the effect estimate by the mean NO_2 concentration from January 1, 2018 through March 21, 2020 and multiplying by 100%.

Sensitivity analyses

To confirm the stability of our results, several sensitivity analyses were performed. First, in the subset of observations for which we had $PM_{2.5}$ data (n = 86,093; 70% of observations in the main model), we added hourly non-traffic $PM_{2.5}$ concentrations to the main model to account for potential confounding by other air pollution sources that may covary with traffic and thus traffic-related NO_2 (e.g., industries that emit both $PM_{2.5}$ and NO_2). To implement this adjustment, we regressed $PM_{2.5}$ on NO_2 (to isolate traffic-related $PM_{2.5}$) and added the residuals (non-traffic-related $PM_{2.5}$) to the main model as a covariate. Second, we imputed missing NO_2 observations (n = 5,708; 4.5%) using the mean NO_2 value for the year, season, time of day, and day of week of each missing observation, and repeated the main analysis. Third, we removed potential outliers (defined as any observations with a model residual value greater than 3 standard deviations from the mean) and repeated the main analysis. Fourth, we repeated the main analysis using March 20 as the start date for NY on Pause, as this was when the policy was announced by the governor (Governor Cuomo Signs, 2020), prompting a decrease in traffic two days before policy implementation (Bian et al., 2021). Fifth, we removed the two monitors from New Jersey and repeated the main analysis, as New Jersey was subject to its own stay-at-home order (Governor Murphy Annoucnes Statewide Stay at Home Order March 21 2020) which may have influenced NO_2 concentrations at those monitors. Finally, we conducted detrending and meteorological normalization to account for short- and long-term trends and meteorology rather than adjusting for these variables in the mixed effects model, and repeated the main analysis.

All analyses were conducted in R version 4.1.1 R Core Team, 2021. The nlme package (nlme 2021) was used to run the mixed effect models. Code to recreate all analyses in this manuscript can be found here: https://github.com/jenni-shearston/NYonPAUSE-NO2-ITS

Results

NO_2 concentrations from January 1, 2018 through June 8, 2020 followed the expected seasonal pattern, with increased concentrations over the winter months and decreased concentrations over the summer months (Fig. 2). Descriptive statistics for NO_2 concentrations and weather parameters before and during NY on Pause are shown in Table 2. Briefly, unadjusted NO_2 concentrations were lower during NY on Pause (mean = 10.9 ppb; standard deviation [sd] = 7.4 ppb) as compared to the period before (mean = 16.8 ppb; sd = 10.5 ppb). Weather parameters remained similar across the two periods, with the exception of short-wave radiation flux downwards, which—given the absence of darker winter months during NY on Pause—was expected to be higher during stay-at-home orders. Additionally, wind roses show some difference in wind patterns between the pre-NY on Pause and NY on Pause periods (Supplemental Fig. 1). A histogram of the NO_2 concentrations showed a mildly right skewed distribution (Supplemental Fig. 3).

Using the fully adjusted ITS model, we found that NY on Pause was followed by a significant 19% decrease in pre-NY on Pause NO_2 concentrations (-3.2 ppb, 95% confidence interval [CI]: -3.5, -3.0) (Table 3).

Table 2
Pre vs. during intervention NO_2 concentrations and weather parameters.

Parameter	Pre-intervention		During-intervention	
	Mean	SD	Mean	SD
NO_2 (ppb)	16.8	10.5	10.9	7.4
Hourly precipitation (mm/hr)	0.12	0.56	0.09	0.41
Short-wave radiation flux downwards (W/m^2)	178.0	255.6	235.3	292.5
Specific humidity (g/kg)	7.9	5.0	6.8	3.0
Surface pressure (kPa)	101.5	0.8	101.2	0.8
Temperature (°C)	11.7	9.9	11.8	5.6
Wind speed (m/s)	5.2	2.7	5.2	2.6

Table 3
Effect of NY on Pause on hourly NO_2 concentrations (ppb) in NYC.

	Percent Decrease[c]	Effect Estimate	95% Confidence Interval
Overall effect[a]	19.0%	-3.2	-3.5, -3.0
Weekdays[b]	19.0%	-3.2	-3.5, -2.9
Weekends[b]	19.0%	-3.5	-3.9, -3.0
Roadside monitors only[a]	16.1%	-2.7	-3.1, -2.3
Non-roadside monitors only[a]	20.2%	-3.4	-3.7, -3.1

[a] Adjusted for day of week, time of day, month, year, wind direction, wind speed, temperature, precipitation, downward flux solar radiation, specific humidity, and surface pressure
[b] Not adjusted for day of week
[c] Percentage of pre-NY on Pause NO_2 concentrations

Model diagnostic plots can be found in the supplemental material (Supplemental Figs. 4-7) and in the R script accompanying this manuscript (2_02_models_no2-its_manuscript, Section 2). Decreases during weekend days vs weekday days were very similar to the overall effect and had insignificant Wald and Cochran test statistics, indicating no effect modification. In contrast, we found evidence for effect modification by roadside vs non-roadside monitors, where non-roadside monitors had larger decreases in NO_2 concentrations compared to roadside monitors (non-roadside = 20.2% [-3.4 ppb], 95% CI: -3.7, -3.1; roadside = 16.1% [-2.7], 95% CI: -3.1, -2.3; p-value < 0.05).

NY on Pause had differential impacts on NO_2 concentrations depending on the hour of day, although there were significant decreases in NO_2 for all hours (Fig. 3). The largest decreases were on the order of ∼ 22 to 27% and occurred for 5 am (26.8% or -4.5 ppb, 95% CI: -5.7, -3.3), 6 am (27.4% or -4.6 ppb, 95% CI: -5.9, -3.4), and 7 am (23.8% or -4.0 ppb, 95% CI: -5.2, -2.8) followed by 6 pm (22.0% or -3.7 ppb, 95% CI: -4.8, -2.6) and 7 pm (22.0% or -3.7 ppb, 95% CI: -4.8, -2.5). The smallest decreases occurred for the hours of 11pm and 1am (both: 11.3% or -1.9 ppb, 95% CI: -3.1, -0.7). Again, both Wald and Cochran tests were significant ($p < 0.05$), providing further evidence of effect modification by hour of day.

We found weak evidence for modification by monitor location, as adding random slopes to the main model caused the AIC to decrease very slightly (although significantly; $p = 0.0026$), with random slopes clustering near the fixed effect (Supplemental Fig. 2).

Results from sensitivity analyses were similar to the main results. In the subset of data with available $PM_{2.5}$ concentrations, adding $PM_{2.5}$ to the model resulted in a slightly attenuated main effect (a 17.9% decrease or -3.0 ppb, 95% CI: -3.2, -2.7). While this effect estimate is not directly comparable to the main analysis, results suggest that $PM_{2.5}$ had minimal impact on our results. Imputing missing NO_2 concentrations, removing NO_2 concentrations greater than 3 standard deviations from the mean, changing the start date of the intervention to March 20 rather than March 22, removing NJ monitors, and conducting detrending and meteorological normalization all resulted in findings very similar to those of the main model (results not shown).

Overall, we found that NY on Pause had a substantial impact on NO_2 concentrations, resulting in a larger Spring seasonal decrease than

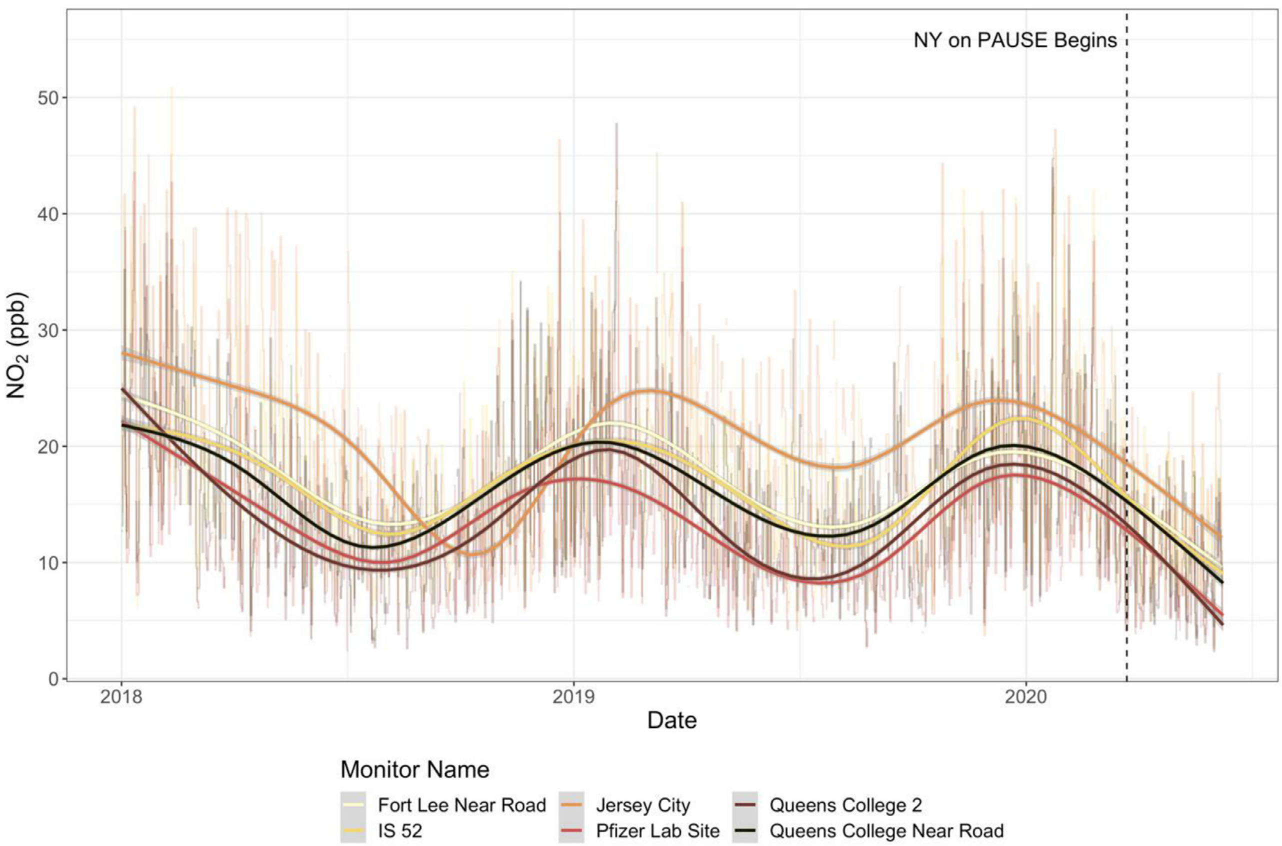

Fig. 2. Time series plot of daily NO_2 concentrations from January 1, 2018 through June 8, 2020. Daily rather than hourly concentrations were used for ease in visualization. The dashed, vertical line indicates the beginning of the stay-at-home order, NY on Pause, on March 22, 2020. Colors indicate the six monitors in the NYC area, and solid-colored lines represent the smoothed average for the entire study period.

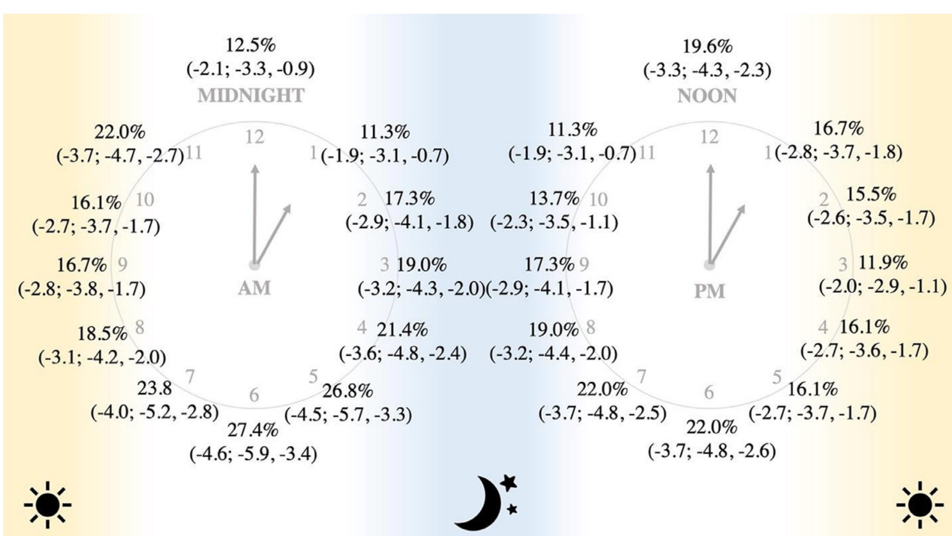

Fig. 3. Percent decrease in pre-NY on Pause concentrations, effect estimates, and 95% confidence intervals describing the impact of NY on Pause on NO_2 (ppb) concentrations in NYC, stratified by hour. Models were adjusted for day of week, month, year, wind direction, wind speed, temperature, precipitation, specific humidity, and surface pressure. Models for 5 am to 7 pm were additionally adjusted for downward flux solar radiation.

would otherwise be expected. In Fig. 4, predicted NO_2 concentrations for both the counterfactual scenario where NY on Pause was not enacted and the actual scenario are shown, depicting the lower-than-expected NO_2 concentrations during the NY on Pause period.

Discussion

NY on Pause caused an average decrease in NO_2 concentrations of 3.2 ppb (95% CI: -3.5, -3.0), or 19% of pre-intervention concentrations. However, this varied dramatically throughout the day, ranging from decreases of 27% to 11%, with the largest decreases observed for 5 to 7 am and 6 to 7 pm. This overlapped with the morning and evening rush hour travel peaks, which in NYC range from approximately 6 to 10 am in the morning and 4 to 8 pm in the evening (The Staten Island Ferry 2022, NJ Transit. Schedule Information. 2021, The Port Authority of New York and New Jersey 2022, Metro Transit Authority 2022). The smallest decreases occurred overnight at 11 pm and 1 am. The diurnal pattern of these decreases (larger during rush hour periods) suggests that commuter traffic, rather than trucks or freight traffic, may have been most impacted by the policy.

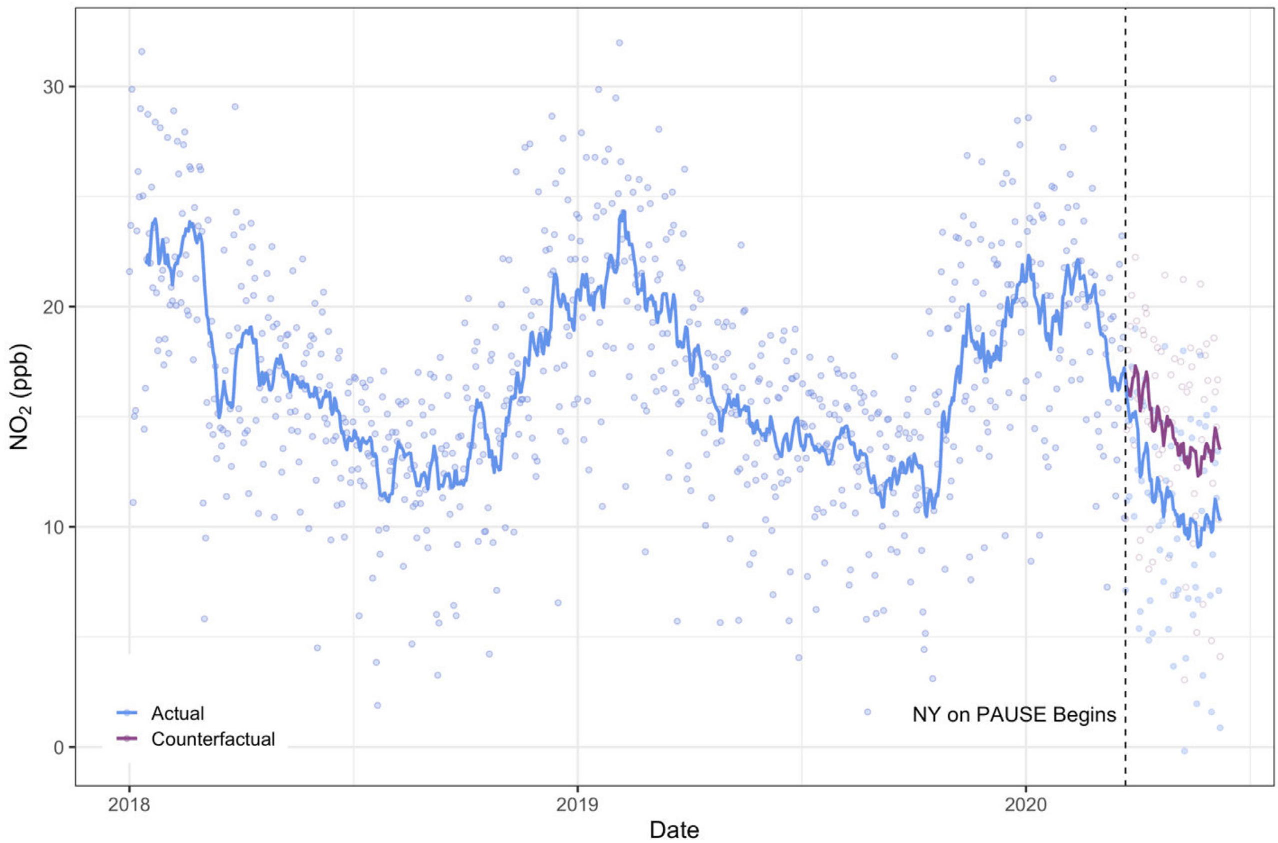

Fig. 4. Time series of daily mean NO_2 concentrations (dots) predicted from our mixed effects model and 14-day rolling averages (lines) for the actual NY on Pause scenario (blue) and the hypothetical counterfactual scenario where NY on Pause was not enacted (purple). The dashed, vertical line indicates the beginning of the intervention, NY on Pause, on March 22, 2020.

Our findings corroborate other studies evaluating the impact of the COVID-19 pandemic and stay-at-home orders on traffic-related air pollution in NYC. Using data from the New York City Community Air Survey, Pitiranggon et al., 2022 found a decrease in NO_2 of 29%, with larger changes occurring in the central business district area of Manhattan (Pitiranggon et al., 2022). While our study found a smaller decrease, Pitiranggon et al. used data with high spatial resolution and coverage in the central business district, an area that is not close to any of the air pollution monitors maintained by the state. This may explain our lower estimates and suggests that our findings may be biased towards the null. Fu et al (Fu et al., 2020) and Elshorbany et al (Elshorbany et al., 2021) also found decreases in NO_2 during stay-at-home orders, using a daily measure of NO_2 Air Quality Index and daily OMI satellite measurements of the NO_2 tropospheric column, respectively. They found decreases ranging from 33.7 to 50% in the NYC area. As each study used a different data source and slightly different comparison period, percentages are not directly comparable between studies; however, their consistency in direction and magnitude are reassuring. Of note, Zangari et al., 2020 did not find a significant impact of stay-at-home orders on NO_2 concentrations using a linear time lag model (Zangari et al., 2020). However, the authors compared linear trends in NO_2 concentrations for January through May for several calendar years, treating 2020 as the intervention year, rather than assessing the impact of the stay-at-home order itself. Additionally, there were many more pre-intervention NO_2 observations included in the time series for 2020 than during-intervention observations, likely biasing the trend towards pre-intervention concentrations.

Additionally, several studies have found that traffic, the primary source of NO_2, also decreased dramatically as a result of NY on Pause (Pitiranggon et al., 2022, Bian et al., 2021, Shearston et al., 2021). Our previous analysis of congestion levels in Manhattan found not only an overall decrease in congestion but also a large depression of the morning and evening rush hour peaks (Shearston et al., 2021). Similarly, Pitiranggon et al., 2022 found decreases in daytime traffic speeds across NYC, with large decreases in travel times during morning rush hour at the Lincoln Tunnel, a major entrance to Manhattan and its central business district (Pitiranggon et al., 2022). Both studies found smaller decreases for overnight times (Pitiranggon et al., 2022, Shearston et al., 2021). These findings support the results of our time-of-day analysis; as the largest decreases in traffic occur during the day and during rush hour peaks, it makes sense that NO_2, as a tracer of TRAP and primary traffic pollutant, would also follow a similar pattern. This is also consistent with a pre-pandemic study of diurnal NO_2 in New York, which also described peaks in NO_2 during similar times of day– in the winter and spring from approximately 6 to 9 am, in conjunction with a similarly timed peak in NO, and in the evening from 3pm to midnight (with a broad and low NO peak) (Civerolo et al., 2017). This diurnal pattern resulted from a combination of increased primary emissions during rush hour, atmospheric chemistry as NO_x begins reacting with sunlight to form ozone later in the day, and a lower planetary boundary layer in the mornings and evenings (Civerolo et al., 2017). Thus, it makes sense that we saw the largest decreases in NO_2 during the same rush hour periods, not only due to decreases in traffic emissions during these peak time periods, but also because the lower planetary boundary layer and weaker sunlight in early morning and evening hours might amplify decreases compared to midday when the boundary layer is higher (diluting impacts) (Jhun et al., 2015).

While we found weak evidence for variation in NO_2 reductions by location, we were limited by the six monitors included in the study. These monitors represented varying types of urban areas and spatial scales, with some being located right next to major roads and some in greener areas further from roads, however, using only 6 monitors may not adequately capture the heterogeneity in NO_2 concentrations. For example, Pitiranggon et al., 2022 found substantial geographic variation within NYC, using highly spatially resolved data (Pitiranggon et al., 2022). Nonetheless, we were able to detect that roadside monitors had smaller decreases in NO_2 than non-roadside monitors. The two roadside monitors were located on major interstate highways (I95 at the George Washington Bridge and I296 at Queens College) and so may have had proportionally more freight and delivery traffic, as well as overall a smaller reduction in traffic, considering their nature as traffic arteries through the city.

The findings of our study have implications for future large-scale traffic policies that may be implemented in NYC. For example, a congestion pricing plan known as the Central Business District Tolling Program has been approved by New York State government and is in the early process of implementation (Gold, 2021). As with many such policies, a major potential benefit of the program is the decrease in traffic-related air pollution that may occur with a successful decrease in congestion and overall traffic. Our analysis of NO_2 changes in response to NY on Pause can be used to inform the design of tolling schemes for the congestion pricing policy and others. Following dramatic decreases in traffic congestion after NY on Pause, and especially decreases during peak rush hour time points, our current study correspondingly found the largest decreases in NO_2 during early morning and evening time periods, and the smallest decreases overnight. Larger decreases during rush hour peaks likely suggest that NY on Pause had a greater impact on commuter vehicles than trucks or freight vehicles. This is supported by vehicle counts from Port Authority bridge and tunnel crossings in NYC (Supplemental Table 1). In January and February of 2020, automobiles made up 91% of all crossings, while trucks made up 6-7%. In April, while counts of all types of vehicles decreased dramatically, the proportion of automobile to freight traffic also shifted: 87% of all crossings were automobiles, and 11% were trucks. These patterns were slightly stronger at the bridge and tunnel site that also included an NO_2 monitor (Fort Lee near road monitor): the George Washington Bridge. It is likely that the Congestion Pricing policy will also have a greater impact on commuter vehicles than freight trucks, as commuters can switch from private vehicles to public transit, while trucks/freight will still need to make deliveries.

While reductions in NO_2 occurred, it should be noted that several studies have found that ozone concentrations increased during stay-at-home orders (Li et al., 2020, Patel et al., 2020, Tobías et al., 2020, Fu et al., 2020), likely due to decreases in NO_x from traffic reductions, as NO scavenges ozone (especially during nighttime hours), leading to decreased ozone concentrations (Jhun et al., 2015). With a reduction in NO_x primary emissions from traffic, we may expect ozone to increase, especially if VOC concentrations do not decrease at similar magnitudes, as VOCs react with NO_x and sunlight to form ozone. This may be the case in NYC, where volatile consumer and industrial products also contribute substantially to VOCs (in addition to vehicular traffic) (Coggon et al., 2021). Accordingly, any traffic policy should also take non-linear ozone chemistry and VOC source contributions into consideration. To achieve NO_2 decreases in the range we report from NY on Pause with congestion reducing policies, this supports implementation of a tolling scheme that charges higher prices during early morning and evening time periods, aiming to both decrease total traffic and spread the overall amount of traffic throughout the day. Such variable tolling schemes have precedent in other major cities, including London and Stockholm, and are a common component of downtown congestion pricing schemes (Lehe, 2019).

In addition to implications for traffic policies in NYC, our study has implications for potential health interventions. Cardiovascular events like stroke and myocardial infarction can be triggered by traffic-related air pollution (Shah et al., 2015, Yorifuji et al., 2013, Hart et al., 2013, Nawrot et al., 2011). Understanding diurnal changes in NO_2 concentrations in NYC can thus lead to recommendations for people at risk of these events (and others) about when to partake in outdoor activities. However, changes in ozone and other pollutants should also be considered in these decisions, as they too are associated with adverse health outcomes (Soares and Silva, 2022, Guo et al., 2022, Liu et al., 2022).

Our study has several strengths and limitations. First, we had access to a clear policy implementation time point and adjusted for numerous covariates, such as meteorology and long-term and seasonal trends, which could have confounded the relationship between NY on Pause and NO_2 concentrations. As with other ITS designs, we cannot rule out the possibility that other factors led to the decrease in NO_2 concentrations, however, given the clear directive of the stay-at-home order and evidence from previous studies that NY on Pause in isolation dramatically impacted traffic (Bian et al., 2021), it is likely that the effect we found was most influenced by NY on Pause. However, there is still the possibility of residual confounding from other variables, especially those pertinent to the fate of atmospheric NO_2 (such as VOCs), and bias from specification of the start date of the NY on Pause intervention. To increase confidence in our results, we conducted several sensitivity analyses, finding our model specification robust to confounding by particulate matter, specification of the start date of the intervention, missingness of NO_2 concentrations, and exclusion of outlier NO_2 values. Second, we included NO_2 monitors from New Jersey in this analysis. Considering that New Jersey implemented its own version of stay-at-home orders, (Governor Murphy Annoucnes Statewide Stay at Home Order, 2020), NO_2 values from these stations likely represented traffic decreases caused by both NY on Pause and by New Jersey policies. Our sensitivity analysis removing New Jersey monitors supports this conclusion, as removing New Jersey monitors decreased the effect estimate by a modest 0.05 ppb. However, this impact was small. Third, we used diurnally resolved air pollution data, which allowed us to assess how NY on Pause impacted traffic-related air pollution at the hourly level and has important policy implications. However, our data had poor spatial resolution, relying upon only six monitors to represent the NYC area. This prevented us from making inferences about variation within NYC, and also may have biased our results toward the null, as we did not have a monitor located in one of the most traffic intensive areas of NYC, the central business district. Of particular concern, we only had two near-road sites. Importantly, poor spatial resolution prevented us from assessing disparities in air pollution reductions as a result of NY on Pause. We echo the calls of other researchers and advocates to predict and evaluate the impact of NY on Pause and future policies like congestion pricing through an environmental justice lens, ensuring that the benefits and costs of new policies are equitably shared. Such work will necessitate the collection and use of highly spatially resolved data.

Conclusion

New York's stay-at-home order (NY on Pause) implemented in response to the COVID-19 pandemic decreased NO_2 concentrations by an average of 3.2 ppb (19%), with substantial diurnal variation. The greatest decreases in NO_2 concentrations were seen from 5 to 7 am and 6 to 7 pm, and lowest decreases for 11 pm and 1 am. Our findings could suggest that other large-scale policies that aim to reduce traffic such as NYC's planned congestion pricing policy may result in substantial NO_2 decreases; however, changes in other pollutants such as ozone should also be considered to assess overall improvements in air quality. Paired with highly spatially resolved air pollution data, our results could be used to investigate equity in implementation of NY on Pause and other future traffic and traffic-related air pollution policies.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Jenni A. Shearston: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft. **Ilan Cerna-Turoff:** Validation, Writing – review & editing. **Markus Hilpert:** Conceptualization, Supervision, Writing – review & editing. **Marianthi-Anna Kioumourtzoglou:** Conceptualization, Methodology, Supervision, Writing – review & editing.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.heha.2022.100032.

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