Title
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Journal
GeoHealth, 8(12)

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Publication Date
2024-12-01

DOI
10.1029/2024GH001050

Peer reviewed

GeoHealth

RESEARCH ARTICLE
10.1029/2024GH001050

Special Collection:
Geospatial data applications for environmental justice

Key Points:
- We evaluated the variable impact of New York on Pause on traffic congestion by neighborhood inequality in New York City
- Prior to New York on Pause, less marginalized and burdened census tracts tended to have higher levels of traffic congestion
- During New York on Pause, this trend reversed: more marginalized and burdened census tracts had smaller decreases in congestion

Supporting Information:
Supporting Information may be found in the online version of this article.

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Citation:
Shearston, J. A., Saxena, R., Casey, J. A., Kioumourtzoglou, M.-A., & Hilpert, M. (2024). Variation in the impact of New York on pause on traffic congestion by racialized economic segregation and environmental burden. *GeoHealth*, *8*, e2024GH001050. https://doi.org/10.1029/2024GH001050

Received 29 MAR 2024
Accepted 2 AUG 2024

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Variation in the Impact of New York on Pause on Traffic Congestion by Racialized Economic Segregation and Environmental Burden

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Abstract During the 2019 coronavirus pandemic, stay-at-home policies such as New York's (NY) NY on Pause dramatically reduced traffic congestion. Despite high traffic burden in NY's environmental justice communities, this reduction has not been evaluated through an environmental justice lens—our objective in this analysis. We obtained census tract-level traffic congestion data from Google traffic maps hourly for 2018–2020. We defined congestion as the percent of streets in a census tract with heavy traffic (red- or maroon-color). We used the Index of Concentration at the Extremes (ICE) to measure racialized economic segregation and the CDC's Environmental Justice Index (EJI) as a measure of combined environmental, social, and chronic disease burden. We divided census tracts into quintiles of ICE and EJI and used linear mixed models stratified by ICE and EJI quintile in an interrupted time series design. Prior to NY on Pause, less marginalized and burdened census tracts (Q5) tended to have higher levels of traffic congestion; during NY on Pause, this trend reversed. For both ICE and EJI, more marginalized and burdened (Q1–Q2 vs. Q4–Q5) tracts had smaller absolute decreases in percent traffic congestion. For example, percent traffic congestion in ICE Q5 decreased by 7.8% (% change: −36.6%), but in Q1, it decreased by 4.2% (% change: −51.7%). NY on Pause, while protecting residents during COVID-19, may have resulted in inequitable reductions in traffic congestion. It is critical that such inequities are measured and acknowledged so that future policies to reduce traffic congestion and respond to pandemics can enhance equity.

Plain Language Summary Stay-at-home orders implemented in response to the COVID-19 pandemic dramatically reduced traffic congestion in cities. This study reports variation in traffic congestion reductions by levels of neighborhood segregation and environmental burden in New York City. Using traffic congestion data from Google traffic maps, we defined "congestion" to mean the percent of streets in a neighborhood that were colored red or maroon on the traffic map. We found that prior to stay-at-home orders, less marginalized and environmentally burdened neighborhoods tended to have higher levels of traffic congestion. However, during stay-at-home orders, this trend reversed, and more marginalized and environmentally burdened neighborhoods had smaller decreases in traffic congestion. While stay-at-home orders protected residents in New York City during COVID-19, they may have resulted in inequitable reductions in traffic congestion. It is important that we measure and acknowledged these inequities, so that future policies to reduce traffic congestion and respond to pandemics can avoid inequitable outcomes.

1. Introduction

NYC was one of the first epicenters of the COVID-19 pandemic in the US (Kariya, 2020). Many interventions were used to curb the spread of COVID-19, including New York State's New York on Pause policy (NY on Pause) (Governor's Press Office, 2020). NY on Pause was an executive order put into effect on 22 March 2020 by Governor Andrew Cuomo, mandating the closure of all non-essential businesses, implementation of social distancing practices by businesses and individuals, and the cancellation of non-essential gatherings (Governor's Press Office, 2020). Previous studies at the county or city level or using counts at specific bridges and tunnels showed that NY on Pause dramatically decreased traffic in NYC, on the order of 48%–66% (Bian et al., 2021; Schuman, 2020; Shearston et al., 2021). However, these studies lacked within-city spatial resolution.

Funding acquisition: Jenni A. Shearston, Marianthi-Anna Kioumourtzoglou, Markus Hilpert
Methodology: Markus Hilpert
Resources: Markus Hilpert
Software: Markus Hilpert
Supervision: Marianthi-Anna Kioumourtzoglou, Markus Hilpert
Validation: Roheeni Saxena
Visualization: Jenni A. Shearston, Joan A. Casey
Writing – original draft: Jenni A. Shearston
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Within NYC, there was likely geographic inequity in traffic decreases during NY on Pause due to three reasons. First, NYC has substantial spatial variability in socioeconomic status (SES) and concentration of racial and ethnic groups, traffic congestion, and industry type by neighborhood (New York City Planning, 2020), allowing for differential impacts by SES and race/ethnicity. Second, some neighborhoods have higher proportions of essential workers and more industries deemed essential (i.e., allowed to stay open during NY on Pause), such as the Port Morris/Mott Haven area of the South Bronx, where the greatest proportion of land use is for manufacturing and industry (18%) (New York City Planning, 2020) and a large proportion of essential workers live (Kim et al., 2021). Third, neighborhoods like Port Morris/Mott Haven may have seen smaller decreases in traffic during NY on Pause because workers may have continued traveling to those neighborhoods to report to essential industries. Additionally, many trucking-intensive industries (e.g., grocery warehouses, waste management) (New York State, 2020) were deemed essential, and so heavy truck traffic would have continued in neighborhoods with many trucking-intensive industries like Port Morris/Mott Haven and the South Bronx.

Certain persistently marginalized populations were also at greater risk of exposure to COVID-19 and of having worse health outcomes when infected. Neighborhoods with a higher proportion of people of color and those with more essential industries/workers had less capacity to socially distance and higher COVID-19 disease burden (Carrión et al., 2021; Sy et al., 2021). Additionally, studies have found that exposure to air pollution contributes to worse COVID-19-related health outcomes (Marquès & Domingo, 2022), and many communities with lower SES and higher proportion of people of color experience greater air pollution exposures (though this is not always true for NYC) (Clougherty et al., 2013; Kheirbek et al., 2013). Thus, it is important to evaluate whether the intervention put in place to curb the spread of COVID-19 (NY on Pause) was equally impactful in neighborhoods with higher proportions of people of color, lower SES, and higher environmental and chronic disease burden. Since the main objective of NY on Pause was to respond to the COVID-19 public health emergency, the policy was not subject to a development process that could have predicted and accounted for potential inequitable impacts. Given this, it is critical that the policy be evaluated for inequitable impacts post-implementation, to ensure that future policies to reduce traffic congestion and respond to pandemics can avoid exacerbating longstanding inequities. However, none of the aforementioned NY on Pause traffic studies have evaluated variation in traffic changes at the neighborhood-level spatial resolution so that environmental justice could be considered.

We focus on traffic congestion, rather than a single pathway through which traffic impacts people (e.g., noise or air pollution) because we wanted to capture the impact of traffic more holistically on communities. Traffic contributes to negative quality of life and health impacts through several pathways. It is a source of traffic-related air pollution (TRAP) (Heydari et al., 2020) and noise (E. Y. Lee et al., 2014) and can result in physical injuries through collisions and decreased safety for adults and children trying to cross streets or access neighborhoods resources (Chong et al., 2018; Naumann et al., 2010; Retallack & Ostendorf, 2019; Wang et al., 2023). Traffic congestion is also a source of stress in neighborhoods (Haider et al., 2013; Matthews & Yang, 2010) and contributes to sleep disturbance through noise (Ouis, 1999). Congestion increases TRAP through repeated acceleration and deceleration and increased vehicle volume (Falcocchio et al., 2015; Wang et al., 2023; Zhang & Batterman, 2013). Furthermore, traffic congestion has high economic costs: it results in additional gasoline consumption and wasted time, costing the US economy an estimated $81 billion in 2022 (Pishue, 2023). To better incorporate all of these pathways, we focus on traffic congestion as our main outcome.

In this paper, we evaluate how NY on Pause impacted traffic congestion in parts of NYC through an environmental justice lens, to inform future pandemic responses and large-scale traffic interventions. We define environmental injustice as an imbalance in the distribution of hazards or benefits from an environmental exposure (Ervin & Bell, 2004)—in this case, an imbalance in the benefit of reduced traffic congestion, which contributes to worse health outcomes overall and from COVID-19, serves as a proxy for social distancing, and may indicate increased risk of acquiring COVID-19. We conceptualized neighborhoods as census tracts and classified tracts using quintiles of two established metrics of inequality: (a) racialized economic segregation, using the Index of Concentration at the Extremes (ICE) (Krieger et al., 2017), and (b) a combined measure of environmental, social, and chronic disease burden, using the Centers for Disease Control and Prevention/Agency for Toxic Substances and Disease Registry (CDC/ATSDR) Environmental Justice Index (EJI) (Centers for Disease Control and Prevention and Agency for Toxic Substances Disease Registry, 2022). Previous studies have found that racialized economic segregation was associated with disparities in death rates from COVID-19, cases of COVID-19, positive test rates of COVID-19, and lower testing rates (Brown et al., 2021; Chen & Krieger, 2021). We hypothesized that reductions in traffic congestion following the implementation of NY on Pause would vary by level

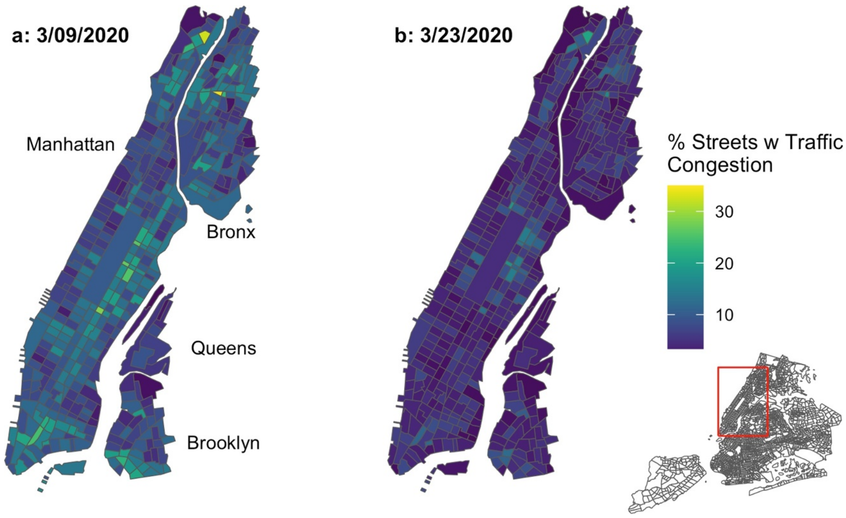

Figure 1. Choropleth map of traffic congestion pre and post NY on Pause. The map shows the daily mean percent of streets with traffic congestion on two Mondays: 2 weeks before (Panel a) and one day after (Panel b) NY on Pause went into effect. Spatial units are 2010 census tracts; the study area is indicated by the red box on the NYC inset map. Higher traffic congestion corresponds to lighter (yellower) shading, while lower congestion corresponds to darker shading.

of neighborhood inequality, such that neighborhoods with greater marginalization and burden would have smaller reductions in traffic congestion.

2. Materials and Methods

2.1. Traffic Congestion Data

We obtained Google traffic maps every hour from 1 January 2018, through 31 December 2020 for a portion of NYC including all of Manhattan, the South Bronx, and a small part of Western Queens and Brooklyn (see geographic extent in Figure 1; data were obtained for a different study). The process of obtaining and cleaning the traffic data has been documented in prior publications (Hilpert et al., 2019, 2021). Briefly, we first specified the centroid of the downloaded array of traffic map tiles, the number of pixels along one side of each square map tile, the zoom level (resolution), and the total number of map tiles to obtain. Details including equations for determining the appropriate zoom level and scripts for downloading, automating, and merging the map tiles into one image are described in Hilpert et al. (2021). We then performed image segmentation to identify the underlying active street network and five traffic congestion colors corresponding to different traffic categories: green for free-flowing traffic, orange for medium traffic, red for traffic congestion, maroon for severe traffic congestion, and gray for too little data to assign a color. Image segmentation was performed using a three-step process: (a) we selected a 2-week sample of images that included day times, night times, weekdays, weekends, and holidays. (b) We identified the active street network in the 2-week sample using a criterion of colors by counting the number of times each pixel took on one of four congestion colors: green, orange, red, or gray (maroon was excluded because it is rare in low-traffic roads), over the 2-week sample. A pixel was considered a part of the street network if it was shown in green at least once and in orange, red, or gray at least once during the 2-week period. To determine the colors used by Google to define the congestion colors, we converted the true-color images to indexed images with 256 colors. Colors used to represent traffic congestion were then identified through visual inspection of the indexed images. (c) We segmented the entire time series of maps to extract the congestion color values within the active street network, assigning all pixels not in the active street network to the image background. We additionally used visual inspection of data, mapping, and time series plots to confirm that image segmentation worked as expected.

The five traffic congestion colors correspond to relative vehicle speed (Weitz, 2009; Wikipedia, 2017); we and others have validated Google traffic data using traffic radar devices (Hilpert et al., 2019), odometer readings from a vehicle (Zalakeviciute et al., 2020), and a second traffic map app (Zalakeviciute et al., 2020), finding that Google traffic data were correlated with these other traffic measures.

We aggregated the traffic congestion data to the census tract level by overlaying a shapefile of 2010 census tracts with the traffic map array and identifying which pixels corresponded to each census tract. We then summed the number of pixels of each color within each census tract, for each hour of the 3-year period. To create a traffic congestion metric for this analysis, we summed the count of maroon and red pixels in each datetime/census tract observation and then divided by the number of pixels in the street network for that census tract. The resulting variable can be interpreted as the proportion of streets with traffic congestion in each census tract each hour. For computational efficiency, we then aggregated hours to days by averaging each tract's hourly proportion of streets with traffic congestion within each day, resulting in 1,096 possible observations for each census tract over the 3-year study period. We excluded all census tracts that crossed the boundaries of the study area, as we had incomplete traffic congestion information for those tracts. We included all days with at least 1 hr of traffic congestion data, excluding $n = 74$ dates missing all 24 hr of congestion data for all census tracts (Figure S1 in Supporting Information S1). This missingness was likely not informative as it did not occur exclusively in specific years, months, or days of the week, and was generally caused by downloading errors or loss of power to the computer collecting the data. For the time period of 21 June to 31 August 2018, visual inspection of images and time series plots revealed that maps were partially corrupted, resulting in lower-than-expected congestion values. Because these falsely low values might bias results toward the null, we predicted congestion measures for this time period only using a linear model with year, season, day of week, number of days elapsed since 1 January 2018 and neighborhood tabulation area as predictors of traffic congestion.

Of note, we conceptualize our traffic congestion metric (proportion of streets with traffic congestion) not as a proxy for exposure to TRAP, but as a measure of traffic congestion itself. We chose to focus on traffic congestion rather than TRAP alone because we felt this metric better captured the many routes through which traffic can harm a community (e.g., air pollution, noise, stress, sleep interruption, safety/access).

2.2. Racialized Economic Segregation Data

We used the ICE as a measure of racialized economic segregation in each census tract within our study area (Krieger et al., 2017). ICE is calculated by the formula $\text{ICE}_i = (L_i - M_i)/T_i$, where L_i is the number of less marginalized persons in spatial unit i, M_i is the number of more marginalized persons in spatial unit i, and T_i is the total number of persons in spatial unit i (Krieger et al., 2017). ICE is a neighborhood—rather than individual-level—metric designed to capture the extent to which people are spatially segregated into groups at the extreme ends of socio-economic marginalization; marginalization is defined by the user for a given research question (Krieger et al., 2017). A value of 1 corresponds to a spatial unit where all individuals are in the least marginalized group, while a value of −1 corresponds to a spatial unit where all individuals are in the most marginalized group. We used race, ethnicity, and household income data from the 2015–2019 American Community Survey, at the census-tract level, to calculate an ICE metric of racialized economic segregation. Following the example of previous studies using ICE in NYC (Krieger et al., 2017), our least marginalized group was defined as individuals who identified as non-Hispanic white and had a household income greater than or equal to the 80th percentile of the NYC household income distribution (corresponding to income of $125,000 or higher) (Krieger et al., 2017). Our most marginalized group was defined as individuals who identified as Black and had a household income less than or equal to the 20th percentile for NYC (corresponding to $24,999 or less) (Krieger et al., 2017). Of note, the American Community Survey does not disaggregate household income by race and ethnicity for groups other than non-Hispanic white people, so we could not determine the number of non-Hispanic Black people with a given household income in a census tract and instead used the number of Black people of any ethnicity with a given household income. An ICE value was calculated for each census tract in the study area; we then classified census tracts into quintiles, with quintile 1 representing more marginalized census tracts and quintile 5 representing less marginalized census tracts.

2.3. Environmental, Social, and Chronic Disease Burden Data

To operationalize environmental, social, and chronic disease burden, we used the 2022 EJI (Centers for Disease Control and Prevention and Agency for Toxic Substances Disease Registry, 2022) created by the CDC/ATSDR. The EJI consists of three modules, capturing different elements of environmental justice: environmental burden, social vulnerability, and health vulnerability (Centers for Disease Control and Prevention and Agency for Toxic Substances Disease Registry, 2022). The EJI combines data from a number of sources, including the Census Bureau, Environmental Protection Agency (EPA), Mine Safety and Health Administration, and CDC into a single metric encompassing 10 domains: racial/ethnic minority status, SES, household characteristics, housing type, air pollution, potentially hazardous and toxic sites, built environment, transportation infrastructure, water pollution, and pre-existing chronic disease burden (Centers for Disease Control and Prevention and Agency for Toxic Substances Disease Registry, 2022). A census tract's final EJI score is a ranked sum incorporating all domains and modules. For this study, we used NYC census tracts to determine rankings rather than all tracts nationally, and then classified census tracts into quintiles, with quintile 1 representing census tracts with more burden and quintile 5 representing census tracts with less burden.

2.4. Study Design

To evaluate the impact of NY on Pause on traffic congestion, we used an interrupted time series (ITS) study design (Bernal et al., 2017). This design is useful for evaluating population-level interventions that are implemented at a clearly defined point in time, such as NY on Pause. We used a temporary level change model (Bernal et al., 2017) to approximate the sudden decrease in traffic congestion following the implementation of NY on Pause on 22 March 2020, followed by a partial rebound on 8 June 2020, when NYC entered Phase 1 of the state's reopening plan (Gold & Stevens, 2021).

2.5. Statistical Analysis

We used a linear mixed effect model to determine the association between NY on Pause (binary intervention variable) and traffic congestion (continuous outcome variable). We assessed separate impacts for each level of the intervention (Pause, Recovery) using two dummy variables: an indicator for NY on Pause, which was assigned as 1 from 23 March to 7 June 2020, and 0 at other times, and an indicator for partial rebound after NYC entered Phase 1 recovery, which was assigned as 0 before 8 June 2020, and 1 thereafter. We used a random intercept for census tract to account for within-census tract clustering in the model. We included year, month, and day of week to account for temporal autocorrelation and potential confounding by time, as well as a tensor product of the latitude and longitude of the centroid for each census tract, with 8 and 4 knots respectively (loosely 1 knot per 1.5 miles), to account for spatial autocorrelation. As required by the ITS study design, we included a time elapsed variable consisting of the count of days in the study period. We did not adjust for variables such as population dynamics or public transit use because these variables are mediators; they are pathways through which NY on Pause impacted traffic congestion.

In our main analysis assessing the relationship between NY on Pause and traffic congestion, we ran stratified models by each census tract quintile of ICE and EJI to determine differential impacts by neighborhood inequality. We also conducted two secondary analyses and assessed (a) differences in the impact of NY on Pause on traffic congestion by each EJI module (environmental burden, health vulnerability, social vulnerability) by splitting the modules into terciles and running stratified models by each tercile (tercile 1 represented more burden and tercile 3 less burden); and (b) effect modification by rush hour time period by further stratifying our main analysis by two periods: rush hour (6–10 a.m. and 4–8 p.m. on weekdays) and non-rush hour (all other hours on weekdays and all hours on weekends).

We conducted several sensitivity analyses to ensure our results were robust to our choices of model parameters and variable specification. First, to test our assumption that one knot per ∼1.5 miles was an appropriate choice for the tensor product to account for spatial autocorrelation while not overfitting, we also assessed the following combinations: lat = 16 and lon = 8 knots, and lat = 11 and lon = 5 knots. Second, to ensure that variables in the EJI index that could strongly correlate with or explain traffic congestion were not unduly biasing our results, we repeated our main analyses while removing indicators for particulate matter of aerodynamic diameter $\leq$2.5 μm ($PM_{2.5}$), diesel particulate matter, and high-volume roads. Third, in our secondary analysis evaluating each EJI module separately, we further adjusted for the other two modules as continuous variables in the mixed effect models to account for potential confounding by those constructs. Fourth, as a form of external validation, we assessed whether our overall findings on changes in traffic congestion during NY on Pause were consistent with changes in a major traffic-related air pollutant (NO_2) by conducting a descriptive analysis of changes in NO_2 concentrations during NY on Pause using community district-level NO_2 concentration data from the New York City Community Air Survey for summer 2019 and summer 2020 (New York City Department of Health et al). We aggregated census tract ICE and EJI quantiles to community districts in our study area by finding the mode for all census tracts within the community district. We only used community districts for which at least 50% of census tracts were inside our study area to ensure we did not inaccurately assign the community district an unrepresentative ICE or EJI quantile (this excluded 37 census tracts [8%]). We then determined change in NO_2 concentration during NY on Pause by subtracting the community district NO_2 concentration for summer 2020 from the value for summer 2019 for each community district at least 50% within our study area.

All analyses were conducted in R version 4.1.1; the tidyverse package version 1.3.2 was used for data management and cleaning (Wickham et al., 2019), ggplot2 version 3.3.6 for creating figures and maps (Wickham, 2017), raster version 3.5.2 (Hijmans et al., 2023) and sf version 1.0.3 (Pebesma, 2018) for geospatial management, and gamm4 version 0.2-6 for running mixed model (Wood & Scheipl, 2020).

3. Results

Our study spanned 1 January 2018 through 31 December 2020 and contained 20% of the 2,168 NYC census tracts (437 for ICE and 436 for EJI analyses). We excluded 69 tracts that crossed the boundaries of the study area, leaving 445 census tracts with traffic congestion data. Our study area included all of Manhattan and the South Bronx as well as a small portion of Western Queens and Brooklyn (Figure 1). As $n = 8$ tracts ($n = 9$ for EJI) did not have enough information to calculate ICE or EJI metrics, $n = 437$ tracts ($n = 436$ for EJI), were included in the analysis.

Using our traffic metric of percent streets in a census tract with traffic congestion, we found a mean percent streets with traffic congestion of 9.3% (standard deviation [SD] = 5.5%) throughout our study period and area. Using this metric, we observed a large decrease in traffic immediately following NY on Pause (Figure 1, Figure S2 in Supporting Information S1). Overall, before NY on Pause (1 January 2018 to 22 March 2020), census tracts had a mean percent of streets with traffic congestion of 10.0% (SD = 5.7%); during NY on Pause (23 March to 7 June 2020) this decreased to 5.0% (SD = 3.4%, a relative decrease of 49%), and during the recovery period (8 June to 31 December 2020) it rebounded to 8.1% (SD = 4.5%, a relative decrease of 17%).

Descriptive statistics for each quintile of ICE and EJI are presented in Table 1. Tracts in Q1 and Q2 of ICE and EJI (more marginalized and burdened) versus Q4 and Q5 (less marginalized and burdened) had higher percent non-Hispanic Black population (28%–39% vs. 2%–3%), lower percent non-Hispanic white population (4%–5% vs. 69%–79%), and lower tract-level median household income for all racial and ethnic groups ($27,000–$29,000 vs. $138,000–$160,000). There was substantial overlap between census tracts classified in the same quintile in both ICE and EJI (Table S1 in Supporting Information S1). Tracts in each quintile clustered together in space (Figure 2), with the most marginalized and burdened tracts in the South Bronx, Harlem, and Lower East Side neighborhoods. Tertiles of the individual EJI modules generally matched the spatial distribution of ICE and EJI quintiles, with the exception of the Environmental Burden Module (EBM), which classified tracts in the South Bronx and Harlem as the least burdened (Figure S3 in Supporting Information S1). To further explore this, we reviewed the breakdown of values for each indicator of the EBM by tertiles, finding that on average, tertile 1 (less burdened) had worse values than tertile 3 (more burdened) for two of four air pollution indicators, four of six potentially hazardous and toxic sites indicators, two of three built environment indicators, zero of three transportation infrastructure indicators, and the single water pollution indicator (Table S3 in Supporting Information S1).

From 2018 through early 2020 (prior to implementation of NY on Pause), a generally increasing trend for traffic congestion was observed for all quintiles (Figure 3), but census tracts in Q4 and Q5 (less marginalized and burdened) had the highest percent of streets with traffic congestion, ranging from 10.7% to 12.3% (Table 1). However, during implementation of NY on Pause, while all quintiles of census tracts had decreases in traffic congestion, tracts in Q4 and Q5 had greater decreases, reversing the pre-Pause relationship between traffic and ICE/EJI quintiles. Mean traffic congestion during both NY on Pause and the recovery period was lower than during the pre-Pause period, for nearly all quintiles.

The ITS models also indicated a disproportionately large decrease in traffic congestion in census tracts in Q4 and Q5 (less marginalized and burdened; Figure 4; Table S2 in Supporting Information S1). For both ICE and EJI, census tracts in Q1 and Q2 (more marginalized and burdened) had smaller decreases in percent traffic congestion. For example, percent traffic congestion in ICE Q1 decreased by 4.2% during NY on Pause (a relative percent change of −51.7%), while percent traffic congestion in ICE Q5 decreased by 7.8% (a relative percent change of −36.6%). Similar patterns of change in percent traffic congestion between more and less marginalized and

Table 1
Population and Traffic Congestion Characteristics of Census Tracts in the Study Area

		Mean (SD)			Median (IQR)	Mean percent of streets with traffic congestion[a] (SD)		
Strata	Census tracts (n)	Population	% Non-Hispanic White population	% Non-Hispanic Black population	Median household income	Pre-pause 1 January 2018 to 22 March 2020	Pause 23 March 2020 to 7 June 2020	Recovery 8 June 2020 to 31 December 2020
ICE[b] (n = 437)								
Q1 (Disadvantaged)	83	5,281 (2,010)	4.0 (5.3)	38.8 (13.8)	$27,227 ($10,313)	8.7 (4.7)	4.9 (2.6)	8.2 (4.1)
Q2	87	5,162 (2.358)	7.2 (9.4)	23.0 (12.9)	$35,557 ($14,391)	8.4 (4.3)	5.7 (3.5)	8.3 (4.4)
Q3	88	5,682 (3,056)	36.3 (22.1)	11.2 (12.4)	$56,090 ($28,444)	10.3 (5.7)	5.9 (4.2)	9.1 (5.2)
Q4	91	5,585 (3,425)	64.1 (11.2)	3.8 (3.2)	$106,904 ($30,919)	10.7 (6.5)	3.8 (2.4)	7.1 (4.1)
Q5 (Advantaged)	88	5,216 (2,639)	75.7 (8.2)	2.4 (2.2)	$159,732 ($42,953)	12.3 (5.9)	5.2 (3.5)	8.5 (4.4)
EJI[c] (n = 436)								
Q1 (High Burden)	88	5,120 (2,094)	5.0 (9.6)	28.2 (13.7)	$29,342 ($12,883)	9.0 (4.5)	5.4 (3.2)	8.5 (4.3)
Q2	88	5,819 (2,694)	7.9 (10.1)	28.1 (17.6)	$34,567 ($20,956)	8.7 (4.9)	5.3 (3.1)	8.2 (4.4)
Q3	86	5,447 (3,157)	43.5 (24.4)	12.2 (14.9)	$63,750 ($39,822)	10.3 (6.1)	5.4 (4.2)	8.5 (5.2)
Q4	87	4,877 (2,432)	65.8 (17.7)	6.4 (11.7)	$120,240 ($58,026)	11.6 (6.2)	4.4 (2.5)	7.9 (4.1)
Q5 (Low Burden)	87	5,740 (3,142)	68.9 (11.5)	3.1 (3.2)	$137,679 ($53,387)	11.1 (5.9)	5.0 (3.6)	8.1 (4.5)

Note. ICE, Index of Concentration at the Extremes; EJI, Environmental Justice Index. [a]Traffic congestion was defined as the % of streets in a census traffic with red or maroon Google traffic color. [b]The systematically more marginalized group was defined as persons identifying as Black and having a household income category less than the NYC 20th percentile ($24,999 or less), while the systematically less marginalized group was defined as persons identifying as Non-Hispanic white and having a household income category greater than the NYC 80th percentile ($125,000 or more). [c]For the EJI index, lower numbers (e.g., Q1) refer to lower burden; we have flipped the quintile labels.

burdened tracts were observed for the recovery period after NYC entered Phase 1 of reopening. Although no quintiles rebounded to the pre-Pause baseline (indicated by an effect estimate, or decrease in percent traffic congestion, of 0), census tracts in Q1 and Q2 (more marginalized and burdened) were much closer to the pre-Pause levels of traffic congestion than census tracts in Q4 and Q5 (less marginalized and burdened).

Secondary analyses evaluating change in percent traffic congestion by EJI terciles were generally consistent with the main model results for the Social Vulnerability Module and the Health Vulnerability Module (HVM) (Figure 4). However, for the EBM, tercile 1 (more burdened) had the greatest decreases, while tercile 3 (less burdened) had the smallest decreases, that is, the opposite of findings for social vulnerability, health vulnerability, and the main analysis. Secondary analyses with further stratification by rush hour time periods (Figure 5) showed much larger decreases in percent traffic congestion for rush hour time periods (e.g., −11% for ICE Q5).

Results from the sensitivity analyses were not substantially different from the main analysis when (a) changing the knot choices for the tensor term (Figure S4 in Supporting Information S1), (b) removing traffic-related variables from the EJI (Figure S5 in Supporting Information S1), and (c) adjusting for the other EJI modules in the secondary analyses with stratified EJI modules (Figure S6 in Supporting Information S1). Results of the descriptive external validation analysis assessing change in community district-level NO_2 concentrations in our study area substantiated the results of the main analysis (Table S4 in Supporting Information S1). The largest decrease in NO_2 (6.45 ppb) was observed for a community district with a mode ICE and EJI quantile of Q5 (less marginalized and burdened). Generally, community districts that were in Q1 or Q2 (more marginalized and burdened) had smaller decreases in NO_2 (Table S4 in Supporting Information S1).

4. Discussion

This study evaluated changes in traffic congestion after NY on Pause by levels of racialized economic segregation and environmental burden. Prior to NY on Pause, less marginalized and burdened census tracts (Q4–Q5) tended to have higher levels of traffic congestion. However, during NY on Pause when NYC saw a large reduction in traffic

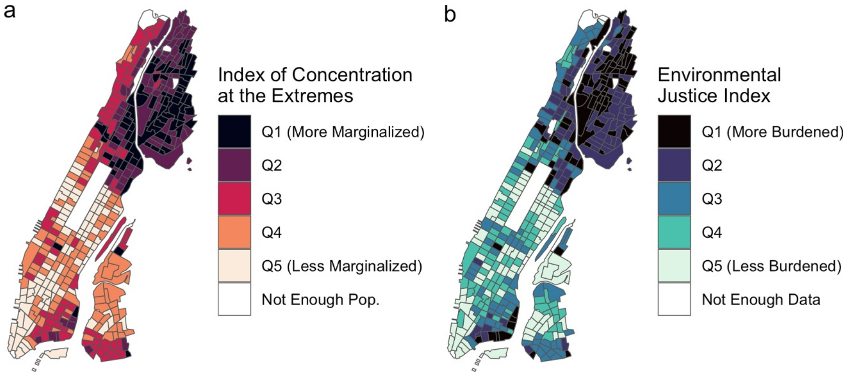

Figure 2. Choropleth map of the distribution of Index of Concentration at the Extremes (ICE) quintiles (Panel a) and Environmental Justice Index (EJI) quintiles (Panel b). Spatial units are 2010 census tracts, and darker shading corresponds to more marginalized or environmentally burdened tracts, while lighter shading corresponds to less marginalized or environmentally burdened tracts.

congestion, this relationship reversed. For both ICE, a measure of racialized economic segregation, and EJI, a combined measure of environmental burden, social vulnerability, and chronic disease burden, more marginalized and burdened census tracts had smaller relative and absolute decreases in percent traffic congestion. Results were similar for both metrics of neighborhood vulnerability, perhaps unsurprising considering the substantial overlap in tracts assigned to quintiles of each metric. These findings support our hypothesis that neighborhoods with more marginalization and burden had smaller decreases in traffic congestion.

Our results are similar to those found by other studies assessing changes in traffic during the COVID-19 pandemic in cities and places across the US. Several studies evaluated changes in traffic volume at high-volume roads like freeways or highways. For example, an analysis of changes in freeway traffic volume in Southern California after pandemic-induced lockdowns began found that freeway traffic volume dropped by up to 50% and then gradually

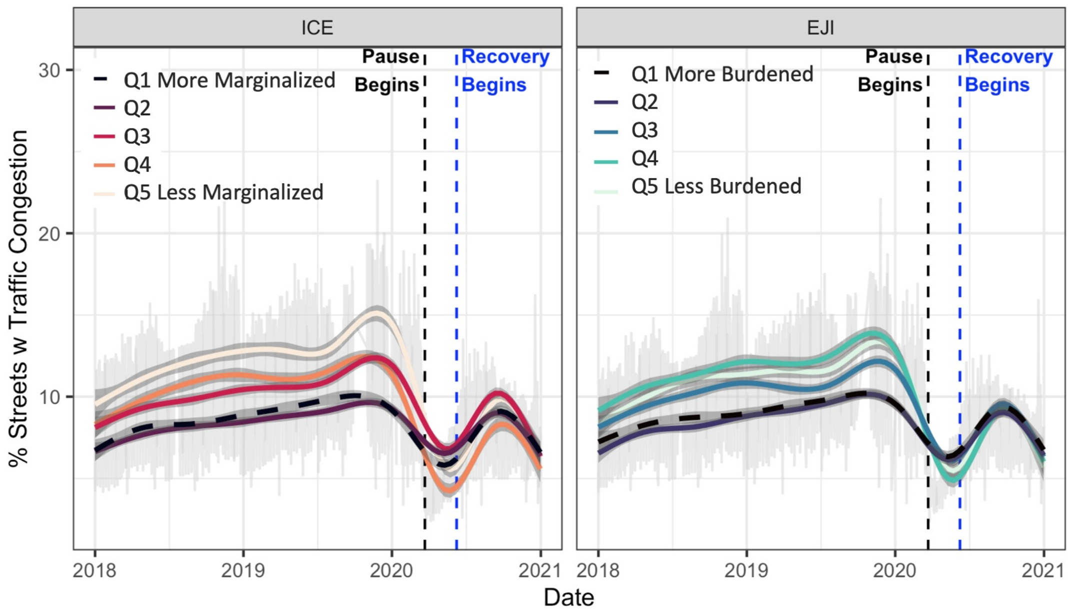

Figure 3. Time series of the percent of streets with traffic congestion. The gray background line is the daily average of the percent of streets with traffic congestion for all quintiles combined. Thick lines are smoothed curves, calculated separately for each quintiles. The left panel shows traffic congestion for census tracts split into quintiles of ICE; the right panel shows traffic congestion for census tracts split into quintiles of EJI. Colors correspond to quintiles, with Q1 dashed for both indices. The vertical, dashed black line indicates the start of NY on Pause, while the vertical, dashed blue line indicates the start of Phase 1 reopening (recovery period). ICE, Index of Concentration at the Extremes; EJI, Environmental Justice Index.

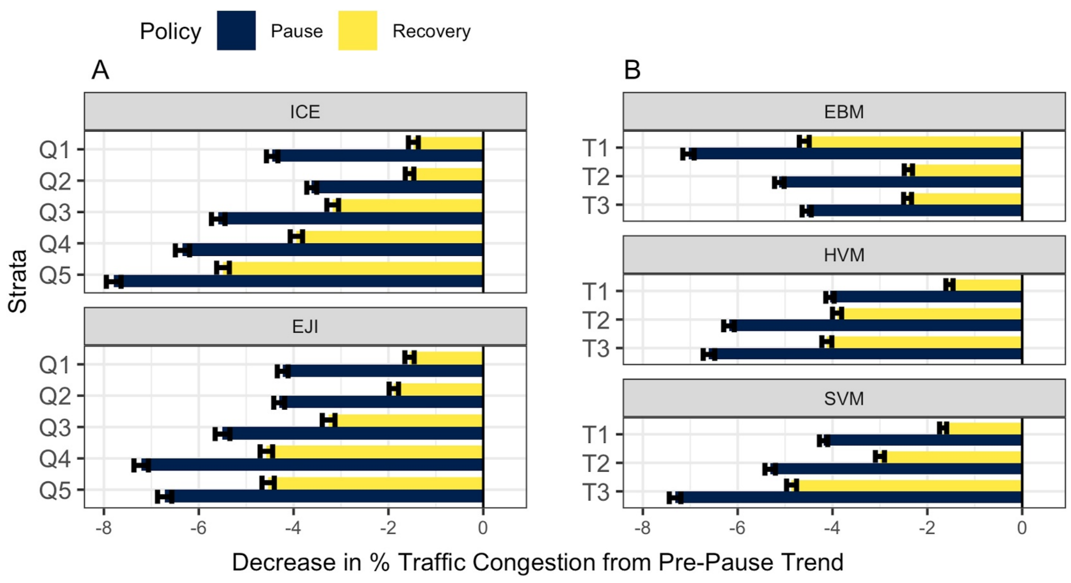

Figure 4. Decrease in traffic congestion after NY on Pause and reopening. Decrease in the percent of streets with traffic congestion after NY on Pause (dark blue color) and after NYC began reopening (yellow color) as compared to pre-NY on Pause traffic congestion. Column A shows the strata-specific estimates (colored bars) and 95% confidence intervals (black error bars) for ICE and EJI quintiles, while Column B shows the strata-specific estimates and 95% confidence intervals for EJI module terciles. For both ICE and EJI, Q1 refers to the more marginalized and burdened group, while Q5 refers to the less marginalized and burdened group. For EJI module terciles, T1 refers to the more burdened group, while T3 refers to the less burdened group. ICE, Index of Concentration at the Extremes; EJI, Environmental Justice Index; EBM, Environmental Burden Module; HVM, Health Vulnerability Module; SVM, Social Vulnerability Module.

rebounded to pre-pandemic levels (Tanvir et al., 2023). This study also found that traffic volume decreased less in disadvantaged neighborhoods, similar to our findings for more marginalized and burdened neighborhoods (Tanvir et al., 2023). Studies in Seattle (Xiang et al., 2020) and Florida (Parr et al., 2020) also found substantial decreases in traffic volumes at major freeways and highways, on the order of 37% (Seattle) to 48% (Florida). Another study using congestion data from TomTom, a mapping and location technology, found a mean decrease in daily congestion of 24% across 22 cities in the US, including NYC (Winchester et al., 2021). We observed similar magnitudes and patterns in declines and rebounds for our Google traffic congestion data (49% decline).

The finding that traffic congestion was higher in census tracts in Q4 and Q5 (less marginalized and burdened) prior to NY on Pause is likely explained by the dynamics of income and traffic in NYC's Central Business District. The Central Business District, defined as the area south of 61st Street in Manhattan, has had historically higher levels of traffic congestion, including low and declining travel speeds (from 9.1 mph in 2010 to 7.1 mph in 2019) (Metropolitan Transportation Authority). In fact, this geographic area has been targeted by the city for a large traffic congestion reduction intervention known as congestion pricing (Metropolitan Transportation Authority). Many census tracts in the Central Business District have higher proportions of non-Hispanic white population and higher income, and fall into Q4 and Q5 (less marginalized and burdened) of ICE and EJI (New York City Planning, 2020). However, it should be noted that a cluster of lower income census tracts with higher proportions of people of color is also present in the Central Business District, in Chinatown, East Village, Lower East Side, NoHo, and Two Bridges (Manhattan Community District 3) (New York City Planning, 2020).

During the pandemic, more affluent people, especially those living in Manhattan, left the city for other locations (Coven et al., 2023). This likely explains a portion of the large decreases in traffic congestion seen for tracts in Q4 and Q5 (less marginalized and burdened) of either ICE or EJI; individuals living in these tracts had higher income and were thus more likely to have owned a car (Blumenberg & Pierce, 2012) and have had the means to leave the city. The Central Business District also contains many tourist sites in NYC, including Times Square and Broadway, which normally attract millions of visitors annually and cause traffic, but were closed or restricted by NY on Pause. Additionally, the Central Business District contains large concentrations of high-rise office complexes, which had been previously filled with workers. Employees in these complexes may have been more

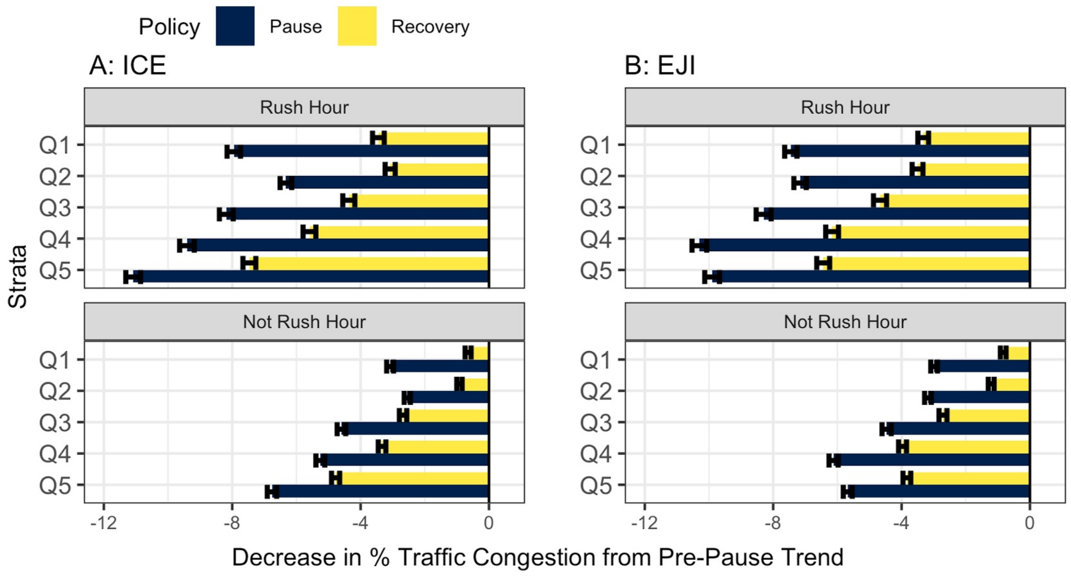

Figure 5. Stratification of traffic congestion decreases by rush hour. Decrease in the percent of streets with traffic congestion after NY on Pause (dark blue color) and after NYC began reopening (yellow color) as compared to pre-NY on Pause traffic congestion. Column A shows the strata-specific estimates (colored bars) and 95% confidence intervals (black error bars) for ICE, while Column B shows the strata-specific estimates (colored bars) and 95% confidence intervals (black error bars) for EJI. Rush hours (6–10 a.m. and 4–8 p.m. on weekdays) are shown in the top panels of each column, while the bottom panels show all other hours. For both ICE and EJI, Q1 refers to the more marginalized and burdened group, while Q5 refers to the less marginalized and burdened group. ICE, Index of Concentration at the Extremes; EJI, Environmental Justice Index.

likely to be able to shift to remote work, allowing for greater decreases in commuters traveling into the Central Business District for work. This combination of factors likely explains the greater traffic declines observed in the Central Business District.

In contrast, we found that during NY on Pause, census tracts in Q1 and Q2 (more marginalized and burdened) had the smallest decreases in traffic congestion. It is thus likely that NY on Pause produced disparities in exposure to traffic-related environmental burdens, as census tracts with worse ICE and EJI scores saw smaller reductions in congestion. This inequity occurred in communities already suffering from higher rates of chronic diseases like hypertension (Fei et al., 2017), obesity (Black et al., 2010), diabetes (D. C. Lee et al., 2018), and cardiovascular disease (Kanchi et al., 2018), which are exacerbated by TRAP (Fuks et al., 2014; Khreis et al., 2017; Mann et al., 2021; Sanidas et al., 2017) and increase risk for more severe COVID-19 related outcomes (Booth et al., 2021; Vasudeva et al., 2022). One of the smallest decreases in traffic congestion was for census tracts in tertile 1 (more burden) of the EJI HVM, which had a reduction in percent streets with traffic congestion of just 4%. Furthermore, these inequities in traffic congestion continued throughout the recovery period as NYC entered Phase 1 reopening and beyond; census tracts in Q1 (more marginalized and burdened) of both EJI and ICE had a decrease in percent streets with traffic congestion of only 1.5%; these tracts had nearly rebounded to pre-pandemic levels by the end of 2020. In the case of NY on Pause, in our study area, the policy unfortunately contributed to environmental injustice in the form of imbalanced benefit of reduced traffic congestion, such that the communities most at risk from worse COVID-19-related outcomes had the least benefit. This injustice could result in potential long-term health effects for individuals, especially those who were infected with COVID-19, if it worsened their symptoms or increased likelihood of contracting long covid or having other harmful sequelae (Booth et al., 2021; Yu et al., 2023). Additionally, if traffic congestion patterns have remained elevated for more marginalized and burdened tracts in the years following 2020, this could have harmful long-term implications for health equity and environmental justice in NYC.

The patterns of change in traffic congestion during NY on Pause that we describe in this analysis are very similar to those observed for nitrogen dioxide (NO_2), an air pollutant used as a tracer of traffic-related emissions (Jarvis et al., 2010). An analysis of NO_2 during NY on Pause using very highly spatially resolved New York City Community Air Survey data found the greatest decreases in NO_2 for the Central Business District (decreases of

~6–14 ppb) (Pitiranggon et al., 2022), consistent with our findings about decreases in traffic congestion in this same area. However, when stratifying analyses by poverty level, that study found NO_2 decreases for all neighborhood poverty levels except those in the low poverty group, with greatest decreases for the medium poverty group (33% reduction) (Pitiranggon et al., 2022). Our analysis of community district level changes in NO_2 from summer 2019 to summer 2020 also using data from the New York City Community Air Survey for districts in our study area found the greatest decrease for the Financial District and Greenwich Village/Soho areas of Manhattan, which are part of the Central Business District and are less marginalized and burdened neighborhoods. In contrast to the analysis stratifying by poverty, we found much lower decreases in NO_2 for more marginalized and burdened community districts. The spatial patterns of decreases in NO_2 during NY on Pause in this and the Pitiranggon et al. study further substantiate our conclusion that decreases in traffic congestion (and correspondingly NO_2) contributed to environmental injustice during NY on Pause.

While nearly all our results were consistent in finding smaller decreases in traffic congestion in census tracts in Q1 and Q2 (more marginalized and burdened), the results for the secondary analysis stratifying by tertiles of the EJI EBM differed. EBM tertile 1, representing the most environmentally burdened group, had the greatest declines in traffic congestion, while tertile 3 representing the least environmentally burdened group had the smallest declines. The majority of census tracts included in the EBM tertile 1 were included in tertile 3 for the other two modules; for example, census tracts with less chronic disease burden and less social vulnerability had slightly more environmental pollution burden. The reason for this reversal is variation in scores for the indicators making up the EBM, which include four air pollution indicators, six potentially hazardous and toxic sites indicators, three built environment indicators, three transportation infrastructure indicators, and an indicator for impaired surface water (Centers for Disease Control and Prevention and Agency for Toxic Substances Disease Registry, 2022). For example, census tracts in tertile 1 and 3 both scored poorly on three of the four air pollution indicators, but census tracts in tertile 1 had worse values on average for two of these indicators than tertile 3: annual mean days above the $PM_{2.5}$ regulatory standard (tertile 1 = 0.87 vs. tertile 3 = 0.63) and ambient diesel PM concentration (tertile 1 = 0.88 vs. tertile 3 = 0.75). Similarly, of the six potentially hazardous and toxic sites indicators, tertile 1 scored worse on average than tertile 3 for four of these indicators (proportion of area within 1-mile of EPA National Priority List site, Toxic Release Inventory Site, Risk Management Plan Site, or coal mine). This underscores the importance of clearly defining environmental burden and injustice: the EJI combines information about social vulnerability, chronic disease burden, and environmental pollution burden, all important components of social justice. However, focusing on only one of these constructs (e.g., environmental pollution burden or social vulnerability alone) does not capture as much of a person's lived experience.

Our analysis had several strengths and limitations. First, a major strength was our use of Google traffic maps, a highly spatially and temporally resolved source of traffic congestion data, to assess how NY on Pause impacted congestion through an environmental justice lens. In addition to high spatial and temporal resolution, this congestion measure also incorporated road size, as larger roads take up more pixels in a given image, contributing a higher count of a specific congestion color (e.g., green or red). However, because we used a novel metric of congestion, it is more difficult to compare our results to those of studies using different traffic metrics. Second, our generalizability was limited by the spatial area included in the analysis. We were only able to obtain traffic congestion data for 20% of NYC census tracts, because the data was originally obtained for a different project focusing on environmental justice in the South Bronx. While there was wide variability in the characteristics of the census tracts included, the majority of tracts included were from Manhattan and the South Bronx. Third, we were missing congestion data for all tracts for $n = 74$ days, due to computer power failures or incomplete map download. However, this missingness is unlikely to bias our results, as it was distributed among years, months, and days of the week. Fourth, traffic congestion data is by nature both temporally and spatially autocorrelated. While we used modeling strategies (e.g., adjusting for time variables, including a tensor product on latitude and longitude) to account for this, it is possible that some residual autocorrelation remained, potentially impacting the estimated standard errors. Fifth, because household income by ethnicity was not available in the census, we were not able to evaluate inequities for people who identify as Hispanic, even though this group had higher rates of mortality from COVID-19 than non-Hispanic whites (Gross et al., 2020) during the pandemic and were more likely to be essential workers (Arasteh, 2021; Williams et al., 2020). Finally, our aim was to evaluate the impact of NY on Pause on traffic congestion, describing variation by ICE and EJI quintiles. NY on Pause was a state-wide intervention; however, because of the unprecedented nature of the pandemic and the wide number of policies instituted in response at local, state, and national levels, we were unable to fully disentangle congestion changes in response to NY on Pause from congestion changes that may be due to other pandemic-related policies. Despite this, given that NY on Pause was arguably the most robust and far-reaching policy for NYC, we feel confident that most of the change in traffic congestion we report was driven by NY on Pause.

We observed inequitable reductions in traffic congestion during NY on Pause. Both during NY on Pause and during the recovery period after NYC entered Phase 1 reopening, census tracts with greater racialized socio-economic disadvantage and combined environmental, social, and chronic disease burden had smaller decreases in traffic congestion compared to less marginalized and burdened tracts. The main goal of NY on Pause was to slow the spread of COVID-19, and it was thus implemented rapidly and was not subject to a policy development process that could have predicted and accounted for potential inequitable impacts. Consequently, it is critical that the inequitable congestion reductions are measured and acknowledged, so that future policies to reduce traffic congestion and to respond to pandemics can avoid additional inequitable impacts. This is especially important because the census tracts with the second smallest decreases in traffic congestion experienced the greatest chronic disease burden, including higher prevalence of diseases such as asthma, hypertension, and diabetes, which are exacerbated by TRAP and increase risk for worse COVID-19 related health outcomes.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

Code used in this analysis is available at https://github.com/jenni-shearston/covid-neighborhood-traffic; the processed data for this project is available at (Shearston et al., 2024).

Acknowledgments
JAS was supported by funding from the National Institute of Health's National Institute (NIH) of Environmental Health Sciences (NIEHS), Grant F31ES033098 and Grant 2T32 ES 732219. This work was also supported by NIEHS P30 ES009089, R21 ES030093, and R01 ES030616, and the National Center for Advancing Translational Sciences at the National Institutes of Health Grant UL1 TR001873. The content is solely the responsibility of the authors and does not necessarily represent the official views of the NIH.

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