Journal of Environmental Economics and Management 110 (2021) 102554

Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

journal homepage: www.elsevier.com/locate/jeem

Environmental justice and the COVID-19 pandemic: Evidence from New York State

Ruohao Zhang [a,b], Huan Li [c], Neha Khanna [d,*]

[a] Kellogg School of Management, Northwestern University, Evanston, IL, United States of America
[b] Pritzker School of Law, Northwestern University, Evanston, IL, United States of America
[c] Department of Economics, North Carolina A&T State University, Greensboro, NC, United States of America
[d] Department of Economics, Binghamton University, Binghamton, NY, United States of America

ARTICLE INFO

JEL classification:
Q53
Q56

Keywords:
Novel coronavirus
Lockdown
Stay-at-home order
Environmental justice
$PM_{2.5}$
Aerosol optical depth
Racial inequality
Seasonality

ABSTRACT

The decline in human mobility and socioeconomic activities during the COVID-19 pandemic has been accompanied by reports of significant improvements in air quality. We evaluate whether there was a uniform improvement in air quality across neighborhoods, with a special attention on differences by race. We focus on the COVID-19 lockdown in New York State, an early epicenter of the pandemic in the United States. Using a triple difference-in-differences model, we find that, despite the seasonal decline in particulate matter pollution starting late March (concurrent with the lockdown period), the lockdown narrowed the disparity in air quality between census tracts with high and low shares of non-white population in rural New York, whereas the racial gap in air quality remained unchanged in urban New York.

1. Introduction

The unprecedented economic slowdown that occurred during the global COVID-19 pandemic has been accompanied by an unintended and dramatic improvement in global and local environmental quality (Reuters, 2020a; New York Times, 2020a; Berman and Ebisu, 2020; Dutheil et al., 2020; Ranjan et al., 2020; Venter et al., 2020; Dang and Trinh, 2021). The United States National Oceanic and Atmospheric Administration reported a nearly 30% decline in nitrogen oxides emissions in the urban northeast during April 2020, along with large reductions in volatile organic compound concentrations (Reuters, 2020a,b). These reports provide important insights and opportunities for studying inequalities in exposure to pollution. We hypothesize that the reported improvement in environmental quality is not distributed equally (Chen et al., 2020), and that, because of pre-existing differences, the improvement in air quality in low-income and minority neighborhoods was different compared to neighborhoods with a majority white population. Given that even short-term exposure to pollution is associated with adverse outcomes in health (Williams et al., 2019), productivity (Lichter et al., 2017; Chang et al., 2016), cognitive ability (Heusinkveld et al., 2016), and longer-term health outcomes (Clay et al., 2014), the differential impacts of the pandemic on environmental conditions across neighborhoods have the potential to alter the economic and social disparities between relatively more and less privileged communities. The purpose of this paper is to document these (anticipated) disparities in air quality improvements in New York State during the pandemic and to highlight the environmental justice implications of the policy response to the pandemic.

* Correspondence to: P.O. Box 6000, Binghamton, NY, 13902, United States of America.
E-mail addresses: ruohao.zhang@law.northwestern.edu (R. Zhang), hli1@ncat.edu (H. Li), nkhanna@binghamton.edu (N. Khanna).

https://doi.org/10.1016/j.jeem.2021.102554
Received 31 July 2020
Available online 14 October 2021

We focus on fine particulate matter ($PM_{2.5}$) pollution in New York State, an early epicenter of the COVID-19 pandemic in the United States. We analyze the change in $PM_{2.5}$ pollution across the State as well as changes in the racial disparities in exposure to $PM_{2.5}$ between majority white and non-white census tracts as a result of the economic lockdown due to the pandemic. We expect that the change in air quality was not uniform across neighborhoods for multiple reasons. First, the extent to which mobility was restricted during the pandemic varied across neighborhoods. Low income households tend to work in the low paying service-sector that is typically not amenable to working from home. Staying at home emerged as a luxury enjoyed by the relatively privileged resulting in a wide gap in the decline in mobility between rich and poor neighborhoods (New York Times, 2020b). A related factor is that the effect of the federal economic impact payment (EIP) on mobility differed by household income. Zhang (2021) shows that the median home dwell time of households with income less than $20,000 was not affected by the EIP whereas relatively higher income households increased their median dwell time by 3%–5% in response to the EIP.

Second, during the pandemic the Trump administration announced a temporary relaxation of several environmental regulations (EPA, 2020), and it is possible that regulated polluters increased toxic emissions subsequent to the announcement. A recent study by Persico and Johnson (2021) shows that counties with more Toxic Release Inventory (TRI) facilities experienced larger increases in daily $PM_{2.5}$ and ozone concentrations, while counties with fewer TRI facilities saw a smaller increase in pollution. Given the pre-existing disparities in the location of point source polluters, we expect this relaxation in environmental regulation and enforcement disproportionally affected disadvantaged neighborhoods, increasing the racial gaps in ambient air quality.

On the other hand, we also expect that racial disparities were narrowed due to the economic lockdown. Due to the disproportionate clustering of polluters in low-income and minority neighborhoods (Banzhaf et al., 2019a,b), we expect a disproportionately larger improvement in air quality in disadvantaged neighborhoods as manufacturing slowed down thereby temporarily narrowing the racial gap in air quality.

We use daily air quality information on a fine spatial resolution from NASA's satellite imagery data, aerosol optical depth (AOD), as well as monitor data from the Environmental Protection Agency's (EPA) network of ground $PM_{2.5}$ monitors to estimate the overall causal effect of the COVID-19 lockdown on $PM_{2.5}$ pollution. The $PM_{2.5}$ monitor sample covers almost exclusively urban areas in New York State, separating itself from the AOD sample which mostly covers rural areas of the State. We utilize both the AOD sample and the $PM_{2.5}$ monitor sample and interpret the difference between the two samples as the difference between urban versus rural areas.

We begin by summarizing the naive pre- and post-lockdown difference in $PM_{2.5}$ pollution as well as the racial disparities in exposure using data between December 2, 2019, and May 24, 2020. We find that, consistent with previous reports, on average, $PM_{2.5}$ pollution declined during the lockdown, regardless of whether we use the AOD measure or the direct concentration measure. As for the racial gap in exposure to $PM_{2.5}$, we find it increased during the lockdown period in rural areas (AOD sample), but it is unclear whether the lockdown had any effect on the racial disparities in urban areas (monitor sample). However, additional analysis shows that these results cannot be explained by any of the expected channels through which the lockdown may affect $PM_{2.5}$ concentration, including changes in human mobility, local economic activity and traffic volume, suggesting these effects might be due to reasons unrelated to the lockdown.

Using the previous 4 years data we detect a strong seasonal pattern in $PM_{2.5}$ which declines annually in March–April, concurrent with the lockdown in New York State. Thus, to investigate causality between the economic lockdown and changes in air quality, we utilize historical data from past years and a triple difference-in-differences setting. We find that after accounting for the seasonality, on average, $PM_{2.5}$ pollution declined in rural areas during the lockdown, though it remained unchanged in urban areas of New York State. But the evidence suggesting that the decline in rural $PM_{2.5}$ is directly triggered by the lockdown is somewhat ambiguous. Nonetheless, we do find clear causal evidence that the lockdown policy decreased exposure to $PM_{2.5}$ pollution among non-white census tracts and narrowed the gap between majority white and non-white census tracts in rural areas, though we do not detect any similar changes in urban areas. This suggests that although the economic lockdown only had a small effect on air quality in New York State as a whole, it significantly narrowed the racial gap in exposure to $PM_{2.5}$ in rural areas. From the perspective of environmental justice, this (presumably) short-term and unintended consequence of the government response to the COVID-19 pandemic raises interesting questions about the nexus between environmental and economic inequities. It remains to be seen whether pollution levels and the associated racial disparities in exposure to $PM_{2.5}$ return to pre-pandemic levels once policy responses to the COVID-19 pandemic are withdrawn.

2. Lockdown policy and $PM_{2.5}$ in New York State

2.1. Policy background and data sources

After New York reported the first case of COVID-19 on March 1, 2020, the total number of cases rose to over 100 within a week. On March 7, the Governor of New York declared a state of emergency, alerting people to the virus. This rapidly evolved to the first statewide lockdown policy on March 12. A week later on March 20, the "New York State on Pause Program" came into effect. It is public impression that the lockdown policy significantly reduced human mobility, traffic volumes, and local economic activities; and as an unintended consequence it dramatically improved local air quality (Reuters, 2020a; New York Times, 2020a,b). In addition, the lockdown also raised concerns regarding increases in racial disparities in exposure to air pollution because the

Fig. 1. $PM_{2.5}$ monitors locations in New York State.

decline in mobility was reported to be much larger in majority white neighborhoods with relatively high income than in minority neighborhoods with relatively low income (New York Times, 2020b).[1]

We focus on air quality in New York State and study the change in $PM_{2.5}$ pollution at the census tract level, following the initial lockdown policy starting from 5:00 pm on March 12, 2020.[2] We begin with comparing the pre- and post-lockdown daily $PM_{2.5}$ pollution, using data between December 2, 2019, and May 24, 2020 (25 weeks/175 days).[3] The EPA provides daily information on $PM_{2.5}$ concentrations through its network of ground monitors which provides our $PM_{2.5}$-at-monitor sample. However, as shown in Fig. 1, there are only 39 $PM_{2.5}$ monitor sites in New York State that are generally located in major population centers (urban areas) and are inadequate to assess air quality beyond the immediate vicinity of each monitor.[4] Hence we draw upon information from a satellite based measurement, aerosol optical depth (AOD), which is a high-frequency and high resolution measure retrieved by the Moderate Resolution Imaging Spectroradiometer (MODIS) on NASA's satellites. As a unitless measure, AOD is a good predictor of $PM_{2.5}$ (Liu et al., 2004; Van Donkelaar et al., 2016), with higher AOD indicating worse air quality and thus higher $PM_{2.5}$ pollution.[5,6] A notable advantage of the AOD data is that it is available at 3 km×3 km resolution, allowing us to approximate the $PM_{2.5}$ concentration in each census tract as an area-weighted average AOD, following Zhang et al. (2020).

In addition to the air quality data, we also collect census tract level information on correlates of $PM_{2.5}$ concentration. This includes daily weather information such as precipitation, temperature, dew point temperature, and wind speed as the basic set of control variables. In order to understand the mechanism driving the air quality changes subsequent to the lockdown policy, we use the median percentage of home dwell time extracted from smart phone GPS data to measure human mobility, satellite based night light intensity data to proxy economic activity, and the length of all primary and secondary roads in each census tract (interacted with lockdown status) to capture the changes in traffic volumes.[7]

2.2. Correlation between the lockdown and $PM_{2.5}$

As noted above, we utilize two samples in our analysis: the AOD sample and the $PM_{2.5}$-at-monitor sample. In the AOD sample, we use the satellite measured AOD as the indicator of $PM_{2.5}$ concentration. In the $PM_{2.5}$-at-monitor sample, we use direct measurements of $PM_{2.5}$ concentration provided by ground monitors.

[1] In Appendix A.1, we plot the racial and income distributions across New York. There is a clear strong negative correlation between the share of non-white population and median household income.

[2] The lockdown policy restricted mass gatherings, with more than 500 people, while gatherings with fewer than 500 people were cut by 50 percent, and allowed only medically necessary visits at nursing homes.

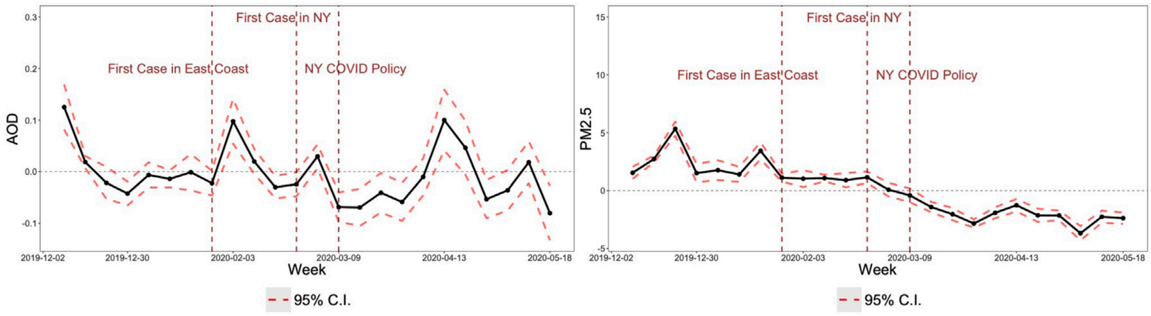
[3] Our study period ends on May 24, two days before the Black Lives Matter protests began to avoid the potential correlation between the protest activities and air quality.

[4] Between December 2, 2019, and May 24, 2020, there were only 36 active monitors for $PM_{2.5}$ in New York. Three inactive monitors are located in Buffalo (2 monitors) and New York City (1 monitor). 16 of 36 active monitors are in New York City. See Figure A1 and A2 for these monitors' locations.

[5] AOD measures the degree to which aerosols prevent transmission of light by absorption or scattering of light through the entire vertical column of atmosphere from ground to satellite sensors.

[6] When using AOD to predict $PM_{2.5}$, there is a slight downward bias when the AOD/$PM_{2.5}$ concentration is high (Fowlie et al., 2019).

[7] Satellite night light data have been used in economics to proxy for economic activity. See for example: Donaldson and Storeygard (2016) and Hoang et al. (2020). We include a detailed data description in the Online Appendix.



(a) Weekly AOD trends (b) Weekly $PM_{2.5}$-at-monitor trends

Fig. 2. Weekly trends in air quality in New York State.

We use the following regression model to determine the weekly trends in $PM_{2.5}$ pollution conditional on weather:

$$q_{it} = \sum_{w=2}^{25} \alpha_w \times 1[Week_t = w] + \beta \times X_{it} + \mu_i + \epsilon_{it} \tag{1}$$

where q_{it} is either the daily average AOD or $PM_{2.5}$-at-monitor for census tract i on date t, X_{it} is a vector of daily weather covariates, and μ_i is the census tract fixed effect. w is the week index from 2 to 25, with week $w = 1$ as the reference week. α_w captures the sample average weekly AOD/$PM_{2.5}$-at-monitor trend, conditional on weather variables. The estimated α_w coefficients are plotted in Fig. 2 (standard errors clustered at county level). We find that, consistent with public impression, $PM_{2.5}$-at-monitor declined sharply during the lockdown. But contrary to our expectations, the trend in AOD was rather flat during the lockdown (albeit with considerable fluctuation).

Alternatively, we compare the conditional difference between the average $PM_{2.5}$ concentration before and after the implementation of the lockdown policy using the following first difference regression model:

$$q_{it} = \alpha \times Lockdown_t + \beta \times X_{it} + \mu_i + \epsilon_{it} \tag{2}$$

where $Lockdown_t$ is a binary variable for any day after March 12, 2020, when the first statewide policy with restrictions on economic and social activities went into effect, α captures the conditional difference in the average daily AOD/$PM_{2.5}$-at-monitor before and during the lockdown. μ_i is a census tract fixed effect capturing the time-invariant socio-economic characteristics across census tracts.[8] X_{it} is the vector of weather and/or additional control variables capturing human mobility (*Median Home Dwell Time*), traffic volume (*Lockdown* × *Primary/Secondary Road*), and local economic activities (*Night Time Light*). Recall that the additional control variables represent the channels through which the lockdown is expected to affect $PM_{2.5}$ concentration, so by including additional control variables in the regression, we expect the correlation between the lockdown and the outcome variables (AOD/$PM_{2.5}$-at-monitor) to be eroded.

Table 1 summarizes the results. The outcome variable is AOD in columns (1)–(4) and $PM_{2.5}$-at-monitor in columns (5)–(8). The results show that, on average, both AOD and $PM_{2.5}$-at-monitor declined during the lockdown. This is consistent with the media reports (Reuters, 2020a,c; New York Times, 2020a) and public impression. However, across all the models in Table 1 the decrease in AOD/$PM_{2.5}$-at-monitor persists even after including the additional control variables, suggesting that the changes in $PM_{2.5}$ pollution cannot be explained by the reduction in human mobility, traffic volume or local economic activities.[9] These results, together with the unclear AOD pattern shown in Fig. 2a, question the causal link between the observed $PM_{2.5}$ concentration reduction and the lockdown.

2.3. Correlation between lockdown and racial disparities in exposure to $PM_{2.5}$ pollution

Even though it is not clear whether the observed decline in $PM_{2.5}$ pollution was triggered by the lockdown, from an environmental justice perspective it is still important to assess whether the lockdown was associated with a change in the racial disparity in $PM_{2.5}$ exposure. To make this assessment, we use the following regression model:

$$q_{it} = \sum_{w=2}^{25} \delta_w \times 1[week_t = w] \times Minority_i + \beta X_{it} + u_i + v_t + \epsilon_{it} \tag{3}$$

[8] We do not include the time fixed effect because there is no time variation in the lockdown within New York State. Therefore, Eq. (2) estimates the average difference in AOD/$PM_{2.5}$-at-monitor before and during the lockdown rather than identifying a causal relationship.

[9] Among all the covariates, "Night Time Light" is always significantly positive for both AOD and $PM_{2.5}$-at-monitor as expected. Contrary to our expectations, "Median Home Dwell Time" is significantly positive for AOD, and "Lockdown×Secondary Road" is significantly positive for $PM_{2.5}$-at-monitor.

Table 1
Daily air quality differences, before and during the lockdown.

	Outcome variable: AOD			
	(1)	(2)	(3)	(4)
Lockdown	−0.020***	−0.037***	−0.040***	−0.033***
	(0.010)	(0.008)	(0.010)	(0.012)
Control variables		Home Dwell	Home Dwell Night Time Light	Home Dwell Night Time Light Lockdown × Road
Weather	Y	Y	Y	Y
Census tract FE	Y	Y	Y	Y
N	78,417	78,133	57,244	57,244
	Outcome variable: $PM_{2.5}$-at-monitor			
	(5)	(6)	(7)	(8)
Lockdown	−3.632***	−3.634***	−3.549***	−3.981***
	(0.199)	(0.191)	(0.264)	(0.153)
Control variables		Home Dwell	Home Dwell Night Time Light	Home Dwell Night Time Light Lockdown × Road
Weather	Y	Y	Y	Y
Census tract FE	Y	Y	Y	Y
N	5036	5036	2437	2437

$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$. The full results are reported in Appendix Table A1 and A2. The control variables are described in the Appendix. Standard errors are clustered at the county level.

where $Minority_i$ is a binary variable, which equals 1 if the census tract is defined as a minority census tract and equals 0 if the census tract is defined as a majority census tract. To distinguish majority and minority census tracts, we use 50% non-white population ratio as an arbitrary cutoff, so that the majority/minority census tracts are defined as those with non-white share less/more than 50%.[10] By this definition, among 4918 census tracts in New York State, 1677 census tracts are defined as minority census tracts.[11] δ_w represents the conditional average weekly difference in $PM_{2.5}$ pollution between majority and minority census tracts. We also include a date fixed effect v_t to capture the baseline trend in $PM_{2.5}$ pollution for majority census tracts. X_{it} is the same vector of weather covariates as in Eq. (1).

Fig. 3 plots the estimates of δ_w conditional on weather variables. In Fig. 3a, there is some tentative evidence of an increase in the racial gap: the weekly AOD gap is positive and statistically significant in 4 of the 10 weeks after the implementation of the lockdown, suggesting a possible causal relationship between the lockdown and racial inequality in exposure to pollution. In Fig. 3b, there is no clear pattern, suggesting that the lockdown did not affect racial gap in $PM_{2.5}$ exposure in the vicinity of ground-based monitors. Similar to Fig. 2, these results also show large differences between the AOD and $PM_{2.5}$-at-monitor samples.

Digging deeper, we use a two-way fixed effect model to analyze changes in racial disparities in exposure to $PM_{2.5}$:

$$q_{it} = \delta \times Lockdown_t \times Minority_i + \beta \times X_{it} + \mu_i + v_t + \epsilon_{it}. \tag{4}$$

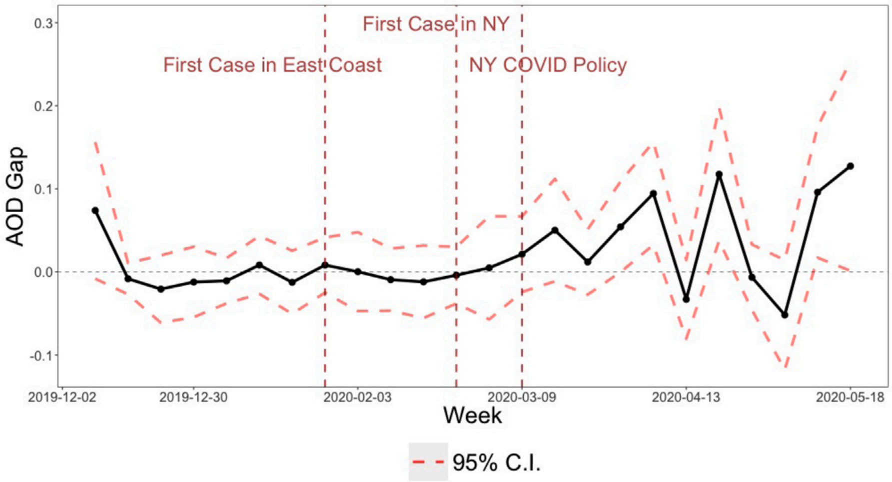
As in Eq. (2), X_{it} is the vector of weather and/or additional control variables. The interaction term "$Lockdown_t \times Minority_i$" identifies the heterogeneity in the association between the lockdown and $PM_{2.5}$ pollution across majority white and non-white census tracts. The census tract fixed effect μ_i and date fixed effect v_t account for census tract and date specific unobserved confounders, allowing us to use the difference-in-differences setting to detect the causal effects of the lockdown on $PM_{2.5}$ concentration in census tracts with different racial demographics (under valid common trend assumptions).[12] Therefore, the model measures the heterogeneous effect of the lockdown relative to the average trend in $PM_{2.5}$ concentration, which is captured by the date fixed effect v_t.

Table 2 summarizes the results. According to the results shown in columns (1)-(4), we find that the lockdown is associated with higher AOD in minority census tracts. This is consistent with Fig. 3a, which provides some suggestive evidence that the lockdown increased the gap in $PM_{2.5}$ exposure between majority and minority census tracts across New York State. Although the results echo the media reports, by including the full set of control variables, we find that the results cannot be explained by the expected economic channels. This again raises concerns about confounding errors and the reliability of these findings. In addition, the results are inconsistent with Currie et al. (2020), who find that increasing stringency in regulation has decreased racial disparities in

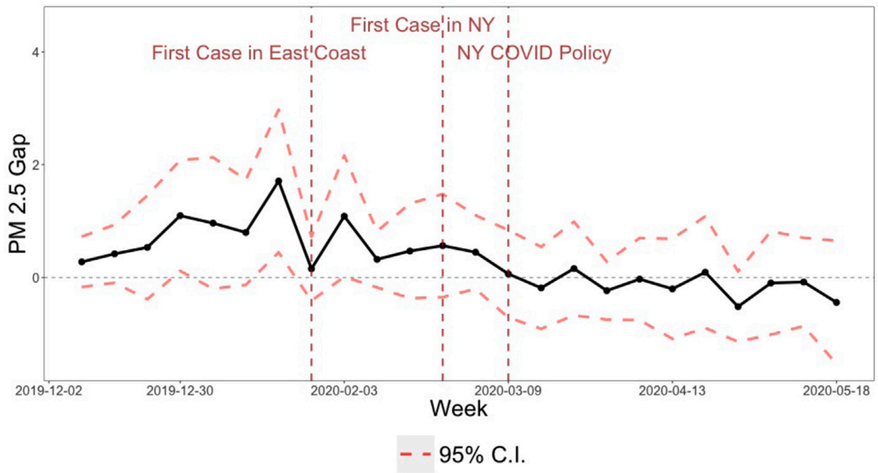
[10] According to the census 2019 5-year estimates, 80% of non-white population in New York State lives in NYC. 33% of New York State census tracts are categorized as non-white areas according to our definition, among which 79% are located in NYC. In non-NYC census tracts, 13% are non-white census tracts.

[11] Based on the ACS 2014–2018 5-year average, for 3423 census tracts in the AOD sample, the mean non-white population share is 0.305 (std.dev. = 0.303) and it is 0.398 (std. dev. = 0.300) for the 36 census tracts in the $PM_{2.5}$-at-monitor sample.

[12] This model does not identify the average causal effect of the lockdown on $PM_{2.5}$ pollution, since there is no time variation in the lockdown within New York. This is also the reason that we cannot include the lockdown dummy without any interactions as an additional variable in this model.



(a) AOD gap between white and non-white census tracts



(b) $PM_{2.5}$-at-monitor gap between white and non-white census tracts

Fig. 3. Weekly racial disparities in New York State.

$PM_{2.5}$ exposure. On the other hand, the $PM_{2.5}$-at-monitor results in columns (5)-(8) show that, on average, there is a decrease in racial disparities during the lockdown, and it might be explained by the changes in local economic activities (*Night Time Light*). However, we hesitate to unambiguously infer any causal relationship between the decrease in the racial gap in $PM_{2.5}$ exposure and the lockdown, because we do not find a clear decline pattern during the lockdown period in Fig. 3b.

2.4. Summary, puzzles and next steps

To summarize, using the single-year AOD and ground monitor measured $PM_{2.5}$ concentration data from December 2, 2019, to May 24, 2020, we fail to find clear evidence that the lockdown lowered AOD across rural New York nor changed the racial gap in exposure to $PM_{2.5}$. For the $PM_{2.5}$-at-monitor sample, we find a clear decline in the average $PM_{2.5}$-at-monitor in the urban areas where these monitors are located, but it is unclear that this decline was caused by the lockdown; nor is it evident that the lockdown had any effect on racial disparities in exposure to $PM_{2.5}$ concentrations.

We recognize that though the decline in measured pollution is consistent with news reports and the public impression, our analysis also presents puzzles. First, we find that the relationship between the lockdown and local $PM_{2.5}$ concentration is inconsistent across the AOD and the $PM_{2.5}$-at-monitor samples. This inconsistency may be driven by either systematic differences between the satellite measured AOD and $PM_{2.5}$ concentrations measured by the ground monitors, or differences in the geographical coverage of the two samples. To test for systematic differences between the two measures, we use the random coefficient model suggested by Lee et al. (2011) to estimate the relationship between AOD and $PM_{2.5}$ using areas throughout New York State where both monitor and

Table 2
Differences in daily air quality gap between majority and minority census tracts, before and during the lockdown.

	Outcome variable: Satellite Measured AOD			
	(1)	(2)	(3)	(4)
Lockdown × Minority	0.062***	0.064***	0.048***	0.046***
	(0.021)	(0.021)	(0.017)	(0.016)
Control variables		Home Dwell	Home Dwell Night Time Light	Home Dwell Night Time Light Lockdown × Road
Weather	Y	Y	Y	Y
Census tract FE	Y	Y	Y	Y
N	78,417	78,133	57,244	57,244
	Outcome variable: Monitor Measured $PM_{2.5}$			
	(5)	(6)	(7)	(8)
Lockdown × Minority	−0.782**	−0.780**	−0.659	−0.142
	(0.342)	(0.341)	(0.416)	(0.257)
Control variables		Home Dwell	Home Dwell Night Time Light	Home Dwell Night Time Light Lockdown × Road
Weather	Y	Y	Y	Y
Census tract FE	Y	Y	Y	Y
N	5036	5036	2437	2437

$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$. The full results are reported in Appendix Table A3 and A4. The control variables are described in the Appendix. Standard errors are clustered at the county level.

AOD data are available. In Appendix A.3, we use AOD to predict $PM_{2.5}$, and plot the correlation between the monitor measured $PM_{2.5}$ and the AOD predicted $PM_{2.5}$. We find a strong linear correlation suggesting that there are no significant and systematic differences between the AOD and $PM_{2.5}$ measurements. Therefore, the differences between the AOD and $PM_{2.5}$-at-monitor samples are more likely driven by the fact that two samples cover different geographical areas: the AOD sample covers most of New York State, but has relatively low coverage in urban areas (especially New York City); the $PM_{2.5}$-at-monitor sample only covers areas where EPA has ground-based $PM_{2.5}$ monitors, and most of the monitors are located in metropolitan areas.[13] It is possible that the lockdown had heterogeneous urban/rural effects on $PM_{2.5}$ pollution. In order to double check whether the inconsistency in results is caused by urban/rural discrepancies, in the rest of the paper, we compare the AOD and $PM_{2.5}$-at-monitor samples with a third sample: AOD-at-monitor sample. If there is an urban/rural discrepancy, then we expect to see differences between the AOD and AOD-at-monitor samples, but similarities between the $PM_{2.5}$-at-monitor and AOD-at-monitor samples.

Second, while we find a clear pattern of improved air quality in directly measured $PM_{2.5}$ concentrations and an increase in the racial gap in exposure in rural areas in the AOD sample, both patterns cannot be explained by the expected channels through which the lockdown may affect local $PM_{2.5}$ pollution, including the changes in human mobility, local economic activities and traffic volumes. This suggests that the lockdown effect found in this section may be spurious: it is possible that the observed pattern occurs coincidentally during the lockdown period, for example, due to seasonality, rather than as a direct consequence of the lockdown policy. To account for this possibility, in the rest of the paper, we use data for the past 4 years and employ a cross-year analysis. By comparing the $PM_{2.5}$ concentration on same days across years, we are able to account for any seasonal patterns.

3. Detecting seasonality

3.1. Data description

Our original study period is December 2, 2019–May 24, 2020 (25 weeks). To account for possible seasonality in the data, we compare trends over the same period in years 2015–16, 2016–17, 2017–18, and 2018–19. The full data set covers 234 weeks starting from December 2, 2015, to May 24, 2020, and it consists of three samples: AOD, $PM_{2.5}$-at-monitor, and AOD-at-monitor. AOD-at-monitor is generated by calculating the area-weighted average AOD in the 1.5 km circle area around each monitor, following the method in Zhang et al. (2020).

Table 3 reports the mean statistics for the outcome variables and weather covariates for the AOD/$PM_{2.5}$-at-monitor/AOD-at-monitor samples from the full multi-year data set. The AOD sample has a much larger number of observations than the other two

[13] AOD data are missing for almost the entire New York City area during December 2, 2019–May 24, 2020. According to personal communication received from NASA on July 20th, 2020, the AOD values are missing mainly because of cloud coverage and brighter surfaces in major urban areas.

Table 3
Summary statistics.

Sample	AOD (unitless)	$PM_{2.5}$-at-Monitor ($\mu g/m^3$)	AOD-at-Monitor (unitless)
Outcome variable	0.261 (0.263)	6.717 (4.006)	0.200 (0.236)
Precipitation (mm)	1.692 (5.185)	3.196 (7.474)	2.228 (5.896)
Temperature (Celsius)	14.214 (8.495)	10.954 (10.308)	14.084 (8.427)
Dew point (Celsius)	7.746 (9.126)	4.684 (10.443)	7.013 (9.077)
Wind speed (m/s)	4.637 (2.612)	5.121 (2.749)	4.729 (2.672)
Number of census tracts	4699	39	37
Number of observations	1,249,682	61,252	10,075

This table reports sample means with standard deviations in parentheses.

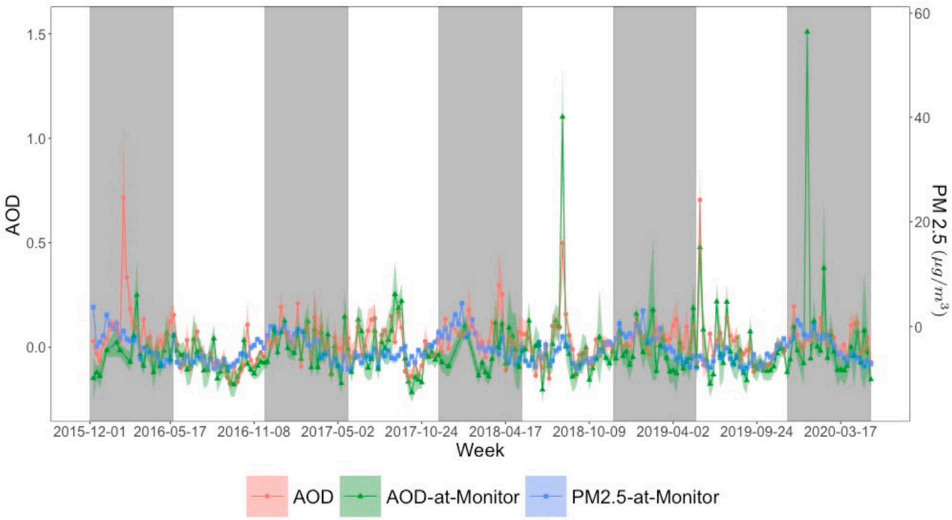


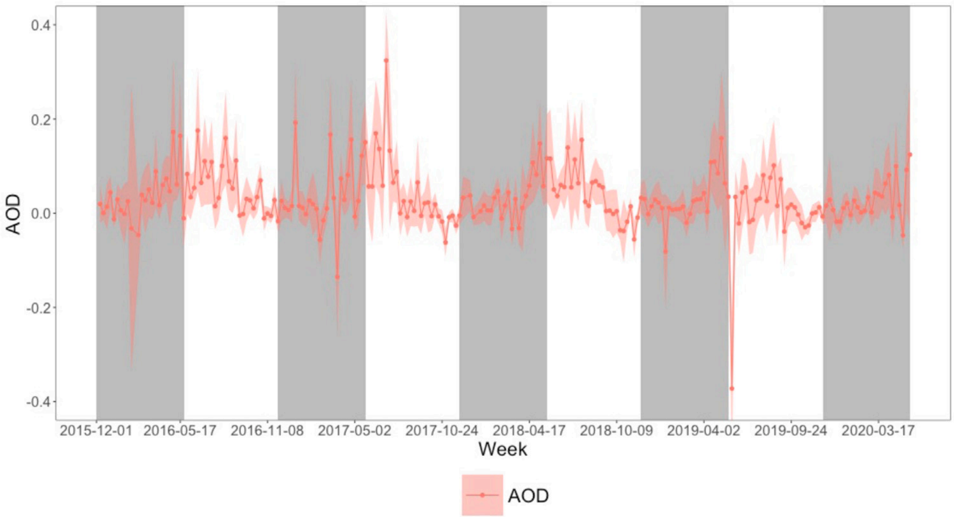
Fig. 4. Weekly conditional trends in $PM_{2.5}$ concentration (α_w) with 95% confidence intervals.

samples, and covers 4699 out of 4919 census tracts in New York State. The AOD-at-monitor sample has a much smaller number of observations than the $PM_{2.5}$-at-monitor sample, because the AOD measurement has low coverage in urban areas where the monitors are usually located. It is a little bit unexpected that the unconditional mean AOD in the AOD-at-monitor sample is smaller than it is in the AOD sample, given the monitors are mostly located in urban areas with relatively higher pollution. This is possibly because of the higher mean precipitation in the AOD-at-monitor sample.

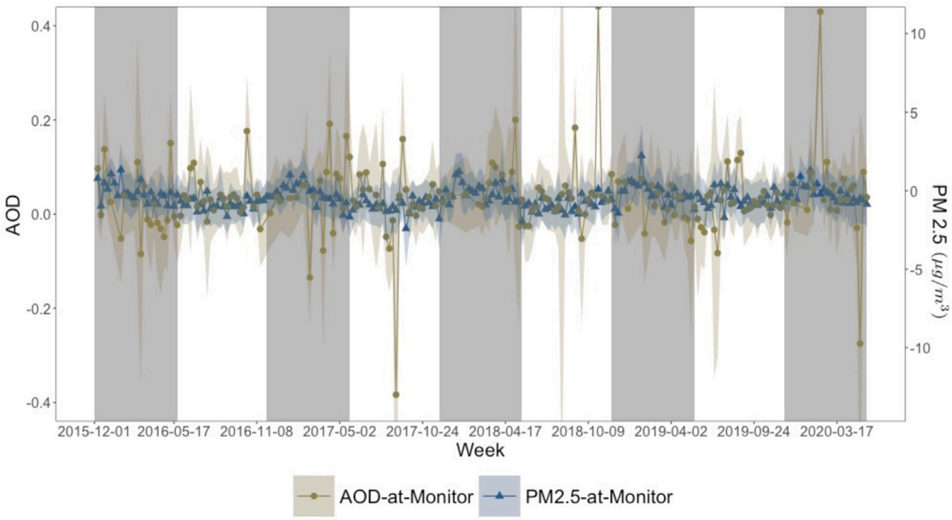
3.2. Weekly air quality trend

To illustrate the seasonal pattern in $PM_{2.5}$, we estimate regression equation (1) using the full data set of 234 weeks. Fig. 4 plots the results. The shaded columns represent the same time period (December 2–May 24, same as the single-year sample and our study period) in different years. In the figure, each point estimate represents the conditional mean of AOD/$PM_{2.5}$-at-monitor/AOD-at-monitor in a given week in relation to the reference week (the week of December 1, 2015), along with its 95% CI.

The $PM_{2.5}$-at-monitor sample shows a clear seasonal trend regardless of lockdown restrictions: there is a declining trend in $PM_{2.5}$-at-monitor during the winter weeks of our study repeated over the years. A similar pattern of seasonality appears in the AOD and AOD-at-monitor samples as well, though the seasonal trends in AOD and AOD-at-monitor are more variable than in $PM_{2.5}$-at-monitor. This seasonality raises the concern that the single-year data in Section 2 might spuriously conflate the seasonality with the effect of the lockdown if not accounted for appropriately.



(a) AOD gap between majority and minority census tracts



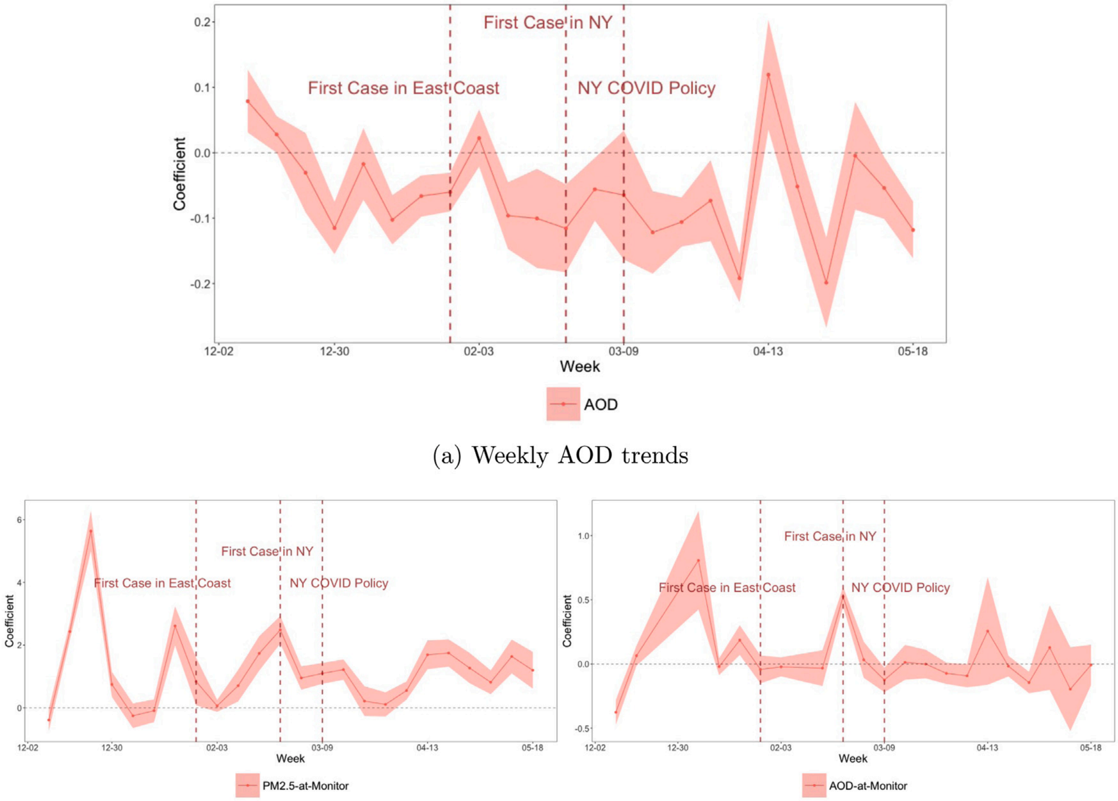
(b) AOD-at-monitor/$PM_{2.5}$-at-monitor gap between majority and minority census tracts

Fig. 5. Weekly conditional racial disparities in New York State with 95% confidence intervals.

3.3. Weekly racial disparities in air quality

We also estimate regression equation (3) using the full data set to assess whether there exist seasonal patterns in the racial disparities in exposure to $PM_{2.5}$ pollution. Fig. 5 plots the conditional racial gap in AOD/$PM_{2.5}$-at-monitor/AOD-at-monitor and its 95% confidence interval.

According to Fig. 5a, we find a clear cyclical increase in the racial gap in AOD measured exposure during our study period. This suggests that the lockdown effect reported in Section 2 using the AOD sample is not causal: the lockdown period coincidentally overlapped with the seasonal increase in racial disparities. According to Fig. 5b, we find that the $PM_{2.5}$-at-monitor and AOD-at-monitor samples have a quite similar pattern: both trends peak at the beginning of each shaded area (around January and February) and decline thereafter. This pattern differs from the trend in the AOD sample, which peaks at the end of each shaded area (around April and May). This suggests that there are systematic differences among census tracts with and without monitors (i.e., rural vs. urban differences), and reaffirms that there are no systematic differences between satellite measured AOD and $PM_{2.5}$ concentrations measured by the ground monitors.



(a) Weekly AOD trends

(b) Weekly $PM_{2.5}$-at-monitor trends

(c) Weekly AOD-at-monitor trends

Fig. 6. Weekly conditional trends for $PM_{2.5}$ in New York State with 95% confidence intervals.

4. Main analysis

In the remaining analysis, we isolate the causal effects of the lockdown (the treatment) on air quality and the racial gap in exposure by accounting for seasonality. Similar to Section 2, our analysis focuses on the time period from December 2, 2019, to May 24, 2020 (treated group), as compared with the same dates from the previous 4 years (control group).[14,15]

4.1. Lockdown effect on $PM_{2.5}$

We first quantify the lockdown effect on weekly $PM_{2.5}$ pollution by considering the following model:

$$q_{iyt} = \sum_{w=2}^{25} \alpha_w \times 1[Week_t = w] \times Treated\ Group_y + \beta \times X_{it} + \mu_i + u_y + v_t + \epsilon_{iyt} \tag{5}$$

where q_{iyt} represents AOD/$PM_{2.5}$-at-monitor/AOD-at-monitor in census tract i on day t in year y, and $Treated\ Group_y$ is a dummy variable that equals 1 if y is the year 2019–2020 and 0 otherwise. μ_i, u_y, and v_t are census tract, year and day fixed effects. Fig. 6 plots the estimated α_w for the three samples. We find that after accounting for the seasonality, neither the AOD sample (Fig. 6a) nor the $PM_{2.5}$-at-monitor sample (Fig. 6b) shows a clear decline pattern after the implementation of the lockdown. In addition, Figs. 6b ($PM_{2.5}$-at-monitor) and 6c (AOD-at-monitor) are quite similar, which reaffirms our conclusion that there are no systematic differences between the AOD and direct concentration measures of $PM_{2.5}$ pollution.

[14] The final data set used for the regression analysis is a subset of the full data set described in Section 3, because it includes observations only within the following date intervals: December 2, 2015, and May 24, 2016; December 2, 2016, and May 24, 2017; December 2, 2017, and May 24, 2018; December 2, 2018, and May 24, 2019; December 2, 2019, and May 24, 2020.

[15] In our cross-year analysis, we do not control for the different channels because *Median Home Dwell Time* data are not available before 2019. That is, the regression models in the remainder of the paper only include weather variables and relevant fixed effects as control variables.

Table 4
The effects of lockdown on local $PM_{2.5}$ concentration.

	Dependent Variable		
	AOD	$PM_{2.5}$-at-Monitor	AOD-at-Monitor
Lockdown	−0.037***	−0.318**	−0.083
	(0.010)	(0.159)	(0.053)
Weather	Y	Y	Y
Year FE	Y	Y	Y
Census Tract FE	Y	Y	Y
Day FE	Y	Y	Y
N	349,559	24,516	2801

***$p < .01$, **$p < .05$, *$p < .1$. The full results are reported in Appendix Table A5. The observation numbers for three samples are all smaller than the observation numbers reported in Table 3. This is because in this analysis we only use observations between December 2 and May 24 in each year.

While the weekly trends do not reveal a clear causal effect it is still possible that, on average, there is a change in daily air quality after the lockdown was imposed. To examine this possibility, we estimate the average treatment effect using the following two-way fixed effects model:

$$q_{iyt} = \alpha \times Lockdown_{yt} + \beta \times X_{it} + \mu_i + u_y + v_t + \epsilon_{iyt} \tag{6}$$

The results are shown in Table 4. We find that, on average, daily AOD is lower across New York State after the implementation of lockdown (column (1) in Table 4), but that the evidence is more tentative for $PM_{2.5}$-at-monitor or AOD-at-monitors (column (2) and (3) in Table 4). Although the coefficient on the lockdown variable is statistically negative in column (2), it appears to be driven by outliers: when we remove the outliers in the week of December 23 (as shown in Fig. 6b), the significance in column (2) is eroded. These results again emphasize the rural–urban differences between the $PM_{2.5}$ concentration measured at ground-based monitor sites (urban areas) and AOD measured in the rest of New York State.[16]

It is important to note that we conservatively interpret the significant coefficient in column (1) in Table 4 as correlation rather than causation due to the lockdown restrictions on AOD. This is because, as shown in Fig. 6a, we see lower AOD in 2019–2020 (treated group) than the previous four years (control group) even before the lockdown policy was implemented, which implies that the declining trend during the lockdown period and the negative coefficient in column (1) may reflect the trend that existed without the lockdown restriction.

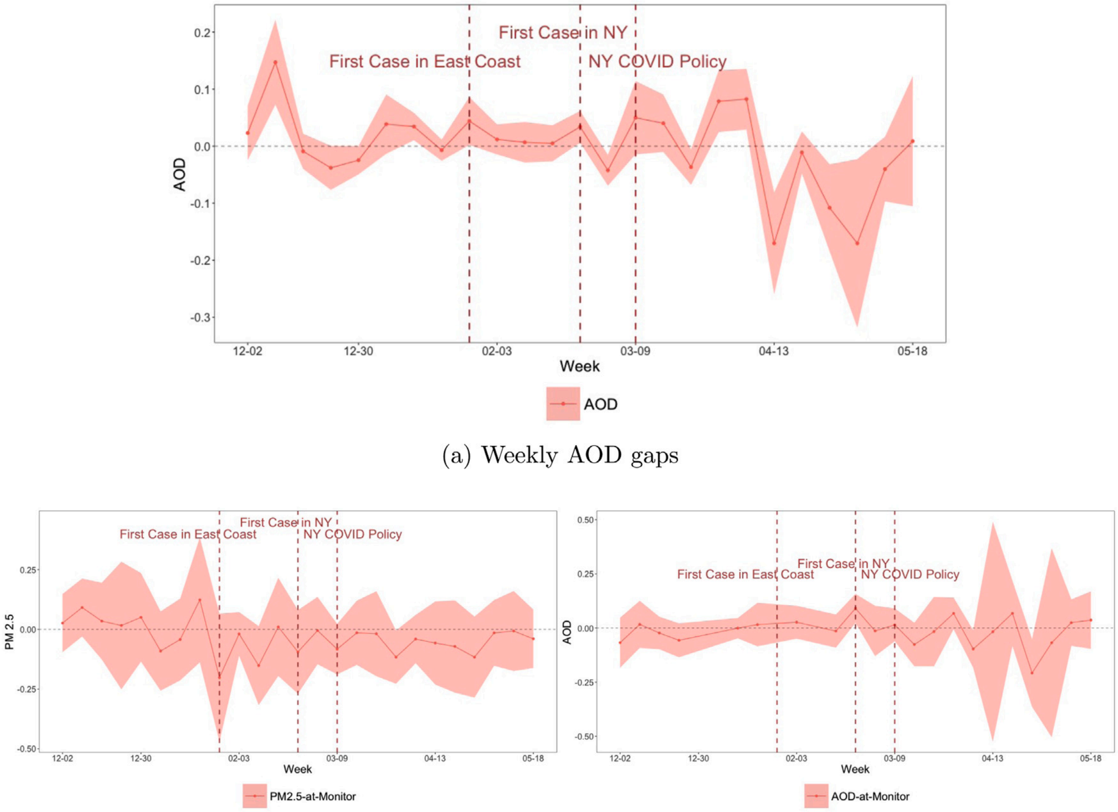
4.2. Lockdown and racial disparities in exposure to $PM_{2.5}$

Although the previous analysis does not identify a clear causal effect of the lockdown on statewide average $PM_{2.5}$ pollution, from an environmental justice perspective, it is important to determine whether the lockdown had heterogeneous effects on census tracts with different racial groups. We assess the relationship between the lockdown and racial disparities in exposure to $PM_{2.5}$ through the following regression model, which compares the differences in the weekly racial gap between the treated and control groups:

$$\begin{aligned} q_{iyt} = & \sum_{w=2}^{25} \alpha_w \times 1[Week_t = w] \times Treated\ Group_y \\ & + \sum_{w=2}^{25} \delta_w^1 \times 1[Week_t = w] \times Minority_i \\ & + \sum_{w=2}^{25} \delta_w^2 \times 1[Week_t = w] \times Minority_i \times Treated\ Group_y \\ & + \beta \times X_{it} + \mu_i + u_y + v_t + \epsilon_{iyt}, \end{aligned} \tag{7}$$

where the variables have the same definition as in Eq. (5). v_t is a date fixed effect that captures the daily $PM_{2.5}$ time trend for majority census tracts in the control group (previous 4 years), α_w captures the difference in the $PM_{2.5}$ weekly trends among the majority census tracts between the lockdown year (i.e., the treated group) and the previous years (control group), δ_w^1 captures the difference in the $PM_{2.5}$ weekly trends between minority and majority census tracts in the control group, and δ_w^2 captures the difference in the gap in the weekly time trend between the majority and minority census tracts between the treated and control groups. Alternatively, δ_w^2 can also be interpreted as the weekly trend for minority census tracts in the treated group relative to the minority census tracts in the control group (conditional on the weekly gap between the treated and the control groups $1[Week_t = w] \times Treated\ Group_y$, and the baseline weekly gap between minority and majority census tracts $1[Week_t = w] \times Minority$), and it identifies the effect of the lockdown on racial disparities in the exposure to $PM_{2.5}$ between majority and minority census tracts. We plot the estimated δ_w^2 in Fig. 7, and causal inferences can be made by comparing δ_w^2 before and after the implementation of the lockdown.

[16] We also try alternative models: in addition to the existing year and day fixed effects, we add a third order polynomial of time (number of days) to further detrend the data. That is, the regressions include time, time square, and time cubed, where time is the count of days starting from the first day of sample (December 2, 2015). The results are very similar to what we present in Table 4.



(a) Weekly AOD gaps

(b) Weekly $PM_{2.5}$-at-monitor gaps

(c) Weekly AOD-at-monitor gaps

Fig. 7. Weekly conditional gaps in $PM_{2.5}$ in New York State with 95% confidence intervals.

According to Fig. 7a, for the AOD sample, the estimated weekly δ_w^2s are quite flat and mostly insignificant before the lockdown (week of March 9), but become significantly negative about a month after the lockdown policy went into effect.[17] This provides some evidence that after the lockdown, minority census tracts throughout New York State saw a decrease in $PM_{2.5}$ concentration, so that the racial gap in exposure to $PM_{2.5}$ pollution also decreases. However, the results are mainly seen in rural areas. For urban areas ($PM_{2.5}$-at-monitor/AOD-at-monitor samples), as shown by Figs. 7b and 7c, the estimated weekly δ_w^2s are always flat and mostly insignificant both before and after the lockdown.

Alternatively, to directly estimate the causal effect of the lockdown on racial disparities in $PM_{2.5}$ exposure, we use the following triple differences regression model:

$$\begin{aligned} q_{iyt} = & \sum_{w=2}^{25} \alpha_w \times 1[Week_t = w] \times Treated\ Group_y \\ & + \sum_{w=2}^{25} \delta_w^1 \times 1[Week_t = w] \times Minority_i \\ & + \Delta \times Minority_i \times Treated\ Group_y \times Lockdown_t \\ & + \beta \times X_{it} + \mu_i + u_y + v_t + \epsilon_{iyt} \end{aligned} \tag{8}$$

where Δ is our coefficient of interest, representing the triple difference: the pre- and post-lockdown period difference (first difference) in the racial gap (double difference) between the treated group and the control group (triple difference).

Table 5 reports the regression results, where the estimated Δ is reported as the coefficient for *Lockdown×Minority*. In columns (1), (3) and (5), we assume that without the lockdown, there is no difference in the weekly time trend between the treated and control groups. So we substitute the first term "$\sum_{w=2}^{25} \alpha_w(1[Week_w = w] \times Treated\ Group_{iyt})$" in regression equation (8) by "$\alpha_w \times Lockdown_{ijt}$", and report the estimated α_w as the coefficient for "Lockdown". In column (2), (4) and (6), we report the results using regression

[17] Recall that we define the lockdown period starting from March 12, 2020, when the first policy that restricts economic and social activities was implemented. The "New York State on pause" policy and stay-at-home order went into effect on March 23, 2020, which might explain the lagged effect shown on Fig. 7a.

Table 5
Main results: The effects of lockdown on racial disparities in $PM_{2.5}$ exposure.

	Dependent variable					
	AOD		$PM_{2.5}$-at-monitor		AOD-at-monitor	
	(1)	(2)	(3)	(4)	(5)	(6)
Lockdown	−0.034***		−0.195		−0.077	
	(0.010)		(0.209)		(0.053)	
Lockdown × Minority	−0.024***	−0.024***	−0.218	−0.368	−0.010	−0.010
	(0.010)	(0.009)	(0.299)	(0.289)	(0.024)	(0.023)
Weather	Y	Y	Y	Y	Y	Y
Minority × Weeks FE	Y	Y	Y	Y	Y	Y
Treated group × Weeks FE	N	Y	N	Y	N	Y
Year FE	Y	Y	Y	Y	Y	Y
Census tract FE	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y
N	349,559	349,559	24,516	24,516	2801	2801

$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$. The full results are reported in Appendix Table A6. The number of observations for three samples are all smaller than the observation numbers reported in Table 3. This is because in this analysis we only use observations between December 2 and May 24 in each year.

equation (8). As shown in Table 5, we find that the lockdown lowered the racial gap in $PM_{2.5}$ concentration only in the AOD sample, but not in the $PM_{2.5}$-at-monitor and AOD-at-monitor samples, which is consistent with Fig. 7. In addition, the effect is insensitive to the assumption of the time trend differences between the treated and control groups, since the coefficients on "Lockdown×Minority" are very similar between columns (1), (3), (5) and columns (2), (4), (6).

To summarize, after accounting for the seasonal patterns in $PM_{2.5}$ pollution, we find that the lockdown is associated with a decline in average $PM_{2.5}$ concentration in New York State, and this decline is mainly seen in rural areas (AOD sample). The estimated coefficients capturing the effect of the lockdown on AOD are between −0.034 (Table 5) to −0.037 (Table 4), which represents a 17%–19% decrease in AOD compared with the sample average of 0.19. However, because of the unclear patterns in the weekly trends in Figs. 6, we err on the side of caution and do not infer an unambiguous causal effect of the lockdown on $PM_{2.5}$ for New York State as a whole.

Nonetheless, in terms of environmental justice, we find a causal effect that the lockdown narrowed racial disparities in exposure to $PM_{2.5}$ by significantly decreasing $PM_{2.5}$ pollution in minority census tracts. The effect of the lockdown on racial disparities in AOD exposure is estimated as −0.024 (Table 5), which is approximately 25.5% of the sample average racial disparity.[18] These effects are also seen mainly in rural areas, and the lockdown has no effect on racial disparities in urban areas in the vicinity of the EPA's monitors. We anticipate that the urban–rural differences in our results are mainly driven by the fact that urban census tracts are much smaller (sample mean area = 13.88 km^2) and mixed together, whereas rural census tracts are larger (sample mean area = 39.65 km^2) and relatively spread out. Therefore, air quality has less variation at the census tract level in urban areas than in rural areas.

4.3. Robustness

The conclusions of our analysis are dependent on our somewhat arbitrary delineation of majority (white) and minority (non-white) census tracts.[19] Hence, we test the robustness of our results with an alternative specification. Instead of using a binary variable for majority/minority census tracts, we use a continuous variable "*Non-white Share*" to characterize each census tract in Eq. (8), so that the regression becomes:

$$\begin{aligned} q_{iyt} = & \sum_{w=2}^{25} \alpha_w \times 1[Week_t = w] \times Treated\ Group_y \\ & + \sum_{w=2}^{25} \delta_w^1 \times 1[Week_t = w] \times Non\text{-}white\ Share_i \\ & + \Delta \times Non\text{-}white\ Share_i \times Treated\ Group_y \times Lockdown_t \\ & + \beta X_{it} + \mu_i + u_y + v_t + \epsilon_{iyt} \end{aligned} \tag{9}$$

Table 6 summarizes the results, which are quite similar to the results reported in Table 5: the lockdown narrowed the racial gap in $PM_{2.5}$ concentration only in the AOD sample, but not in the $PM_{2.5}$-at-monitor and AOD-at-monitor samples. This suggests that the results are robust with respect to our majority/minority classification.

[18] In our sample, the average AOD is 0.18 for majority census tracts, and 0.27 for minority census tracts. The sample average racial disparity in AOD is calculated as 0.27-0.18 = 0.09.

[19] Recall that we use 50% non-white population as the cutoff that defines majority (white) and minority (non-white) census tracts. We also use each county's median percentage of white population as the cutoff and the results are insensitive to the change in the cutoff. See Table A8 in the appendix.

Table 6
The effects of lockdown on racial disparities in local $PM_{2.5}$ concentration, using continuous non-white population ratio.

	Dependent variable					
	AOD		$PM_{2.5}$-at-monitor		AOD-at-monitor	
	(1)	(2)	(3)	(4)	(5)	(6)
Lockdown	−0.030***		−0.010		−0.067	
	(0.010)		(0.238)		(0.051)	
Lockdown × Non-white share	−0.039***	−0.043***	−0.737	−0.975*	−0.036	−0.027
	(0.015)	(0.014)	(0.577)	(0.561)	(0.041)	(0.041)
Weather	Y	Y	Y	Y	Y	Y
Non-white share × Weeks FE	Y	Y	Y	Y	Y	Y
Treated group × Weeks FE	N	Y	N	Y	N	Y
Year FE	Y	Y	Y	Y	Y	Y
Census Tract FE	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y
N	349,559	349,559	24,516	24,516	2801	2801

***$p < .01$, **$p < .05$, *$p < .1$. The full results are reported in Appendix Table A7. The observation numbers for three samples are all smaller than the observation numbers reported in Table 3. This is because in this analysis we only use observations between December 2 and May 24 in each year.

It is also worth noting that since our analysis is at census tract level, large variations in total population across census tracts imply that our analysis may not represent the per-capita exposure to $PM_{2.5}$ pollution because we put equal weight on all census tracts regardless of population. As shown in Figure A12, census tract population in our sample tends to fall between 1,000 and 7,000. In light of this wide range in census tract population, we re-estimate the triple differences model in Eq. (8) using population weighted least square estimation. The results are reported in Table A9, and are generally consistent with Table 5. While the estimated effect of the lockdown on the racial gap in exposure to $PM_{2.5}$ pollution in the AOD sample has a slightly lower statistical significance, it is very similar in magnitude.

5. Conclusion

There is a long literature studying environmental justice issues in the U.S., but it tends to focus on systemic factors like the location of polluting factories and other point sources such as landfills and hazardous waste facilities and the response of/to the housing and labor market (see, for example, Banzhaf et al. (2019a,b)). By analyzing the change in air quality due to restricted economic activity during the COVID-19 pandemic, we add to that understanding by documenting an unintended, relatively short-term and perhaps temporary change in pre-existing inequities in local environmental quality.

As far as we are aware, this is the first paper to document the impacts of the policy response to the COVID-19 pandemic on inequality in environmental exposure. Focusing on New York State, we find that despite the strong seasonal pattern in which air quality improves every year during the months that are coincidentally the same as the COVID-19 lockdown period in New York State, the economic restrictions caused the racial disparities in $PM_{2.5}$ exposure to decrease in rural New York. We do not find any corresponding changes in the racial gap in urban areas of New York. Although the economic disruption caused by the lockdown was unprecedented, our results suggest a case for more aggressive regulation of air pollution with a view to rectifying the existing racial disparities in environmental exposure.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeem.2021.102554.

References

Banzhaf, H.S., Ma, L., Timmins, C., 2019a. Environmental justice: Establishing causal relationships. Annu. Rev. Resour. Econ. 11, 377–398.

Banzhaf, S., Ma, L., Timmins, C., 2019b. Environmental justice: The economics of race, place, and pollution. J. Econ. Perspect. 33 (1), 185–208.

Berman, J.D., Ebisu, K., 2020. Changes in U.S. air pollution during the COVID-19 pandemic. Sci. Total Environ. 739, 139864.

Chang, T., Graff Zivin, J., Gross, T., Neidell, M., 2016. Particulate pollution and the productivity of pear packers. Amer. Econ. J.: Econ. Policy 8 (3), 141–169.

Chen, L.A., Chien, L.-C., Li, Y., Lin, G., 2020. Nonuniform impacts of COVID-19 lockdown on air quality over the united states. Sci. Total Environ. 745 (1), 141105.

Clay, K., Troesken, W., Haines, M., 2014. Lead and mortality. Rev. Econ. Stat. 96 (3), 458–470.

Currie, J., Voorheis, J., Walker, R., 2020. What caused racial disparities in particulate exposure to fall? New evidence from the Clean Air Act and satellite-based measures of air quality. NBER Working Paper 26659.

Dang, H.-A.H., Trinh, T.-A., 2021. Does the COVID-19 lockdown improve global air quality? New cross-national evidence on its unintended consequences. J. Environ. Econ. Manag. 105 (1), 102401.

Donaldson, D., Storeygard, A., 2016. The view from above: Applications of satellite data in economics. J. Econ. Perspect. 30 (4), 171–198.

Dutheil, F., Baker, J.S., Navel, V., 2020. COVID-19 as a factor influencing air pollution? Environ. Pollut. (Barking, Essex: 1987) 263, 114466.

EPA, 2020. COVID-19 implications for epa's enforcement and com- pliance assurance program. Memorandum. https://www.epa.gov/sites/production/files/2020-03/documents/oecamemooncovid19implications.pdf.

Fowlie, M., Rubin, E.A., Walker, R., 2019. Bringing satellite-based air quality estimates down to earth. AEA Pap. Proc. 109 (1), 283–288.

Heusinkveld, H.J., Wahle, T., Campbell, A., Westerink, R.H., Tran, L., Johnston, H., Stone, V., Cassee, F.R., Schins, R.P., 2016. Neurodegenerative and neurological disorders by small inhaled particles. Neurotoxicology 56, 94–106.

Hoang, T.X., Le, D.T., Nguyen, H.M., Vuong, N.D.T., 2020. Labor market impacts and responses: the economic consequences of a marine environmental disaster. Journal of Development Economics 147, 102538.

Lee, H., Liu, Y., Coull, B., Schwartz, J., Koutrakis, P., 2011. A novel calibration approach of MODIS AOD data to predict $PM_{2.5}$ concentrations. Atmos. Chem. Phys. 11 (15), 7991–8002.

Lichter, A., Pestel, N., Sommer, E., 2017. Productivity effects of air pollution: Evidence from professional soccer. Labour Econ. 48, 54–66.

Liu, Y., Park, R.J., Jacob, D.J., Li, Q., Kilaru, V., Sarnat, J.A., 2004. Mapping annual mean ground-level $PM_{2.5}$ concentrations using multiangle imaging spectroradiometer aerosol optical thickness over the contiguous United States. J. Geophys. Res.: Atmos. 109 (D22).

New York Times, 2020a. India savors a rare upside to coronavirus: Clean air. New York Times https://www.nytimes.com/2020/04/08/world/asia/india-pollution-coronavirus.html?searchResultPosition=3.

New York Times, 2020b. Location data says it all: Staying at home is a luxury. New York Times https://www.nytimes.com/interactive/2020/04/03/us/coronavirus-stay-home-rich-poor.html?searchResultposition=10.

Persico, C.L., Johnson, K.R., 2021. The effects of increased pollution on COVID-19 cases and deaths. J. Environ. Econ. Manag. 102431.

Ranjan, A.K., Patra, A., Gorai, A., 2020. Effect of lockdown due to SARS COVID-19 on aerosol optical depth (AOD) over urban and mining regions in India. Sci. Total Environ. 745 (1), 141024.

Reuters, 2020a. Chinese official hails 'incomparable' improvement in air quality as virus hits industry. Reuters https://www.reuters.com/article/us-china-pollution-smog/chinese-official-hails-incomparable-improvement-in-air-quality-as-virus-hits-industry-idUSKBN22R0S3.

Reuters, 2020b. Urban air quality improves as coronavirus empties U.S. highways. Reuters https://www.reuters.com/article/us-health-coronavirus-usa-pollution/urban-air-quality-improves-as-coronavirus-empties-us-highways-noaa-idUSKBN22P1OV.

Reuters, 2020c. U.S. manufacturing production posts record decline. Reuters https://www.reuters.com/article/us-usa-economy-output/us-manufacturing-production-posts-record-decline-idUSKBN22R24A.

Van Donkelaar, A., Martin, R.V., Brauer, M., Hsu, N.C., Kahn, R.A., Levy, R.C., Lyapustin, A., Sayer, A.M., Winker, D.M., 2016. Global estimates of fine particulate matter using a combined geophysical-statistical method with information from satellites, models, and monitors. Environ. Sci. Technol. 50, 3762–3772.

Venter, Z.S., Aunan, K., Chowdhury, S., Lelieveld, J., 2020. COVID-19 lockdowns cause global air pollution declines. Proc. Natl. Acad. Sci. 117 (32), 18984–18990.

Williams, A.M., Phaneuf, D.J., Barrett, M.A., Su, J.G., 2019. Short-term impact of $PM_{2.5}$ on contemporaneous asthma medication use: Behavior and the value of pollution reductions. Proc. Natl. Acad. Sci. 116 (12), 5246–5253.

Zhang, R., 2021. Economic impact payment, human mobility and COVID-19 mitigation in the USA. Empir. Econ. 1–20.

Zhang, R., Li, H., Khanna, N., Sullivan, D.J., Krupnick, A.J., Hill, E.L., 2020. Spatial Spillovers in Airborne Pollution: Air Quality Impacts of Shale Gas Development in Pennsylvania. Working Paper.