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DISCUSSION PAPER SERIES

IZA DP No. 13231

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ABSTRACT

Deregulation in a Time of Pandemic: Does Pollution Increase Coronavirus Cases or Deaths?*

The COVID-19 virus, also known as the coronavirus, is currently spreading around the world. While a growing literature suggests that exposure to pollution can cause respiratory illness and increase deaths among the elderly, little is known about whether increases in pollution could cause additional or more severe infections from COVID-19, which typically manifests as a respiratory infection. Using variation in pollution induced by a rollback of enforcement of environmental regulations by the Environmental Protection Agency (EPA) and a difference in differences design, we estimate the effects of increased pollution on county-level COVID-19 deaths and cases. Despite popular media coverage to the contrary, we find that counties with more Toxic Release Inventory (TRI) sites saw increases in pollution following the EPA's rollback of enforcement, while counties with fewer sites saw a smaller increase in pollution. We find that increases in pollution are associated with increases in cases and deaths from COVID-19.

JEL Classification: Q53, I10, I14

Keywords: pollution, COVID-19, coronavirus, health, mortality

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I. Introduction

COVID-19, which is currently spreading throughout the United States at an alarming rate, represents a serious threat to public health and well-being. COVID-19 (sometimes referred to as the coronavirus) commonly manifests as a respiratory infection, and in severe cases, there is progressive respiratory failure leading to death (Xu et al. 2020). While a growing literature suggests that exposure to pollution can increase asthma attacks and cause people to get sick with a respiratory illness (Currie et al. 2009; Jans, Johansson, and Nilsson 2014; Ransom and Pope 1992; Simeonova et al. 2019), little is known about whether increases in pollution could cause more infections from the coronavirus. However, a growing literature shows that small increases in air pollution from inversion episodes (Jans, Johansson, and Nilsson 2014), changes in wind direction (Anderson 2019; Deryugina et al. 2019), retrofitting school buses (Beatty and Shimshack 2011), or airport delays (Schlenker and Walker 2011) increase respiratory illnesses in children, mortality, hospital visits, and hospitalizations. Additionally, pollution is shown to decrease mental acuity in otherwise healthy adults. (Archsmith, Heyes, and Saberian 2018; Kunn, Palacios, and Pestel 2019). Conversely, there is evidence that small reductions in air pollution, such as those caused by congestion taxes (Simeonova et al. 2018) are associated with reductions in childhood asthma.

More seriously, there is growing evidence that days of high air pollution can cause deaths (Anderson 2019; Schwartz, Bind, and Koutrakis 2017; Deryugina et al. 2019; Deschenes and Greenstone 2011). Anderson (2019) finds that living downwind of a highway increases the mortality of persons over 75 years old. Anderson further finds that this increased mortality is from a range of different causes (Anderson, 2019). In addition, Deryugina et al. (2019) find that vulnerable populations, such as the elderly or those with existing chronic conditions, are more susceptible to the mortality increases that result from increases in pollution. Overall, there is strong evidence that even small increases in pollution can have detrimental effects across a wide variety of measures and outcomes. While this evidence is compelling, little is known about the factors influencing how the COVID-19 virus spreads or whether pollution might be a factor in increasing the spread of the virus or deaths from COVID-19. However, recently Setti et al. (2020) discovered that coronavirus can be detected on particles of air pollution called Particulate Matter 10, which suggests that increased air pollution could increase infections and deaths from COVID-19.

On March 26, 2020, the United States Environmental Protection Agency (EPA) announced a freeze in civil enforcement of environmental regulations due to the coronavirus pandemic. In particular, the EPA stated that it does "not expect to seek penalties for violations of routine compliance monitoring, integrity testing, sampling, laboratory analysis, training, and reporting or certification obligations in situations where the EPA agrees that Covid-19 was the cause of the noncompliance" (EPA 2020).

Most of the facilities impacted by this rollback are likely to be required to report their emissions on the Toxic Release Inventory (TRI), a database maintained by the EPA on industrial or federal facilities that release toxic chemicals. This allows us to track which US counties were most likely to see an increase in air pollution after the new policy was announced. In 2017, Toxic Release Inventory (TRI) sites alone (which represent only one type of industrial plant) released 3.97 billion pounds of (untreated) toxic chemicals in America into the air, land and water, out of 30.57 billion total pounds of toxic chemicals created in production-related wastes (EPA 2017).

There are currently about 21,800 TRI sites operating across the United States and more than 221.5 million people had a TRI site operating in their zip code in 2016. [1]

We use data from Johns Hopkins University on the number of daily COVID cases and deaths matched to EPA data on daily air quality and pollution sites to sort counties into two groups: those who are in the top third in terms of the total number of TRI sites operating in the county and those who are in the bottom two thirds. The top third of polluting counties have 6 or more TRI sites with at least one that releases air pollution. To address concerns about the possible selection of TRI sites into counties, we limit our main sample to only counties that have at least one TRI site emitting air pollution. Fig. 1 shows that there is a large and statistically significant increase in air pollution after the rollback of environmental regulations.[2] On average, counties in the top third of the TRI distribution in terms of the number of TRI sites experience about 12 percent (i.e., 0.82 ug/m^3) higher pollution after the rollback, relative to counties in the bottom two thirds of the TRI distribution.

Using the timing of these changes in short-term pollution exposure by county, we use a generalized difference in differences design with population-weighted Poisson regression to estimate whether counties that experience increased pollution after the rollback of enforcement of environmental regulations see increases in the conditional number of daily COVID deaths and cases, controlling for social distancing, stay at home orders, days since the first COVID death, weather, day of the week, and state-county and month fixed effects. In our primary specification, we estimate the effects of predicted pollution on outcomes, but we also estimate the results using an indicator for whether the county is in the treated group after the rollback. To address concerns that population density might drive the findings, we also show the results when limiting the

[1] We made this calculation based on linking zip code level census counts of the population to TRI data.
[2] Note that day +3 is a Sunday, which partially explains the drop in pollution.

counties in the control group to only counties that have population density of greater than 700 persons/mile^2.

We find that increases in predicted pollution resulting from the rollback of EPA enforcement led to large and statistically significant increases in COVID-19 cases and deaths. In particular, Particulate Matter 2.5 and ozone are associated with increases in the virus's spread and deaths. In addition, we find that pollution exposure is worse for counties with a higher fraction of Black individuals, counties with higher unemployment, and counties that have lower income.

Evidence of the extent to which air pollution affects cases and mortality from COVID-19 is important for three reasons. First, any changes in environmental policy should be informed by the costs associated with those changes, and the costs of deregulation right now could easily outweigh the benefits. Second, it informs our understanding of how pollution affects the transmission of viruses and the death toll during a pandemic, which could create opportunities for live-saving interventions. For example, air purifiers could be employed in in-patient facilities that treat COVID patients on particularly high air pollution days. Third, if reduction of pollution might assist to decrease the death rate, tangentially related interventions like stay at home orders could be modified to maximize the potential reduction in pollution.

II. Data

To examine how pollution affects deaths and cases from COVID-19, we used data from Johns Hopkins University Center for Systems Science and Engineering Coronavirus Resource Center on the daily number of cases and deaths by county matched to daily data on air pollution by county from the EPA's Air Quality System. The AQS has daily data on PM2.5, PM10 and ozone throughout this time period. We also matched these data to daily weather data from the National Oceanic and Atmospheric Administration (NOAA). The Johns Hopkins data adds county-level counts of daily COVID-19 cases and deaths starting on March 22, 2020 the time period for the regressions on deaths and cases is limited to March 22, 2020 through the present.

Because pollution emissions could be confounded by social distancing behaviors, we also use data on the degree of social distancing by county from Unacast's Social Distancing Dataset. To construct this measure of social distancing, Unacast uses cell phone geolocation data on the average distance traveled from pre-COVID-19 days to estimate the percent change in total distance traveled in the four weeks before the pandemic, compared to each day during the pandemic starting on March 22, 2020 in each county. The social distancing measure is at the daily level by county across all counties in the United States. Further details about the sample are reported in the Data Appendix.

III. Empirical Strategies

Most of the facilities impacted by the environmental rollback are likely required to report their emissions on the Toxic Release Inventory (TRI), which is a database maintained by the EPA on industrial or federal facilities that release toxic chemicals over threshold amounts. This allows us to track which US counties were most likely to see an increase in air pollution after the new policy was announced. We use data from the 2018 TRI to sort counties into two groups: those who are in the top third in terms of the total number of TRI sites operating in the county and those who are in the bottom two thirds. In order to be considered in the top third of polluting counties, the county must have 6 or more TRI sites with at least one that releases air pollution. To address concerns about the possible selection of TRI sites into counties, we limit our main sample to only counties that have at least one TRI site emitting air pollution. However, the results are robust to including all counties in the United States that are represented in the Johns Hopkins data (i.e., 2777 counties), even counties with no TRI sites.

Using daily data on air pollution by county from the EPA's Air Quality System (AQS) from February 24th through April 25th, 2020, we use a generalized difference in differences design to estimate the amount pollution has increased because of the rollback. We regress the amount of PM2.5 on an indicator for being in a treated county (with more TRI sites) before versus after the rollback, compared to being in a control county before versus after the rollback as follows:

(1) $$Pollution_{id} = \beta_1 TreatedPost_{id} + X_{id} + \sigma_i + \varphi_d + \varepsilon_{id}$$

In this equation, $Pollution_{id}$ is the daily amount of PM2.5 pollution in ug/m^3 in state-county *i* on day of the week *d*. $TreatedPost_{id}$ is a binary indicator for being in a county in the top third of the distribution in terms of the number of TRI sites after the rollback of environmental regulations. X_{id} is a vector of daily state-county variables (i.e., whether there is a stay at home order on that day and daily social distancing measures). σ_i are state-county fixed effects, φ_d are day of the week fixed effects.[3] The amount that pollution increased within a county in the top third of the TRI distribution post-environmental regulation rollback relative to counties with fewer TRI sites is given by β_1. This equation can be used to estimate the predicted amount of pollution in treated versus control counties.

While portrayals in the popular media suggests that pollution has decreased everywhere, our preliminary analyses in Fig. 1 shows that there is a large and statistically significant increase

[3] Note that there are no year fixed effects because the time period is constrained to only occur within the time window of the pandemic (from March 2020 onwards).

in air pollution after the rollback of enforcement of environmental regulations. This makes sense, considering that pollution from transportation only makes up 28 percent of greenhouse gas emissions in the United States (EPA 2020) and that emissions globally are only estimated to fall by 5.5 percent from 2019 levels because of COVID-19 (Evans 2020). Even though car pollution has likely decreased, in counties with more TRI sites, the total amount of average daily pollution as measured by EPA pollution monitors has increased. We find that, on average, counties in the top third of the TRI distribution in terms of the number of TRI sites experience about 9 percent (i.e., 0.82 ug/m^3) higher pollution after the rollback, relative to counties in the bottom two thirds of the TRI distribution.

While it is tempting to analyze this data cross-sectionally (for example, some studies compare counties with more versus less long-term pollution), long term pollution exposure might be associated with a variety of other characteristics of counties, such as social distancing proclivities, racial composition, employment levels, or income. Thus, there also may be selection into more polluted counties for people with worse underlying health or who practice different health behaviors related to social distancing.

Our primary identification strategy is a generalized difference in differences design in which we exploit the within-county change in pollution over time induced by the EPA's environmental rollback, controlling for county, month, and year fixed effects, as well as a variety of county-level demographic control variables and Unacast's measure of social distancing. The basic generalized difference in differences model we will use is as follows:

(1) $$log\, Y_{idm} = \beta_1 TreatedPost_{idm} + W_{idm} + X_{idm} + \sigma_i + \varphi_d + \gamma_m + \varepsilon_{idm}$$

In this equation, Y_{idm} is the number of daily deaths (or confirmed cases) in state-county i on day of the week d in month m. $TreatedPost_{idm}$ is an indicator for being in a county in the top third of the distribution in terms of the number of TRI sites after the rollback of environmental regulations. W_{idm} are weekly average weather controls for temperature and precipitation, and X_{idm} is a vector of daily state-county variables (i.e., whether there is a stay at home order, days since the first death from COVID-19, and the number of confirmed cases[4]) and daily social distancing measures. σ_i are state-county fixed effects, φ_d are day of the week fixed effects, and γ_m are month fixed effects.[5] The effect of being in a county in the top third of the TRI distribution post-environmental regulation rollback on cases or deaths is given by β_1. In our main specification we utilize county population-weighted Poisson pseudo-maximum likelihood regressions (PPML) with multi-way fixed effects to estimate the effects of policy-induced increases in pollution on deaths or cases.[6]

To address concerns about the selection of TRI sites into counties, we limit the sample to only counties that have at least one TRI site emitting air pollution. By controlling for social distancing, the number of confirmed cases and the number of days since the first death in a county, we are controlling for time trends that could affect the spread and severity of cases of COVID-19. In order to estimate the effect of the policy-induced change in pollution, we estimate the predicted amounts of a variety of different types of pollutants, such as Particulate Matter 2.5 (PM2.5), Particulate Matter 10 (PM10), and ozone, based on the within-county variation induced by the rollback of enforcement of environmental regulations, controlling for social distancing, stay at home orders and county and day of the week fixed effects. In our main specification, we also estimate the effects of this predicted pollution on deaths and cases. On average, counties in

[4] We only control for the daily number of confirmed cases by counties in regressions of the effect of environmental regulations on the log of deaths.
[5] Note that there are no year fixed effects because the time period is constrained to only occur within the time window of the pandemic (from March 2020 onwards).
[6] This estimation strategy allows us to make minimal assumptions about the distribution of the data. See Correia, Guimaraes and Zylkin (2020) for technical details on the estimation .

the top third of the TRI distribution in terms of the number of TRI sites experience about 12 percent (i.e., 0.82 ug/m^3) higher pollution after the rollback, relative to counties in the bottom two thirds of the TRI distribution.

Our main identifying assumption is that in the absence of the environmental rollback, outcomes in the treated counties with more TRI sites would have followed a parallel trajectory to the counties in the control group. We provide evidence supporting the parallel trends assumption in several ways. First, we show that the characteristics of counties with more and fewer TRI sites are similar across a variety of different demographic characteristics in Table 1. We also show that our main results are robust to dropping counties with population densities of less than 700 persons/mile^2 in the control group so that the population density in control group counties are similar to those in treated counties In Table 5 we also show that these results are robust to dropping New York County or counties in the treatment group with population densities of more than 1000 persons/mile^2.

We also show an event study of the treatment and control counties in Figure 2 indicating that the counties are on similar trajectories in the pre-treatment period. The basic event study model we use is given by:

$$(2) \quad log\, Y_{id} = \beta_0 + \sum_{j=-2}^{6} \beta_j \mathbb{1}[\tau_{id} = j]_{id} + X_{id} + \eta_i + \theta_d + \epsilon_{ist}$$

We include two days of lags and six days of leads for the treatment, where τ_{it} denotes the day relative to the rollback of the EPA's enforcement of environmental regulations. For example, a value of τ_{it} = -1 represents the deaths one day before the day in which the day the EPA released the memo saying it would not enforce environmental regulations (March 26, 2020). β is the effect of the environmental rollback on COVID-19 deaths.

IV. Results

Table 2 presents the results of our main difference in differences regressions using county-population-weighted Poisson pseudo-maximum likelihood regressions (PPML) with multi-way fixed effects. Column 1 present the results from our main specification for the effects of a predicted increase in PM2.5 of 1 ug/m^3 induced by the rollback in treated counties (with more TRI sites) on COVID-19 deaths, compared to control counties (with fewer TRI sites). Column 2 of Table 2 presents the overall effects of increased pollution in treated counties compared to control counties before versus after the rollback. Because there is a concern that population density furthers the spread of the virus, column 3 presents the results of our main specification limiting the control group to more population-dense counties (with population density > 700 persons/mi^2). Columns 4-6 present a similar pattern of results for COVID-19 cases rather than deaths.

Overall, we find that increases in pollution substantially increased the conditional daily COVID-19 death rate and daily new case rate of COVID-19 – a one ug/m3 increase in predicted PM2.5 leads to a near doubling of the conditional death rate from COVID-19. Because many people with COVID-19 do not show symptoms (Hu et al. 2020; Kenji et al. 2020), the rate of daily new cases likely represents more severe cases, indicating that pollution might cause COVID-19 cases to become worse. Table A1 presents results from our OLS specification using the policy-induced predicted pollution increase and the overall effect of being in a treated county after the rollback. The larger results for the Poisson regressions on deaths but not cases suggest that the OLS results are downwardly biased.[7] However, overall the results are robust to using both Poisson and OLS difference in differences regressions that control for social distancing,

[7] In the presence of heteroskedasticity, the parameters of log-linearized models estimated by OLS are inconsistent (Correia, Guimaraes, and Zylkin 2020).

stay at home orders, days since the first COVID death, weather, day of the week, and state-county and month fixed effects. The results on deaths are also robust to controls for the daily number of confirmed cases. In addition, as shown in Table A2 the results are very similar when we include all counties in the United States that are represented in the Johns Hopkins data (i.e., 2777 counties), even counties with no TRI sites.

Fig. 2 displays the main results of our event study on the log of COVID-19 deaths using OLS regression. While COVID-19 deaths were falling slightly in the treated counties in the pre-period, after the announced rollback of enforcement, deaths increased substantially in counties with more TRI sites relative to counties in the control group. The event study suggests that the environmental rollback led to a 17 to 20 percentage point increase in the death rate above the treatment group.

Table 3 presents the results for different types of pollutants using predicted pollution. Overall, PM2.5 and ozone have the largest negative effects on COVID-19 deaths and cases, suggesting that they might exacerbate respiratory distress. However, an increase in predicted PM10 also increases the conditional death rate by 18 percent.

In Table 4, we also examine the results by different characteristics of counties in the 2018 American Community Survey. We find that counties with higher than median percentages of Black individuals have much worse outcomes as a result of predicted pollution exposure. There is some evidence that non-White individuals are overrepresented in neighborhoods around TRI sites (Currie et al. 2011), which might explain the higher death rate for counties with more Black individuals. There is also suggestive evidence that Black Americans are dying at higher rates than Whites (Garg et al. 2020), and our results suggest that pollution might be a driving factor in this. In addition, the outcomes are worse in counties that had above-median unemployment or below-median income according to the 2018 census. If industrial sites lower housing values, the lower income individuals might be more likely to live closer to TRI sites, resulting in a higher death rate. In addition, lower income individuals might have less access to healthcare.

However, one might worry that especially population dense counties in the treatment group might also be driving the results. So, in Table 5 we also show that our results are robust to dropping New York County and treated counties with population density over 1000 persons/mi^2. It is worth noting that New York County is in the control group in all regressions since it contains fewer than 6 TRI sites.[8]

V. Discussion

Whether pollution increases the COVID-19 case rate or death rate is an extremely important question for public health, and there is a race to discover the factors that cause more deaths. Our results show that increased pollution nearly doubles the conditional daily COVID-19 death rate and case rate. These results are stronger for counties with higher fractions of Black individuals, lower income individuals and unemployed individuals, suggesting that the burden of pollution exposure is unequal. Pollution might have the largest impacts on the most vulnerable members of society, causing higher death rates and more severe cases of COVID-19.

This study also suggests that deregulation efforts may come with extremely high costs in terms of human lives during pandemics. Our results are consistent with a broader literature that finds that pollution increases respiratory infections and mortality. However, these findings suggest that unequal pollution exposure might exacerbate preexisting inequalities in health and

[8] The Johns Hopkins data on COVID-19 cases and deaths unfortunately does not include some counties in New York City, such as Queens county, Bronx County and King County, which includes Brooklyn.

result in more COVID-19 deaths. This work also underscores the importance of continuing to enforce existing regulations during pandemics.

Finally, this work also suggests several opportunities for intervention. For example, air purifiers could be employed in intensive care units and in-patient facilities that treat COVID-19 patients on high air pollution days. In addition, targeted policy and regulatory efforts to reduce pollution might assist to decrease the death rate. Our pattern of results further suggest that preventative measures should be focused on vulnerable populations, who are more at risk after exposure to pollution. Further research is needed to understand the mechanisms by which reducing pollution might affect COVID-19 cases and deaths.

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Table 1: Characteristics of Counties

	(1) Characteristics of Counties in the U.S. in 2018 with 1 or More TRI sites	(2) Characteristics of Counties in the Top Third of the TRI Distribution	(3) Characteristics of Counties in the Bottom Two Thirds of the TRI Distribution	(4) Characteristics of Counties in the Bottom Two Thirds of the TRI Distribution, Limited to Population Density of >700
Total Population	143,446	358,507	47,437	199,826
Population Density	576.1	1,265	267.6	3,064
Percent White	0.821	0.792	0.834	0.767
Percent Black	0.104	0.115	0.0995	0.129
Percent Hispanic	0.0902	0.111	0.0808	0.108
Percent Poverty	0.110	0.0988	0.116	0.0914
Median Income	53,202	59,070	50,582	65,129
Unemployment Rate	3.357	3.497	3.295	3.415
Total TRI Sites	9.953	24.25	3.570	4.850
Total Confirmed Cases	178.2	393.2	82.14	1,167
Total Deaths	7.140	13.15	4.458	70.71
Number of Counties	2,106	650	1,456	80

Note: This table depicts the characteristics of counties in the sample. Column 1 shows characteristics of all counties in the United States with at least one TRI site releasing air pollution. Column 2 shows characteristics of counties in the top third of the TRI distribution in terms of the number of sites. These are the treated counties. Column 3 shows characteristics of counties in the bottom two thirds of the TRI distribution in terms of the number of sites. Column 4 shows characteristics of counties in the bottom two thirds of the TRI distribution limited to those with population density of less than 700 persons/mi.

Table 2: The Effects of Pollution on Deaths and Cases

	(1) COVID-19 Deaths	(2) COVID-19 Deaths	(3) COVID-19 Deaths	(4) Confirmed COVID-19 Cases	(5) Confirmed COVID-19 Cases	(6) Confirmed COVID-19 Cases
Predicted PM2.5 Pollution (μg/m^3)	0.9951** (0.4461)		1.0046** (0.4843)	0.9710*** (0.1568)		0.9796*** (0.1637)
Treated Counties in Post Period		0.8116** (0.3638)			0.7919*** (0.1278)	
Poisson fixed effects regression	X	X	X	X	X	X
Limited to Counties with Population Density >700 in the Control Group			X			X
Observations	52126	52126	36557	91118	91118	47202

Note: Columns 1-3 present the results for different regression specifications with the log of COVID-19 deaths as the outcome. Columns 4-6 present the same specifications with the log of confirmed COVID-19 cases as the outcome. All results use county-population-weighted Poisson pseudo-maximum likelihood regressions (PPML) with multi-way fixed effects and control for social distancing, stay at home orders, days since the first COVID death, weather, and day of the week, and state-county and month fixed effects. Columns 1-3 additionally control for daily confirmed COVID-19 cases. Coefficients labeled as ***, **, and * are statistically significant at the 1, 5, and 10 percent levels, respectively.

Table 3: The Effects of Different Types of Pollution on Deaths and Cases

	(1)	(2)	(3)	(4)	(5)	(6)
	COVID-19 Deaths	COVID-19 Deaths	COVID-19 Deaths	Confirmed COVID-19 Cases	Confirmed COVID-19 Cases	Confirmed COVID-19 Cases
Predicted PM2.5 Pollution (μg/m^3)	0.9951** (0.4461)			0.9710*** (0.1568)		
Predicted Ozone (ppm)		182.9583** (82.0244)			178.5285*** (28.8202)	
Predicted PM10 (μg/m^3)			0.1812** (0.0813)			0.1768*** (0.0285)
Poisson with Fixed Effects Regression	X	X	X	X	X	X
Observations	52126	52126	52126	52126	24284	30230

Note: Columns 1-3 present the results for different predicted pollution types with the log of COVID-19 deaths as the outcome. Columns 4-6 present the same specifications with the log of confirmed COVID-19 cases as the outcome. All regressions present results from county-population-weighted Poisson pseudo-maximum likelihood regressions (PPML) with multi-way fixed effects and control for social distancing, stay at home orders, days since the first COVID death, weather, and day of the week, and state-county and month fixed effects. Columns 1-3 additionally control for daily confirmed COVID-19 cases. Coefficients labeled as ***, **, and * are statistically significant at the 1, 5, and 10 percent levels, respectively.

Table 4: Heterogeneity by County Characteristics in 2018

	COVID-19 Deaths					
	(1)	(2)	(3)	(4)	(5)	(6)
	County is Below Median Percent Black	County is Above Median Percent Black	County is Below Median Percent Unemployed	County is Above Median Percent Unemployed	County is Below Median Income	County is Above Median Income
Predicted PM2.5 Pollution	0.6650** (0.3288)	1.0481** (0.4869)	0.9451** (0.4100)	1.2239*** (0.4662)	1.9692*** (0.2246)	0.7506 (0.4588)
Observations	20724	31402	25136	26990	21406	30720
Average of dependent variable	0.10	0.10	0.033	0.033	53,959	53,959

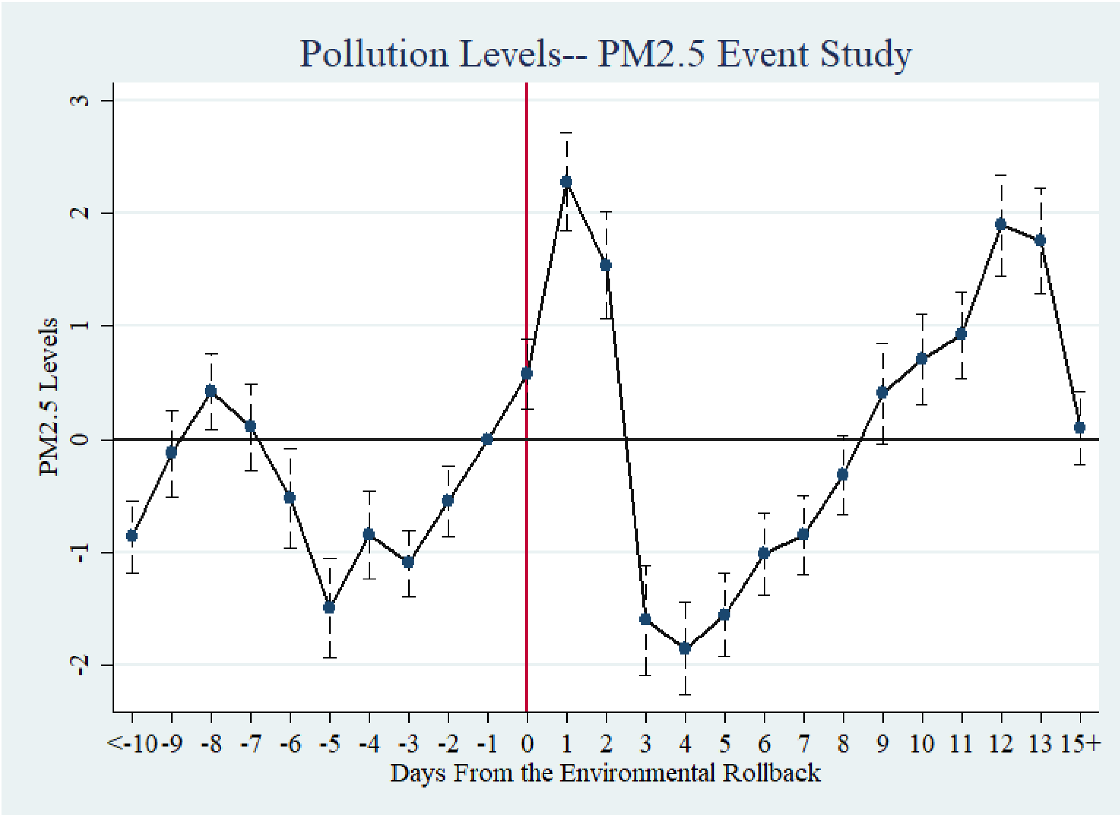
Note: Each column presents the results for a different subgroup with the log of COVID-19 deaths as the outcome. All regressions present results from county-population-weighted Poisson pseudo-maximum likelihood regressions (PPML) with multi-way fixed effects and control for social distancing, stay at home orders, days since the first COVID death, weather, daily confirmed COVID-19 cases, and day of the week, and state-county and month fixed effects. Coefficients labeled as ***, **, and * are statistically significant at the 1, 5, and 10 percent levels, respectively.

Table 5: Results when Dropping Population Dense Counties

	(1)	(2)	(3)	(4)
	COVID-19 Deaths	COVID-19 Deaths	Confirmed COVID-19 Cases	Confirmed COVID-19 Cases
Predicted PM2.5 Pollution	1.7357***	1.0227**	0.9550***	1.1122***
	(0.2656)	(0.4361)	(0.1698)	(0.2274)
Poisson fixed effects regression	X	X	X	X
Dropping New York County	X		X	
Limited to Counties with Population Density <1000 in the Treatment Group		X		X
Observations	52070	38940	91062	77559

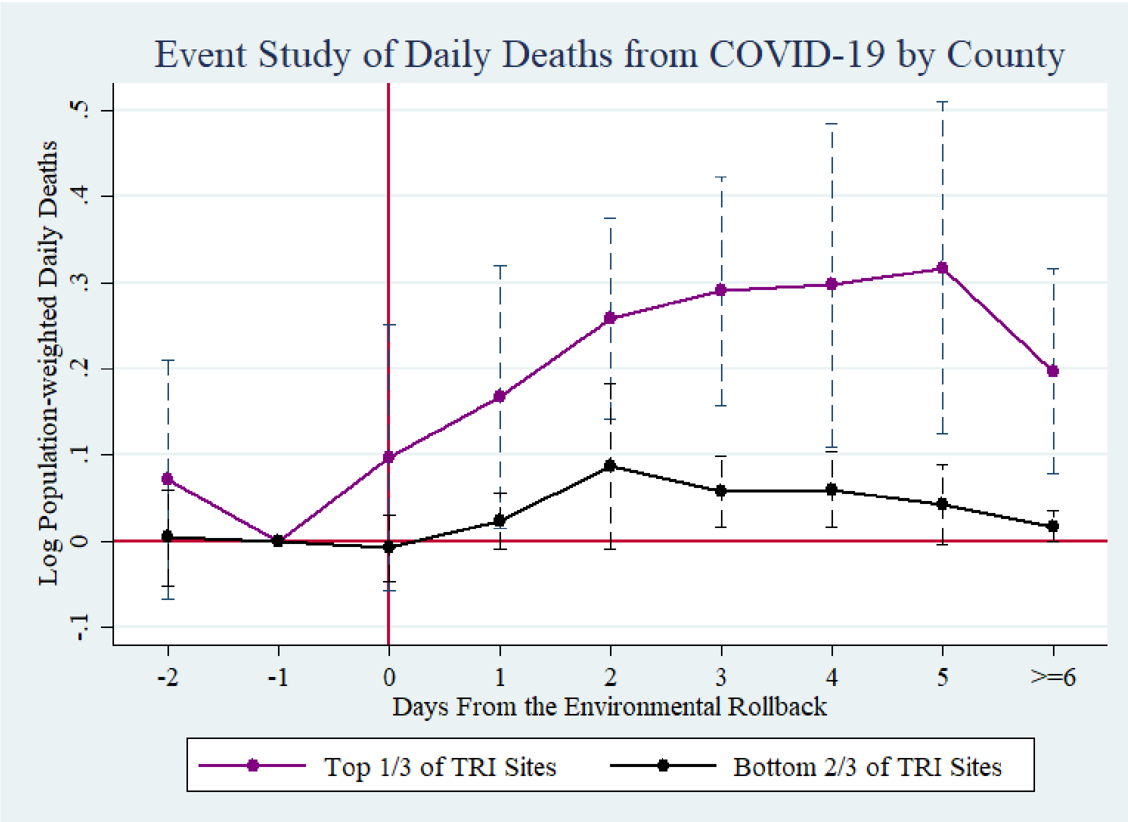
Note: Columns 1-2 present the results for different predicted pollution types with the log of COVID-19 deaths as the outcome. Columns 3-4 present the same specifications with the log of confirmed COVID-19 cases as the outcome. Columns 1 and 3 present estimates in which we drop New York County. Columns 2 and 4 present estimates in which we drop treated counties with population densities of more than 1000. All regressions present results from county-population-weighted Poisson pseudo-maximum likelihood regressions (PPML) with multi-way fixed effects and control for social distancing, stay at home orders, days since the first COVID death, weather, and day of the week, and state-county and month fixed effects. Columns 1-2 additionally control for daily confirmed COVID-19 cases. Coefficients labeled as ***, **, and * are statistically significant at the 1, 5, and 10 percent levels, respectively.

Figure 1: Particulate Matter 2.5 Event Study by County



Note: Figure 1 plots the coefficients from an OLS effects regression of mean level of PM2.5 on leads and lags of time from the rollback of environmental laws on March 26, 2020 using pollution data from March and April 2020. Time 0 is March 26, 2020 and all coefficients are normalized such that the coefficient in the day prior to the rollback (-1) is zero. Dotted lines represent 0.95 confidence intervals for the coefficients. The regression controls for stay at home orders, social distancing measures, county fixed effects and day of the week fixed effects. Standard errors are clustered at the county level.

Figure 2: Event Study of Daily Deaths from COVID-19 by County



Note: Figure 2 plots the coefficients from an OLS effects regression of the log of daily COVID-19 deaths on leads and lags of time from the rollback of environmental laws on March 26, 2020 using pollution data from March and April 2020. Time 0 is March 26, 2020 and all coefficients are normalized such that the coefficient in the day prior to the rollback (-1) is zero. Dotted lines represent 0.95 confidence intervals for the coefficients. The regression controls for stay at home orders, social distancing measures, days since the first death by county, number of confirmed cases by county, county fixed effects and day of the week fixed effects. Standard errors are clustered at the county level.

Appendix Tables and Figures

Table A1: Results using OLS Regression with Fixed Effects

	(1)	(2)	(3)	(4)
	Log COVID-19 Deaths	Log COVID-19 Deaths	Log Confirmed COVID-19 Cases	Log Confirmed COVID-19 Cases
Predicted PM2.5 Pollution	0.1414** (0.0629)		1.3132*** (0.1544)	
Treated Counties in Post Period		0.1153** (0.0513)		1.0710*** (0.1259)
OLS Fixed Effects Regression	X	X	X	X
Observations	102242	102242	102242	102242

Note: Columns 1-2 present the results for the effects of predicted pollution or being in a treated county after the rollback with the log of COVID-19 deaths as the outcome. Columns 3-4 present the same specifications with the log of confirmed COVID-19 cases as the outcome. All results in this table use county population-weighted OLS regressions and control for social distancing, stay at home orders, days since the first COVID death, weather, and day of the week, and state-county and month fixed effects. Columns 1-2 additionally control for daily confirmed COVID-19 cases. Coefficients labeled as ***, **, and * are statistically significant at the 1, 5, and 10 percent levels, respectively.

Table A2: Results using All Counties, Including Counties with No TRI Sites

	(1)	(2)	(3)	(4)
	Log COVID-19 Deaths	Log COVID-19 Deaths	Log Confirmed COVID-19 Cases	Log Confirmed COVID-19 Cases
Predicted PM2.5 Pollution	1.0738** (0.4692)		1.0401*** (0.1665)	
Treated Counties in Post Period		0.8182** (0.3575)		0.7925*** (0.1269)
OLS Fixed Effects Regression	X	X	X	X
Observations	57855	57855	115619	115619

Note: Columns 1-2 present the results for the effects of predicted pollution or being in a treated county after the rollback with the log of COVID-19 deaths as the outcome using all counties in the sample, including those with no TRI sites. Columns 3-4 present the same specifications with the log of confirmed COVID-19 cases as the outcome. All results use county-population-weighted Poisson pseudo-maximum likelihood regressions (PPML) with multi-way fixed effects and control for social distancing, stay at home orders, days since the first COVID death, weather, and day of the week, and state-county and month fixed effects. Columns 1-2 additionally control for daily confirmed COVID-19 cases. Coefficients labeled as ***, **, and * are statistically significant at the 1, 5, and 10 percent levels, respectively.

Online Data Appendix

The Unacast data on social distancing is calculated as follows. The base line comparison is against the 4 weeks prior to 03-08-2020. Unacast took the average of each weekday and each county for those 4 weeks. They assign a person to a county based on the total duration of the identifier in the county on that day. The county in which we see the device the most that day is the county they assign it to. There are 15-17 million identifiers per day in the entire dataset. The social distancing measure we use is calculated as: (average post-period distance traveled - average pre-period distance traveled) / average pre-period distance traveled.

Additional data on stay at home orders by state was gathered by the COVID-19 State Policy database, sponsored by Julia Raifman at the Boston University School of Public Health.