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The effects of increased pollution on COVID-19 cases and deaths☆

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ABSTRACT

The SARS-COV-2 virus, also known as the coronavirus, has spread around the world. A growing literature suggests that exposure to pollution can cause respiratory illness and increase deaths among the elderly. However, 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. During the pandemic, the Environmental Protection Agency (EPA) rolled back enforcement of environmental regulation, causing an increase in pollution in counties with more TRI sites. We use the variation in pollution and a difference in differences design to estimate the effects of increased pollution on county-level COVID-19 deaths and cases. We find that counties with more Toxic Release Inventory (TRI) sites saw a 11.8 percent increase in pollution on average following the EPA's rollback of enforcement, compared to counties with fewer TRI sites. We also find that these policy-induced increases in pollution are associated with a 53 percent increase in cases and a 10.6 percent increase in deaths from COVID-19.

1. Introduction

The SARS-COV-2 coronavirus disease 2019 (COVID-19), which has spread throughout the United States at an alarming rate, represents a serious threat to public health and well-being. It is critically important to discover the factors that cause more cases and deaths from COVID-19, as well as why outcomes vary from place to place. COVID-19 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 body of literature suggests that exposure to pollution can increase mortality and cause people to get sick with a respiratory illness (Currie et al., 2009; Deryugina et al., 2019; Jans et al., 2014; Ransom and Pope, 1992; Simeonova et al., 2019), 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.

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There are two main reasons that pollution could affect COVID-19 outcomes. First, pollution could increase the transmission rate for COVID-19 because pollution harms the immune system, leaving people more vulnerable to airborne diseases (Beatty and Shimshack, 2011; Miyashita et al., 2020). Second, pollution could cause existing cases of COVID-19 to become worse because pollution might harm the immune system of infected people. For example, there is evidence that pollution can increase inflammatory cytokines, which have been implicated in deaths from COVID-19 infections due to "cytokine storms" (Tay et al., 2020).

Nevertheless, 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, 2020a). However, it is unclear how the EPA will enforce environmental laws without the required reporting.

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 such as those commonly found in pollution from factories, power plants, mining, recycling and waste treatment, and other facilities. Most TRI sites (72% in 2018) primarily emit air pollution and usually release a variety of pollutants such as PM2.5, PM10, lead, and ozone. This allows us to track which US counties were most likely to see an increase in air pollution after the new policy was announced. TRI sites are common: there are currently about 21,800 TRI sites operating across the United States and more than 221.5 million people (i.e., 2/3 of the U.S. population) had a TRI site operating in their zip code in 2016.[1] TRI sites also release billions of pounds of toxic chemicals into the air, land, and water annually (EPA, 2018).

We use EPA data on 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 counties have 6 or more TRI sites with at least one that releases air pollution. To address the possible selection of TRI sites into counties, we limit our main sample to counties that have at least one TRI site emitting air pollution, so the comparison group includes counties with 1—5 TRI sites. First, we use daily air quality measures from the EPA and a difference in differences design to show that counties with more TRI sites experienced higher pollution after the rollback. Using the timing of these changes in short-term pollution exposure by county and data on COVID-19 cases and deaths from Johns Hopkins University, we then employ a difference in differences design to estimate whether counties with more TRI sites experienced increases in COVID-19 deaths and cases as a result of the pollution increase, compared to counties that had fewer TRI sites. We control for a variety of social distancing measures, stay at home orders, re-openings, days since the first COVID-19 death, total tests administered, weather, day of the week, cumulative confirmed cases (in the specification on deaths), and county, day of the week, and month fixed effects. To ensure that our results do not simply reflect factors such as population density our main specification limits the sample to counties without a COVID-19 death in the period before the rollback and limits the control group to counties population density of 250 persons per mile or more. We also estimate the effects of the number of TRI sites on cases and deaths nonparametrically, showing that counties with more TRI sites have higher mortality rates from COVID-19.

This paper makes three important contributions. First, this is the first paper to document that in the response to the rollback of environmental enforcement, counties with more TRI sites saw increases in pollution. We find that there is a large, sustained, and statistically significant increase in air pollution after the rollback of environmental regulations in counties with more TRI sites. On average, counties with 6 or more TRI sites experience about 11.8% (i.e., 0.778 $\mu g/m^3$) higher Particulate Matter2.5 (PM2.5) pollution after the rollback and a 5% increase in ozone, relative to counties in the bottom two thirds of the TRI distribution. This suggests that firms respond in the absence of regulatory incentives to increase pollution.

Second, we find that increases in pollution resulting from the rollback of EPA enforcement led to large and statistically significant increases in COVID-19 cases and deaths. Counties with 6 or more TRI sites experienced a 10.6 percent increase in daily COVID-19 deaths and a 53.0 percent increase in daily confirmed COVID-19 cases after the rollback, compared to counties with 1—5 TRI sites. In addition, we find that increased pollution exposure is worse for counties with a higher fraction of Black individuals. This suggests that the rollback is associated with large, heretofore unmeasured social costs. These results are robust to using weekly (rather than daily) cases and deaths, and a variety of alternative comparison groups and specifications. Finally, this is the first paper to find that exposure to pollution worsens cases and deaths during a pandemic.

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 the COVID-19 pandemic, which could inform the creation of 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, tangentially related interventions like stay-at-home orders could be modified to maximize the potential reduction in pollution.

[1] We made this calculation based on linking zip code level census counts of the population to TRI data.

2. Background

2.1. Pollution, regulation, and the environmental rollback on March 26, 2020

The EPA issued a memo on March 26th that stated that it intends to exercise enforcement discretion not to pursue violations of "routine compliance monitoring, integrity testing, sampling, laboratory analysis, training, reporting, and certification" because the pandemic "may" constrain the ability of companies to perform these obligations. For example, under this policy companies would not be required to monitor emissions or check for leaks. According to a lawsuit filed by 9 states against the EPA over this rollback of environmental enforcement, the EPA issued the nonenforcement policy after the American Petroleum Institute (API) wrote to the EPA on March 23, 2020 (State of New York v. EPA, 2020). The API requested that EPA "temporarily waiv[e] non-essential compliance obligations" under various federal environmental laws in light of the pandemic. The API, which represents more than 600 oil and gas companies across the U.S., cited "physical challenges" that would impinge compliance with "on-site testing/monitoring/reporting requirements."

These monitoring and reporting requirements are used across a huge swath of federal air water and waste laws and regulations to demonstrate industry compliance. In addition, it is not clear what proof, if any, companies must show to demonstrate that the pandemic was the cause of the noncompliance. Moreover, without the compliance and monitoring data the EPA usually collects, it is unclear how the EPA would become aware of violations in the first place. The nonenforcement policy also does not require that companies will make information about noncompliance available to states or the general public, even if companies choose to report their noncompliance to the EPA. Thus, this policy leaves significant room for potential gaming behavior on the part of noncompliant firms who might wish to increase their emissions. This policy also comes at a time when the EPA, under the Trump administration, has presided over the lowest enforcement of environmental laws in terms of number of civil enforcement cases and fine amounts in the past 25 years (Fredrickson et al., 2018). Later in the paper, we provide evidence that counties in the treatment group with more facilities that are "serious violators" of federal law drive these pollution increases.

While some recent research suggests that some kinds of pollution have decreased on average during the pandemic (Cicala et al., 2020),[2] other studies find that pollution has actually increased in some areas and overall (Bekbulat et al., 2020; NOAA, 2020; Schade, 2020). For example, Bekbulat et al. (2020) find that PM2.5 concentrations are higher than expected across the United States based on long term seasonal trends. Schade (2020) finds the pollution has increased in some parts of Texas, such as Houston, which has many TRI sites. The NOAA (2020) reported that atmospheric carbon dioxide just reached the highest monthly reading ever recorded in May 2020.[3] Though car pollution has likely decreased, and electricity consumption may have decreased in some places (Cicala et al., 2020), in counties with more TRI sites the total amount of average daily pollution as measured by EPA pollution monitors has increased. This makes sense, considering that pollution from ground transportation only makes up 20.6 percent of greenhouse gas emissions (Le Quere et al., 2020) and that emissions globally are only projected to fall by 5.5 percent from 2019 levels because of COVID-19 (Evans, 2020). The largest emitters of pollution are electricity generation, industry, and agriculture, jointly accounting for more than 58% of the total pollution emissions in the U.S. (EPA, 2020b). Also, air pollution is by far the most common type of pollution emitted by TRI sites, with 72% of all TRI sites emitting enough air pollution that it was the primary reported pollution type.

Firms may have an incentive to pollute more if reducing pollution is more costly or the fines for exceeding standards are removed. For example, monitoring pollution to be within acceptable limits requires staff hours and proper disposal might require running additional equipment. Recent survey evidence also suggests that the enforcement of environmental regulations from a traditional regulatory structure is the biggest motivator for many facilities' environmental compliance decisions (Gray and Shimshack, 2011). Clay and Muller (2019) also find that pollution has increased 5.5% overall in the U.S. since 2016, which coincided with a decline in enforcement. This suggests that firms respond to regulatory incentives by changing the amount of pollution they release over time.

2.2. The link between pollution and COVID-19 outcomes

Little is known about the environmental factors affecting COVID-19 transmission, but there is some evidence that increased air pollution increases cases of respiratory illnesses. Particulate matter (PM2.5 and PM10) has been linked to reduced lung function and increased incidence of pneumonia and other lung diseases, and there has been a trend to measure and study finer particles over time (Brunekreef and Holgate, 2002; Liu et al., 2017). For example, Jans et al. (2014) find that worsening air quality due to inversion episodes (increasing the amount of PM10) causes an increase in respiratory illnesses among children. Beatty and Shimshack (2011) find that retrofitting school buses, which decreases children's exposure particulate matter and ozone, was associated with reductions in bronchitis, asthma, and pneumonia incidence for at-risk populations. Additionally, Simeonova et al. (2019) show that the implementation of a congestion tax in Stockholm decreased

[2] While Cicala et al. (2020) estimate that CO2 and PM2.5 emissions are projected to decline over this time period via estimates of electricity consumption and distance traveled, they also find substantial heterogeneity in their estimates and do not make use of pollution monitor data from 2020.

[3] While carbon dioxide is not a regulated pollutant, carbon dioxide is often co-produced with particulate matter and ozone from the combustion of fossil fuels.

PM10 and the rate of acute asthma attacks among children. Similarly, high ground-level ozone concentrations are associated with aggravated respiratory illness and increased respiratory symptoms, leading to hospitalizations (Moretti and Neidell, 2011). Thus, increases in air pollution might leave people more susceptible to COVID-19 infections through harming lung health.

There is also growing evidence that days of high air pollution can increase morbidity and mortality. Research has shown that wind direction (Anderson, 2019) and airport delays (Schlenker and Walker, 2011) can cause small changes in air pollution, which then impact mortality and hospitalizations. Anderson finds that living downwind of a highway increases exposure to PM10 and the mortality of persons over 75 years old. Deryugina et al. (2019) use daily changes in wind direction as an instrument for increases in fine particulate matter (PM2.5) and find that acute exposure to PM2.5 causes increases in mortality, emergency room visits, and hospitalizations among the elderly. Yuyu et al. (2013) find that people living north of the Huai River who are allowed to use coal fired heat are exposed to higher particulate matter and have life expectancies that are 5.5 years lower, compared to people south of the river. In addition, several other associational studies have consistently found a link between particulate matter (PM2.5 and PM10) and increased morbidity and mortality (e.g., Dockery et al., 1993; Laden et al., 2000; Samet et al., 2000; Pope and Dockery, 2006; Schwartz et al., 2017). Overall, there is evidence that even small increases in particulate matter and ozone can have detrimental effects across a wide variety of health indicators and outcomes. Several of these studies find that the elderly and those with chronic conditions are the most affected by pollution. Elderly people and people with existing chromic conditions also have worse outcomes from COVID-19, suggesting that there could be a link between pollution and COVID-19 outcomes.

Recently Zhang et al. (2020) identified airborne transmission in fine aerosols as the dominant route for the spread of COVID-19 and show that the outbreak in Wuhan, China corresponded with increased PM2.5 levels. Setti et al. (2020) discovered that COVID-19's genetic material can be detected on particles of air pollution called Particulate Matter 10. Another recent study finds that PM10 upregulates the receptor used by COVID-19 to infect host cells (Miyashita et al., 2020). Taken together, this suggests that increased air pollution could increase infections and deaths from COVID-19. However, there is currently no published causal research on this question.

3. Data

To examine how pollution affects deaths and cases from COVID-19, we use data compiled by the Johns Hopkins University Center for Systems Science and Engineering Coronavirus Resource Center (JHU) on the daily number of cases and deaths by county (Hopkins University, 2020). While the data in its raw form is a set of cumulative totals of cases or deaths by county and day, we transform the data into the total new cases or new deaths reported each day. We match this data to daily data on air pollution by county from the EPA's Air Quality System (AQS). We use data on the number of TRI sites by county from the EPA's 2018 TRI Basic Data Files, which is the most recent year of TRI data. We also match these data to daily weather data from the National Oceanic and Atmospheric Administration (NOAA) (National Oceanic and Atmospheric Administration, 2020). The AQS has daily data on PM2.5, PM10 and ozone from January through July 2020. We aggregate this to the county level by matching each pollution monitor to a zip code and imputing data to zip codes with missing monitors using the closest monitor and inverse distance weighting. We do not impute data from monitors more than 30 km away or for zip codes in counties without at least one monitor. Grainger and Schreiber (2019) suggest that monitors are often strategically positioned by local regulators to avoid pollution hotspots. Therefore, aggregating the pollution monitor data in this way is likely to lead to downwardly biased levels of pollution. Nevertheless, the pollution monitor data represents the best data available over a short time window.

We match additional daily data on cases and deaths in all five counties comprising New York City from the New York City Department of Health (New York City Department of Health, 2020).[4] The JHU data adds county-level counts of cumulative daily COVID-19 cases and deaths starting on March 22, 2020, so we matched additional data on the pre-period from the New York Times data repository. Thus, we have data on all recorded COVID-19 deaths, cases, and social distancing measures from February 24th through July 11th, 2020. Following Harris (2020), we standardize the JHU data on cases and deaths to be in terms counts of new cases and deaths each day by subtracting each day's cumulative case or death count from the one before it (by county).[5] To address state testing capacity, we additionally match data from the COVID Tracking Project (COVID Tracking Project, 2020) on the number of COVID-19 tests administered per day by state.

Because pollution emissions could be confounded by social distancing behaviors, we also use five different measures of social distancing from Unacast (Unacast, 2020) and SafeGraph (Safegraph, 2020). First, we use three measures on the degree of social distancing by county from Unacast's restricted access data by county, which they use to compute the three metrics in the Social Distancing Scoreboard. The first measure we use is the percent change in total distance traveled each weekday compared to the average of the four corresponding days in the weeks before March 8, 2020. Second, we use the percent change in visitation of non-essential venues (such as restaurants, clothing stores, etc.) on each day, compared to the four

[4] New York, Bronx, Richmond, Queens, and Kings county were omitted from the John's Hopkin's data, so we updated the data on all of New York City from the NY Department of Health. The results are robust to the omission of this additional data.

[5] Another issue is that Utah reports data by health districts, which are collections of counties, and Kansas City, Missouri is reported separately in the JHU data from the four counties containing Kansas City. The results are robust to dropping these counties and Utah.

weeks before the pandemic. Third, we use the rate of encounters between two devices, expressed as a fraction of the pre-pandemic baseline. To construct these measures of social distancing, Unacast uses cell phone geolocation data on the average distance traveled from pre-COVID-19 days. These social distancing measures are at the daily level by county across all counties in the United States from February 24, 2020 until the present.[6] In addition, we construct two additional measures of physical distancing by county using SafeGraph's social distancing data. For our fourth measure, we estimate the percent of people each day in each county that are likely to be working full time, part time, or making deliveries. Fifth, we estimate the percent of people who are not at home or work per day in each county.[7] In other words, we use mobile device behavior to estimate the percentage of people each day that are (1) at work, or (2) who are outside of the home, but not at work.

We additionally match these data to data from the COVID-19 United States Policy Database (Raifman et al., 2020) on the exact timing of official stay at home orders and re-openings by state. We use the date businesses reopened in a state as the reopening date. We also match these data to county-level data on demographics and essential workers by industry sector from the 2018 Census and 2019 Bureau of Labor Statistics data from the Quarterly Census of Employment and Wages. Further details about the sample and weighting procedures are reported in the Data Appendix.

4. Identification strategy

Naïve correlations between air pollution and COVID-19 outcomes cannot be interpreted as causal because pollution is not randomly assigned. To disentangle the effects of pollution on COVID-19 outcomes from other county-specific factors that could influence COVID-related outcomes, we use a difference in differences design with county fixed effects to estimate whether being in a county with more TRI sites after the rollback led to an increase in pollution and whether increases in pollution led to increases in cases and deaths.

Most of the facilities impacted by the environmental rollback are likely required to report their emissions on the Toxic Release Inventory (TRI) database. The EPA's memo specifically mentions "reporting facilities," which include all TRI sites. 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. 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. We chose 6 or more TRI sites because this is where we start to see larger pollution increases and worse outcomes.[8] We then compare outcomes within a county before versus after the rollback in counties with more than 6 TRI sites, compared to counties with 1−5 TRI sites.

One concern, however, is that the timing of the rollback of environmental law might have coincided with the worsening of the pandemic. A related potential threat to internal validity is reverse causality: the worsening of the pandemic might have caused companies to pollute more if, for example, workers became ill and could not perform monitoring tasks. To avoid these issues, we limit the sample in four important ways. First, we limit to counties that had no COVID-19 deaths in the period before the rollback in all of our analyses.[9] There were 220 counties with one or more COVID deaths in the pre period that we drop in our main sample.[10] Note that the number of cases in the pre-period is similarly limited by dropping counties with no COVID-19 deaths in the pre-period.[11] The counties with deaths before March 26th tended to be large urban counties, like those in New York City, which were outliers in terms of pandemic severity. On average there were 6 cases in the pre-period across all counties in the sample after dropping counties with one or more COVID-19 deaths in the pre-period. Thus, limiting the sample in this way ensures that the increase in pollution must have preceded the first COVID death in a county, and that no counties were suffering from a severe outbreak at the time of the pollution increase.

Second, we limit our main sample to counties with at least one TRI site emitting air pollution to address concerns about the possible selection of TRI sites into counties. 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. Third, to ensure that especially large or small counties do not drive our results, we drop outliers in terms of population in both the treatment and control groups, limiting the sample to counties that have between 10,000 and 1.64 million people. This trims the bottom 10 percent of the control group and the top 1 percent of the treatment group so that treatment and control counties have similar population distributions. Fourth, to alleviate concerns that our control group might be less population dense than our treatment group, our main specification further limits the control group to counties with 250 or more persons per square mile. The results are also robust to using other numbers of TRI sites as cutoffs and plotting the effects nonparametrically by the number of TRI sites. We discuss these specifications in section V.D. of the paper. We further address why the EPA's rollback might have led to an increase in pollution later in the paper.

[6] Additional information on the construction of these measures is explained in our Data Appendix.

[7] We estimate both of these as the fraction of devices in each category divided by the total number of devices per county and day. Additional details of how we construct these measures are also available in the Data appendix.

[8] See Figs. 2 and 4, which show the results plotted nonparametrically for pollution emissions and deaths, respectively.

[9] Arguably deaths from COVID-19 are more accurately reported than cases since cases suffer from reporting delays.

[10] The results are robust to including these counties and those results are included in Table A1.

[11] Our results are also robust to limiting the counties to those with fewer than 20 COVID-19 cases in the pre-period, rather than counties with no deaths.

4.1. Comparability of treated and control counties

Table 1 presents the characteristics of all counties in the sample, as well as treatment and control counties separately. Overall Table 1 indicates that counties with 6 or more TRI sites are quite similar demographically to counties with 1–5 TRI sites in terms of the percentage of people who are essential workers,[12] White, Black, Hispanic, in poverty, or over 65, as well as the unemployment rate in 2018. However, counties with 1–5 TRI sites differ in terms of total population, the number of cases and deaths from COVID-19, and population density. Thus, we also show the characteristics of an additional control group we employ in our main specification of counties with 1–5 TRI sites that also have population densities of more than 250 persons/mi. Fig. A1 shows two maps of treated and control counties from our two main specifications (in Table 3), as well as counties that are not included in our main analysis. Fig. A1 shows that treated and control counties are widely distributed among nearly every state.[13] While there is some clustering, treated and control counties are interspersed with each other and there are usually control counties bordering treated counties. Our preferred specification limits to the 103 counties with higher population densities shown in Panel B of Fig. A1.

Table 1
Descriptive statistics of counties in the sample.

	(1)	(2)	(3)	(4)
	Characteristics of Counties in the U.S. in 2018 with 1 or More TRI sites	Characteristics of Counties with 6 or More TRI sites	Characteristics of Counties with 1–5 TRI sites	Characteristics of Counties with 1–5 TRI sites, Limited to Population Density of >250
Total Population	95,769	160,736	39,194	86,136
	[143,050]	[186,315]	[34,600]	[58,831]
Population Density	343.2	574.9	141.7	619.7
	[681.6]	[847.5]	[396.6]	[957.9]
Percent Essential Workers	0.551	0.553	0.544	0.524
	[0.059]	[0.0566]	[0.0691]	[0.0730]
Percent White	0.838	0.827	0.848	0.853
	[0.148]	[0.140]	[0.154]	[0.135]
Percent Black	0.090	0.098	0.0834	0.070
	[0.136]	[0.129]	[0.143]	[0.101]
Percent Hispanic	0.089	0.095	0.084	0.084
	[0.125]	[0.119]	[0.130]	[0.126]
Percent With Less Than a High School Degree	0.208	0.198	0.217	0.189
	[0.092]	[0.0783]	[0.102]	[0.0831]
Percent Poverty	0.110	0.103	0.115	0.0961
	[0.046]	[0.0409]	[0.0498]	[0.0402]
Median Income	52,206	55,217	49,584	57,905
	[12,535]	[12,827]	[11,666]	[16,493]
Unemployment Rate	0.033	0.034	0.03277	0.03189
	[0.011]	[0.0099]	[0.01164]	[0.00974]
Percent Over 65	0.170	0.167	0.180	0.192
	[0.0452]	[0.0420]	[0.0559]	[0.0649]
Percent Change in Daily Distance Traveled	−0.165	−0.177	−0.155	−0.214
	[0.0899]	[0.0827]	[0.0945]	0.112
Total TRI Sites	8.498	15	2.835	3.485
	[10.36]	[12.24]	[1.331]	[1.399]
Total Confirmed Cases	753.7	1330	252.1	512.1
	[1687]	[2286]	[487.9]	[637.0]
Total Confirmed Cases in the Pre-rollback Period	6.150	10.87	2.043	5.786
	[17.84]	[24.50]	[6.055]	[11.20]
Total Deaths	21.60	38.22	7.116	18.29
	[72.46]	[101.8]	[18.97]	[36.40]
Number of Counties	1463	681	782	103

Notes: This table shows the average characteristics of counties in our main sample with standard deviations in brackets below each mean. 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 treated counties (with more than 6 TRI sites). Column 3 shows characteristics of control counties (with 1–5 TRI sites). Column 4 shows characteristics of control counties (with 1–5 TRI sites) limited to those with population density of more than 250 persons/mi. Our main sample is limited to those counties without deaths before the rollback and outliers in terms of population are dropped.

[12] See the data appendix for more on how we estimated the percentage of people by county who are likely to be essential workers.

[13] Dropping states without control counties does not change the results.

4.2. Estimating pollution increases from the Epa's rollback of environmental enforcement

Using daily data on air pollution by county from the EPA's Air Quality System (AQS) from January 1st through July 11th, 2020, we use a difference in differences design to estimate the amount pollution has increased because of the rollback on March 26th, 2020. We regress the amount of pollution on an indicator for being in a treated county (with 6 or more TRI sites) after the rollback as follows:

$$Pollution_{it} = \beta_1 TreatedPost_{it} + Post_t + X_{it} + \sigma_i + \phi_t + \varepsilon_{it} \tag{1}$$

In this equation, $Pollution_{it}$ is the daily amount of PM2.5 (or ozone) pollution in $\mu g/m^3$ (or ppm) in county i on day of the week t. $TreatedPost_{it}$ is a binary indicator for being in a county in the top third of the distribution in terms of the number of TRI sites (with 6 or more TRI sites) after the rollback of environmental enforcement. X_{it} is a vector of daily county-level variables (i.e., whether there is a stay-at-home order on that day, state re-openings, and average temperature and precipitation). σ_i are state-county fixed effects, ϕ_t are day of the week fixed effects.[14] 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. Standard errors are clustered at the county level.

4.3. Estimating cases and deaths from the policy-induced pollution increase

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.

Thus, our primary identification strategy is a 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. We compare counties with 6 or more TRI sites to counties with 1–5 TRI sites before relative to after the rollback of environmental enforcement. The basic difference in differences model we will use is as follows:

$$Y_{it} = \beta_1 TreatedPost_{it} + Post_t + X_{it} + \sigma_i + \phi_t + \varepsilon_{it} \tag{2}$$

In this equation, Y_{it} is the log of the number of daily deaths (or confirmed cases) in county i in time t. We apply the inverse hyperbolic sine (IHS) transformation to each daily count of deaths or cases to account for zeros in daily death or case values: $\text{asinh}(Y_{it}) = \log(Y_{it} + (Y_{it}^2 + 1)^{0.5})$. The IHS transformation is approximately equal to $\log(2(Y_{it}))$, except for very small values, and can be interpreted in the same way as a logarithmic transformation (as a percent change). $TreatedPost_{it}$ is an indicator for being in a county with 6 or more TRI sites after the rollback of environmental regulation enforcement. $Post_t$ is a binary variable for being in the period after the EPA's rollback of civil enforcement, which took place on March 26th, 2020 for the entire United States. Note that a binary variable for being in the treatment group ($Treated_i$) will be omitted due to multi-collinearity when using county fixed effects. X_{it} is a vector of daily county variables (i.e., daily average temperature and precipitation, whether there is a stay at home order, state re-openings, whether a mask mandate is in place, days since the first death from COVID-19, the number of confirmed cases, daily total tests administered by state, and daily social distancing measures). We only control for the daily number of confirmed cases by counties in regressions of the effect of the rollback on the log of deaths. σ_i are county fixed effects and ϕ_t are a vector of day of the week fixed effects and month fixed effects. Standard errors are clustered at the county level. 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.[15]

Counts of daily deaths from COVID-19 are likely to be less biased than counts of daily cases, since cases might be reported many days after people become sick. Thus, we think our estimates on daily cases are largely picking up COVID-19 cases that became worse because of exposure to pollution. However, we estimate both cases and deaths using both daily and weekly measures, allowing for lags in both, later in the paper.

By using county fixed effects, we are controlling for all time-invariant characteristics of counties, such as political affiliation, the state's existing environmental policies, and the underlying propensity of residents to engage in health behaviors such as mask wearing, which are unlikely to change over time. In addition, we rely on policy-induced variation in pollution. Table 2 and Fig. 1 suggest that there was an immediate increase in pollution from this policy in the treatment group compared to the control group. By controlling for daily social distancing, the cumulative number of confirmed cases, total COVID-19 tests administered, and the number of days since the first death in a county, we are effectively controlling for time trends that could

[14] 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).

[15] The results are about twice as large when using county population weighting.

Table 2
Difference in Differences Results for Being in County with 6 or more TRI sites on Pollution Levels After the EPA's Rollback of Enforcement Compared with Placebo Years.

	(1) Daily Mean PM2.5 Concentration	(2) Daily Mean Ozone Concentration	(3) Daily Mean PM10 Concentration
	Panel A: 2020 (Treatment Year)		
Treated County Post Rollback (March 26, 2020)	0.7782***	0.0021***	1.5419*
	(0.2350)	(0.0004)	(0.9307)
	Panel B: 2019 (Placebo Year)		
Treated County Post March 26, 2019	−0.3249*	0.0017***	0.5188
	(0.1964)	(0.0002)	(0.5920)
	Panel C: 2018 (Placebo Year)		
Treated County Post March 26, 2018	0.2602	−0.0008***	−0.8180
	(0.1654)	(0.0003)	(0.7210)
	Panel D: 2017 (Placebo Year)		
Treated County Post March 26, 2017	−0.0185	−0.0005	−0.8370
	(0.2378)	(0.0003)	(0.7523)
Mean of Dependent Variable	6.618	0.040	16.198
Observations	105673	109739	35239

Notes: This table shows the effects of being in a county with 6 or more TRI sites after March 26th on pollution in different years, compared to before March 26th. Panel A presents the results of being in a county with 6 or more TRI sites after the rollback of environmental enforcement on March 26th, 2020, compared to being in a county with 1−5 TRI sites. Panels B, C and D present the results of a series of placebo tests using other years. We use the same difference in differences specification in equation (1) and regress PM2.5 levels on an indicator for being in a county with 6 or more TRI sites after March 26th through the end of May in each of the years indicated. Notably, all three pollutants only increase on March 26th in the year of the environmental rollback (2020). All models control for temperature, precipitation, month, day of the week fixed effects and county fixed effects. The models in Panel A additionally control for stay at home orders and re-openings. Standard errors are clustered at the county level and are in parenthesis. Coefficients labeled as ***, **, and * are statistically significant at the 1, 5, and 10 percent levels, respectively.

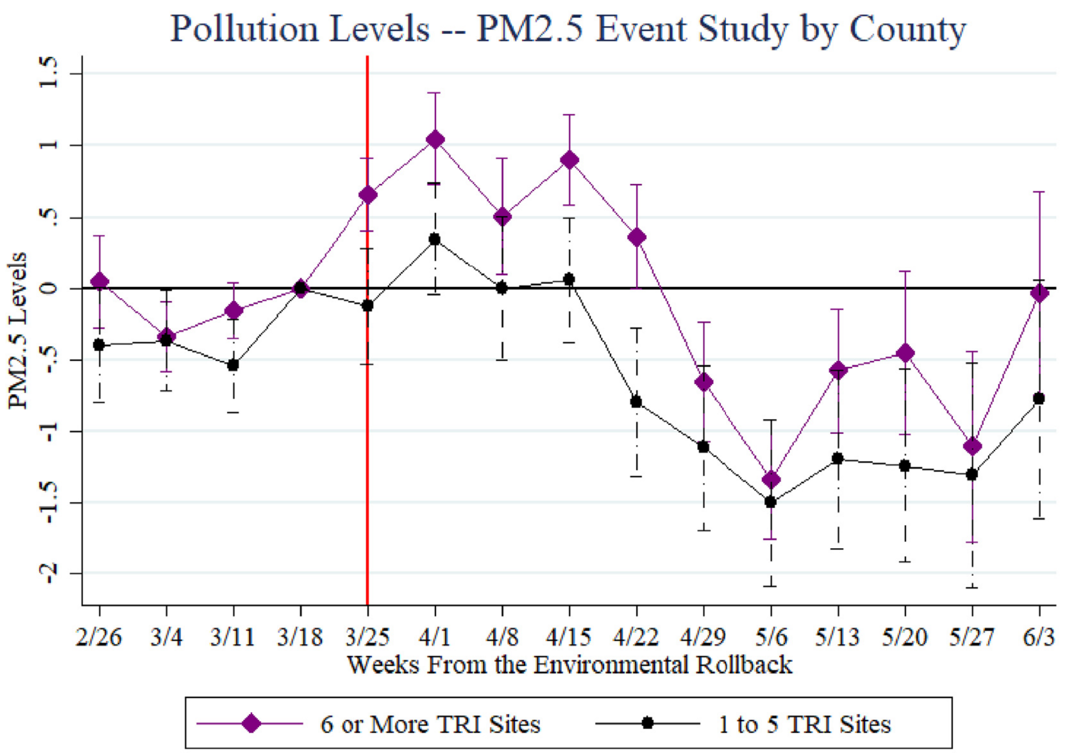
affect the spread and severity of cases of COVID-19, as well as state capacity for testing. We also estimate model (2) with state fixed effects (rather than county fixed effects) and control for a variety of county level demographic variables directly (in addition to the daily controls mentioned in the previous paragraph): total population, population density, percent white, percent Black, percent Hispanic, poverty rate, the unemployment rate, median income, and percent of workers who are likely to be essential. Nevertheless, there are likely to be unobserved time invariant characteristics of counties that could leave them susceptible to worse cases of COVD-19, so our primary specification uses county fixed effects rather than state fixed effects.

Our main identifying assumption is that in the absence of the environmental rollback, outcomes in the treated counties (those with more TRI sites) would have followed a parallel trajectory to outcomes in counties in the control group. While we control for a wide variety of factors that could bias the relationship between pollution and COVID-19 outcomes, there also could be other time-varying local policies or factors that were not included and could cause some error. 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 (even if they are also different in some important ways). We also show that our main results are robust to county-specific linear time trends, as well as a variety of alternative control groups and specifications. Third, in Section V.D. we show that these results are robust to dropping a variety of different types of counties or states that could be problematic. Fourth, we show that before the pandemic, treated and control counties show similar trends in monthly deaths overall (see Fig. A3).

We also show an event study of the treatment and control counties using data on total weekly COVID deaths in Fig. 3, indicating that the counties are on similar trajectories in the pre-treatment period. This makes sense, since all counties in the sample are limited to those with no COVID-19 deaths in the pre-period. The basic event study model we use is given by:

$$logY_{it} = \beta_0 + \sum_{j=-15}^{28} \beta_{j1}[\tau_{it} = j]_{it} + X_{it} + \eta_i + \varepsilon_{it} \tag{3}$$

We include 3 weeks in the pre-period and 11 weeks in the post-period for the treatment, where τ_{it} denotes the week relative to the rollback of the EPA's enforcement of environmental regulations. For example, a value of $\tau_{it} = -1$ represents the deaths one week before 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. η_i are county fixed effects. X_{it} is a vector of daily county-level variables defined above (taking the average over the week), and standard errors are again clustered at the county-level.



Notes: Figure 1 plots the coefficients from an OLS effects regression of weekly 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 February through early May 2020. The red line marks the week of March 26, 2020 and all coefficients are normalized such that the coefficient in the week prior to the rollback (3/18) is zero. Dotted lines represent 0.95 confidence intervals for the coefficients. We limit our sample to counties with no deaths in the period before the rollback. The regression controls for stay at home orders, re-openings, temperature, precipitation, and county fixed effects. Standard errors are clustered at the county level.

Fig. 1. Event Study of Weekly PM 2.5 by County.

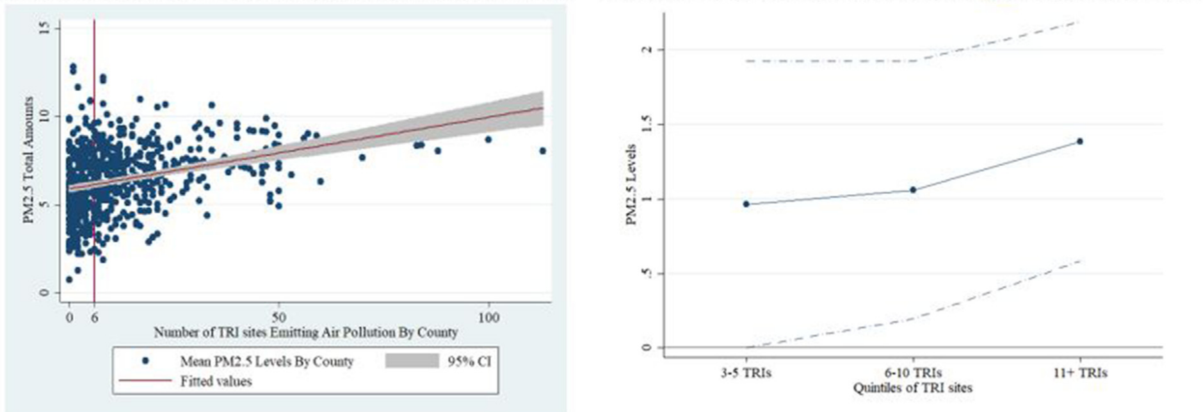
5. Results

5.1. Results on pollution increases

While some measures of pollution have been reported to be lower in some locations during the pandemic, aggregated analyses of pollution might mask important heterogeneity in pollution releases and exposure. Our analyses in Panel A of Table 2 and Fig. 1 show that there is a statistically significant increase in air pollution after the rollback of enforcement of environmental regulations in counties with 6 or more TRI sites, relative to counties with 1–5 TRI sites. We find that counties in the top third of the TRI distribution in terms of the number of TRI sites experience about 11.8 percent (i.e., 0.778 $\mu g/m^3$) higher PM2.5 and 5 percent higher ozone after the EPA's rollback, relative to counties in the bottom two thirds of the TRI distribution. This suggests that in the absence of regulatory incentives, firms may have responded by releasing more pollution.

This increase in pollution is also unique to 2020. Panels B, C and D of Table 2 show results when running the same regressions for previous years using a March 26th cutoff in each year (and the same counties in the treated and control groups). We observe a different pattern of results for PM2.5, ozone, and PM10 in previous years: the coefficients in 2017, 2018 and 2019 are largely negative and not statistically significant (with one exception – ozone is positive in 2019). In addition, the event study of weekly PM2.5 in 2020 depicted in Fig. 1 is a visual representation of our first stage. Fig. 1 shows that pollution was

Panel A: Number of TRI Sites Emitting Air Pollution by County Panel B: Pollution Increases Post-Rollback By Number of TRI sites



Notes: Panel A plots the relationship between the number of TRI sites in a county and the observed levels of PM2.5 pollution. As there are more TRI sites, counties experience higher pollution on average. Counties with more than 6 TRI sites comprise the treatment group in our analysis. Panel B shows how PM2.5 pollution after the rollback of environmental enforcement varied by counties based on the number of TRI sites in that county. The Y-axis plots the coefficients on the interaction between being after the EPA's rollback of civil enforcement with the stated bin for the number of TRI sites. The omitted category is counties with 1-2 TRI sites. This model includes stay at home orders, re-openings, temperature, precipitation, county fixed effects, month fixed effects and day of the week fixed effects. The dotted lines show 95% confidence intervals based on standard errors clustered on county.

Fig. 2. Association Between PM2.5 and the Number of TRI Sites Emitting Air Pollution by County.

lower in February and March until the week of the EPA's rollback, at which point pollution in counties with 6 or more TRI sites became higher over the next six weeks[16] compared to pollution in control counties.[17] In contrast, the same event study in 2019 depicted in Fig. A2 shows that PM2.5 pollution was largely falling over March and April, possibly due to the discontinuation of winter heating.[18] In addition, Panel A of Fig. 2 shows the association between average PM2.5 and the number of TRI sites emitting pollution by county overall in January through July of 2020. As the number of TRI sites increases, the total amount of pollution by county increases as well. There is substantial heterogeneity by county in the number of TRI sites and pollution levels, but the number of TRI sites is positively associated with total pollution by county on average. Panel B of Fig. 2 plots the coefficients on the interaction between an indicated for being after the EPA's rollback of civil enforcement ($POST_i$) with the stated bin for the number of TRI sites, controlling for stay-at-home orders, re-openings, temperature, precipitation and month, day of the week and county fixed effects. The omitted category is counties with 1 or 2 TRI sites. Counties with higher numbers of TRI sites see larger increases in pollution after the announced reduction in enforcement. The overall pattern of results suggests that the EPA's rollback of environmental enforcement caused an increase in pollution in counties with more TRI sites that otherwise would not have occurred due to weather or seasonal patterns.

5.2. Main results on COVID-19 deaths and cases

Fig. 3 displays the main results of our weekly event study of the timing of the environmental rollback on the log of COVID-19 deaths. Our main sample consists of counties with no deaths in the pre-period, so any variation there is due to our control variables. Deaths began increasing substantially the week of the announced enforcement rollback in counties with more TRI sites relative to counties in the control group. This suggests that pollution affected deaths, at least in the short term, perhaps by causing existing COVID-19 cases to worsen.

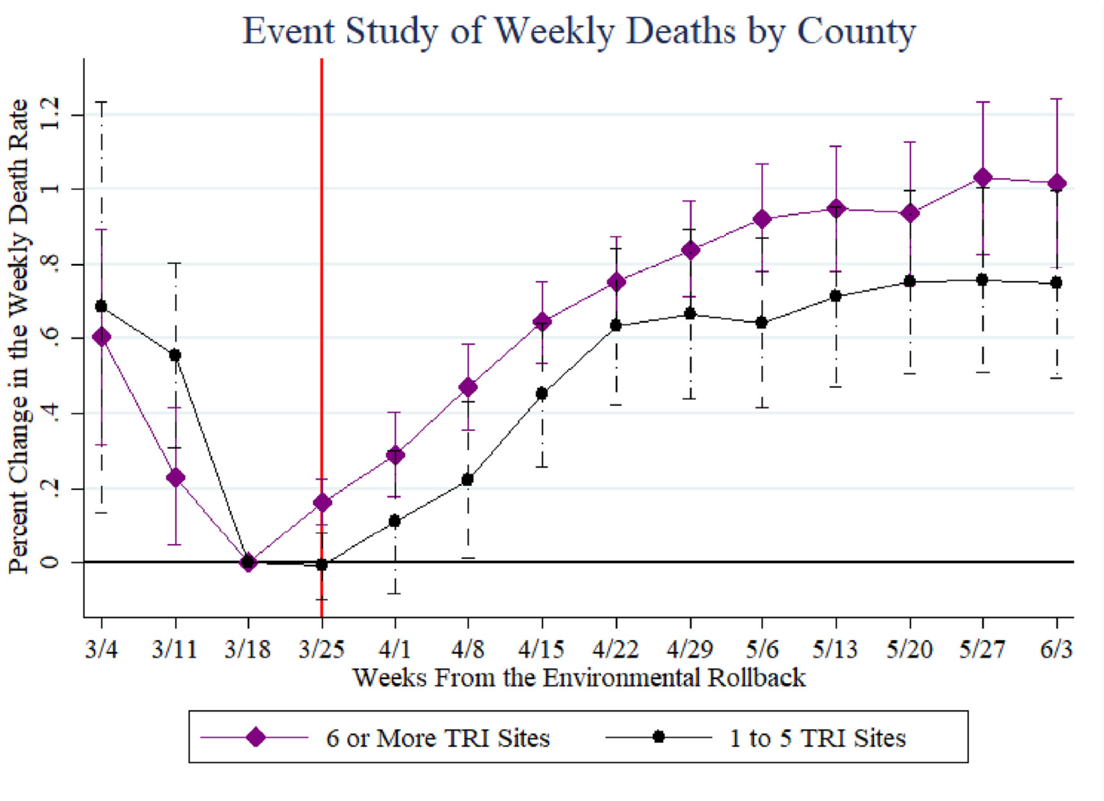
We also use data from the CDC Wonder database on all deaths by month in 2018 to get a sense of whether deaths followed similar trajectories in the treatment and control groups.[19] The log of average deaths per month for the same treatment and control groups are shown in Fig. A3. While the total number of deaths per month differs, the treatment and control groups

[16] Unfortunately, we lose 39 monitors 1473 daily observations between March and May. In addition, Zou (2017) finds that polluters often engage in strategic behavior with monitoring systems wherein air quality is worse on unmonitored days and that monitors are strategically shut off during times of high air pollution (Mu et al., 2021). This might explain the dip in pollution observed at the end of April in Fig. 1 if some pollution monitors were taken offline at that time. As a result, it is difficult to determine conclusively the extent to which the pollution increase was sustained past April since we do not observe the same set of pollution monitors.

[17] We describe our event study methodology in section IV.C. The event studies in Fig. 1 and A2 differ from Fig. 3 in that the outcome is weekly estimates of PM2.5 pollution, instead of daily estimates of log deaths. In addition, the event study in Fig. 1 controls for only stay at home orders, state re-openings, weather and daily social distancing.

[18] Event studies in 2017 and 2018 show similar patterns of results, wherein pollution levels are largely falling over March and April in both treated and control counties.

[19] 2018 is the most recent year of county-level data by month.



Notes: Figure 3 plots the coefficients from an OLS effects regression of the log of weekly COVID-19 deaths on leads and lags of time from the rollback of environmental laws on March 26, 2020 using data from deaths from March through June 2020. The rollback occurs on the week of March 25, 2020 and all coefficients are normalized such that the coefficient in the week prior to the rollback (3/18) is zero. Dotted lines represent 0.95 confidence intervals for the coefficients. We limit our sample to counties with no deaths in the period before the rollback and drop counties with populations under 10,000 or over 1.64 million. The regression controls for stay-at-home orders, re-openings, mask mandates, social distancing measures, number of confirmed cases by county, total tests administered, temperature, precipitation, and county fixed effects. Standard errors are clustered at the county level.

Fig. 3. Event Study of Weekly Deaths from COVID-19 by County.

show very similar trends over time in total deaths per month. Taken together, these figures suggest that the environmental rollback led to a large increase in the death rate above the treatment group that might not have occurred in the absence of the rollback.[20]

Table 3 presents the main results of our difference in differences models. Columns 1 and 5 present the results of a state fixed effects model with county-level demographic, economic, and daily controls.[21] However, even with robust controls there might be other time-invariant characteristics of counties that could affect COVID-19 cases and deaths. Thus, columns 2 and 6 present the results from a specification using county fixed effects and daily controls (equation (2)).

These models use a sample of counties that have one or more TRI sites, have no deaths in the period before the rollback, and are limited to populations between 10,000 and 1.64 million people (shown in Panel A of Fig A1). Reassuringly, the results from our state fixed effects model with additional county-level controls and our county fixed effects model with daily controls are very similar – being in a treated county after the rollback led to a 15.3 percent increase in the daily death rate and a 70.8 percent increase in the daily case rate using the county fixed effects model, compared to a 13.3 percent increase in COVID-19

[20] In addition, we estimate a similar event study using the daily COVID-19 death rate per 10,000 individuals (dropping counties with less than 10,000) and find very similar results.

[21] These include controls for total population, population density, percent white, percent Black, percent Hispanic, poverty rate, the unemployment rate, median income, percent of workers who are likely to be essential, daily average temperature and precipitation, whether there is a stay at home order, state re-openings, days since the first death from COVID-19, the number of confirmed cases, daily social distancing measures at the county level, and month, state and day of the week fixed effects.

Table 3
The effects of pollution on deaths and cases.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log COVID-19 Deaths	Log COVID-19 Deaths	Log COVID-19 Deaths	Log COVID-19 Deaths	Log Confirmed COVID-19 Cases	Log Confirmed COVID-19 Cases	Log Confirmed COVID-19 Cases	Log Confirmed COVID-19 Cases
Treated Counties After the Rollback	0.1331***	0.1533***	0.1055***	0.1410***	0.6856***	0.7078***	0.5296***	0.2308**
	(0.0160)	(0.0168)	(0.0272)	(0.0348)	(0.0450)	(0.0479)	(0.0962)	(0.0989)
With State Fixed Effects and controls	X				X			
With County Fixed Effects and daily controls		X	X	X		X	X	X
With County-Specific Linear Time Trends				X				X
Limited to Counties with Population Density >250 in the Control Group			X	X			X	X
Limited to Populations between 10K and 1.64 million	X	X	X	X	X	X	X	X
Mean of the Dependent Variable	0.194	0.194	0.194	0.194	1.148	1.148	1.148	1.148
County-Day Observations	137716	137815	84126	84126	137716	137815	84126	84126

Notes: Columns 1−4 present the results for different regression specifications with the log of COVID-19 deaths as the outcome. Columns 5−8 present the same specifications with the log of confirmed COVID-19 cases as the outcome. Columns 1 and 5 show the results for the sample of counties with 1 or more TRI sites, no deaths in the period before the rollback, and limited to populations between 10,000 and 1.64 million using state fixed effects, controlling for total population, population density, percent white, percent Black, percent Hispanic, poverty rate, the unemployment rate, median income, and the percent of workers who are likely to be essential. Columns 2 and 6 show the results on the same sample with county fixed effects. Columns 3 and 7 show our preferred specification that further limits the control group to counties with a population density of more than 250 persons/mi. Columns 4 and 8 show the results from Columns 3 and 7 with county-specific linear time trends. All models also control for an indicator for being after the EPA's rollback, social distancing, stay at home orders, re-openings, mask mandates, days since the first COVID death, total tests, weather, and day of the week, county and month fixed effects. Columns 1-4 additionally control for daily confirmed COVID-19 cases. Standard errors are clustered at the county level and are in parenthesis. Coefficients labeled as ***, **, and * are statistically significant at the 1, 5, and 10 percent levels, respectively.

deaths and a 68.5 percent increase in cases using the state fixed effects model. While the means for daily deaths were relatively low in these counties (i.e., 0.301 deaths/day), a 15 percent increase is still concerning. An increase of 70.8 percent in daily cases implies an additional 7.1 cases per county per day. In addition, Panel A of Table A1 shows that the results are 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. Panel B shows that the results are also similar when we limit to counties with 1 or more TRI sites without limiting the population to similarly sized counties.

To address the concern that population density furthers the spread of the virus, columns 3 and 7 present the results of our main specification further limiting the control group to more population-dense counties (with population density > 250 persons/mi^2). Note that this specification leaves less population dense counties in the treatment group. Columns 4 and 8 of Table 3 present results from our main specification in Columns 3 and 7, adding a control for county-specific linear time trends to account for the fact that some places might have worse cases over time for reasons other than pollution. While the point estimate becomes smaller for deaths and cases uses our population-dense control group, we think this specification is more reasonable since the control group is more directly comparable to the treatment group. Thus, we use this smaller, more population-dense control group as our main specification in the rest of the paper.

Overall, we find substantial evidence that increases in pollution increased the conditional daily COVID-19 death rate and daily new case rate of COVID-19 − being in a county with 6 or more TRI sites after the rollback led to between a 10.6 and 15.3 percent increase in the daily mortality rate, compared to counties with 1−5 TRI sites. As a comparison, Anderson (2019) finds that a 1 standard deviation in time spend downwind of a highway (or 43% increase in pollution) is associated with a 6% increase in deaths among the elderly. Thus, these estimates are large in comparison, likely because pollution may interact with a deadly virus that spreads nonlinearly. We also find that being in a treated county after the rollback is associated with a 53 percent increase in daily cases. The large increase in cases and deaths might reflect the fact that pollution increases the transmission rate of the virus. This, combined with the non-linear spread of COVID-19, would lead to large numbers of additional COVID-19 cases and deaths over time.

We also address the concern that data on daily cases and deaths could suffer from serial correlation, errors in reporting, or delays before the onset of symptoms and testing by showing our main results using weekly estimates instead of daily estimates in Table 4. Table 4 depicts the results of being in a treated county after the rollback using weekly estimates of the total deaths and cases in the same week, and deaths and cases one week later, two weeks later, and three weeks later. The estimates using weekly variation are nearly three times the size of the estimates using daily variation − we observe a 32 percent increase in weekly deaths and a 59 percent increase in weekly cases. The largest effects on deaths occur in the same week, followed by one week later, and then two weeks later, with the smallest effects three weeks later. This suggests that some people might become sicker with COVID-19 because of exposure to pollution but die a few weeks later after symptoms progress.

Table 4
Results for weekly COVID-19 death and cases in the same week and allowing for a delay.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log Weekly COVID-19 Deaths (same week)	Log Weekly COVID-19 Deaths 1 Week Later	Log Weekly COVID-19 Deaths 2 Weeks Later	Log Weekly COVID-19 Deaths 3 Weeks Later	Log Weekly COVID-19 Cases (same week)	Log Weekly COVID-19 Cases 1 Week Later	Log Weekly COVID-19 Cases 2 Weeks Later	Log Weekly COVID-19 Cases 3 Weeks Later
Treated Counties After the Rollback	0.3218*** (0.0834)	0.2573*** (0.0898)	0.2302** (0.0895)	0.1445* (0.0821)	0.5886*** (0.1464)	0.5464*** (0.1242)	0.4862*** (0.1124)	0.5326*** (0.1037)
Whole Sample with 1 or More TRIs, using County and Month Fixed Effects	X	X	X	X	X	X	X	X
County-Week Observations	12975	12267	11555	10833	12975	12983	12825	12129

Notes: Columns 1—4 present the results for the effects of being in a treated county after the rollback with the log of weekly COVID-19 deaths as the outcome. Columns 5—8 present the results with log of weekly COVID-19 cases as the outcome. Columns 1 and 5 presents the effects on confirmed deaths or cases in the same week. one week later, Columns 2 and 6 present the effects one week later, Column 3 and 7 present the effects 2 weeks later, and Columns 4 and 8 present the effects 3 weeks later. All models control for an indicator for being after the EPA's rollback, social distancing, stay at home orders, re-openings, mask mandates, days since the first COVID death, total tests administered, weather, and county and month fixed effects. Columns 1-4 additionally control for daily confirmed COVID-19 cases. Coefficients labeled as ***, **, and * are statistically significant at the 1, 5, and 10 percent levels, respectively.

However, the number of new cases shrinks more slowly over time, suggesting that pollution could be contributing somewhat to the spread of the pandemic by making people more vulnerable to illness. Nevertheless, this is also in line with a literature that suggests that it takes a few days to develop symptoms after a COVID-19 infection, and the time to taking a test might vary by the availability of the tests in a location and the severity of the infection (Center for Disease Control and Prevention, 2020). Some tests might occur right away, while others might occur only once someone is hospitalized after several weeks of being sick. Thus, the observed increase in cases might indicate that pollution worsens existing COVID-19 cases, causing people to get tested, or that pollution causes new cases. Because COVID-19 cases are likely reported with some delay and data on hospitalizations are only available at the state level, we are unfortunately unable to disambiguate fully between these two hypotheses. The pattern of results suggests that pollution has both contemporaneous and delayed negative effects on COVID-19 cases and deaths. However, the largest results on deaths are contemporaneous, suggesting that pollution may cause existing COVID cases to worsen.

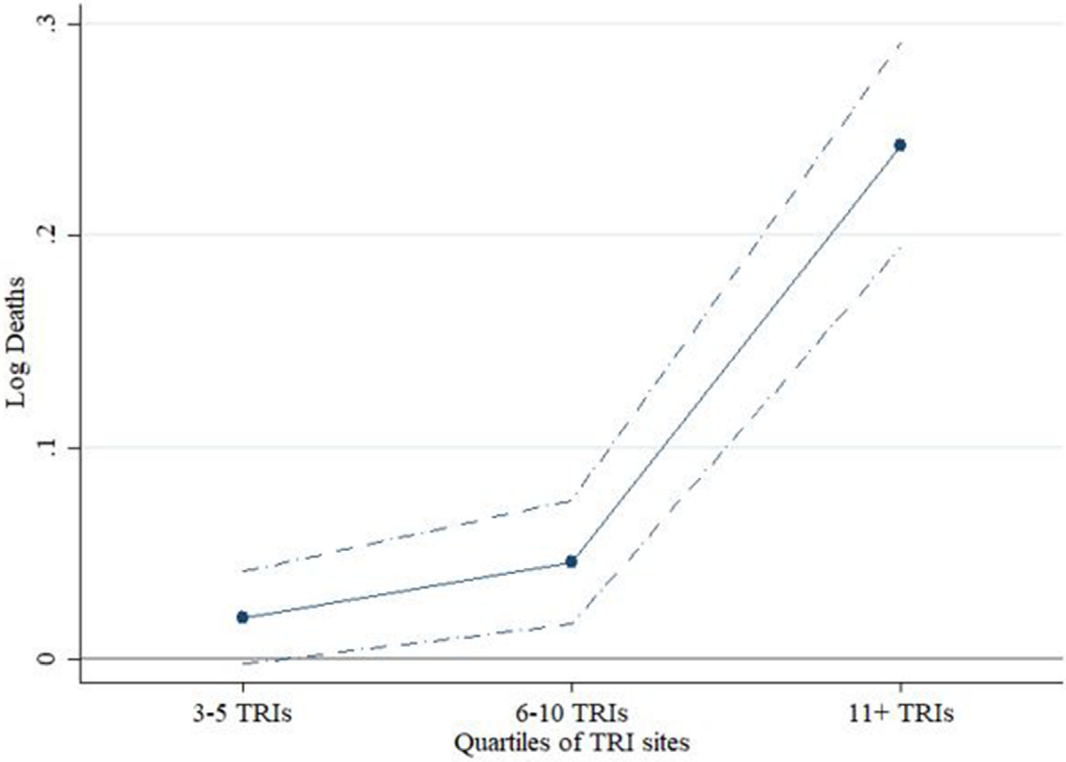
5.3. Effects by pollution type and subgroup

In Table 5, 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 pollution exposure after the rollback. There is some evidence that non-White individuals are overrepresented in neighborhoods around TRI sites (Currie et al., 2015), 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

Table 5
Heterogeneity by county characteristics in 2018.

Log COVID-19 Deaths								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	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 Percent Poverty	County is Above Median Percent Poverty	County is Below Median Percent Over 65	County is Above Median Percent Over 65
Treated Counties After the Rollback	0.0241 (0.0278)	0.1806*** (0.0330)	0.0728** (0.0298)	0.1370*** (0.0336)	0.1370*** (0.0336)	0.0701*** (0.0266)	0.0988*** (0.0296)	0.1177*** (0.0339)
Observations	84126	84126	84126	84126	84126	84126	84126	84126
Average of dependent variable	0.10	0.10	0.033	0.033	53,959	53,959	0.167	0.167

Notes: Each column presents the results for a different subgroup with the log of COVID-19 deaths as the outcome. All models control for an indicator for being after the EPA's rollback, social distancing, stay at home orders, re-openings, mask mandates, days since the first COVID death, weather, daily confirmed COVID-19 cases, total tests administered, and day of the week, county and month fixed effects. Standard errors are clustered at the county level and are in parenthesis. Coefficients labeled as ***, **, and * are statistically significant at the 1, 5, and 10 percent levels, respectively.



Notes: This figure shows how our estimates vary based on the effect of having more TRI sites in a county. The Y-axis plots the coefficients on the interaction between being after the EPA's rollback of civil enforcement with the stated bin for the number of TRI sites. The omitted category is counties with 1-2 TRI sites. This model includes stay at home orders, re-openings, mask mandates, social distancing measures, days since the first death by county, number of confirmed cases by county, total tests administered, temperature, precipitation, county fixed effects, month fixed effects and day of the week fixed effects. The dotted lines show 95% confidence intervals based on standard errors clustered on county.

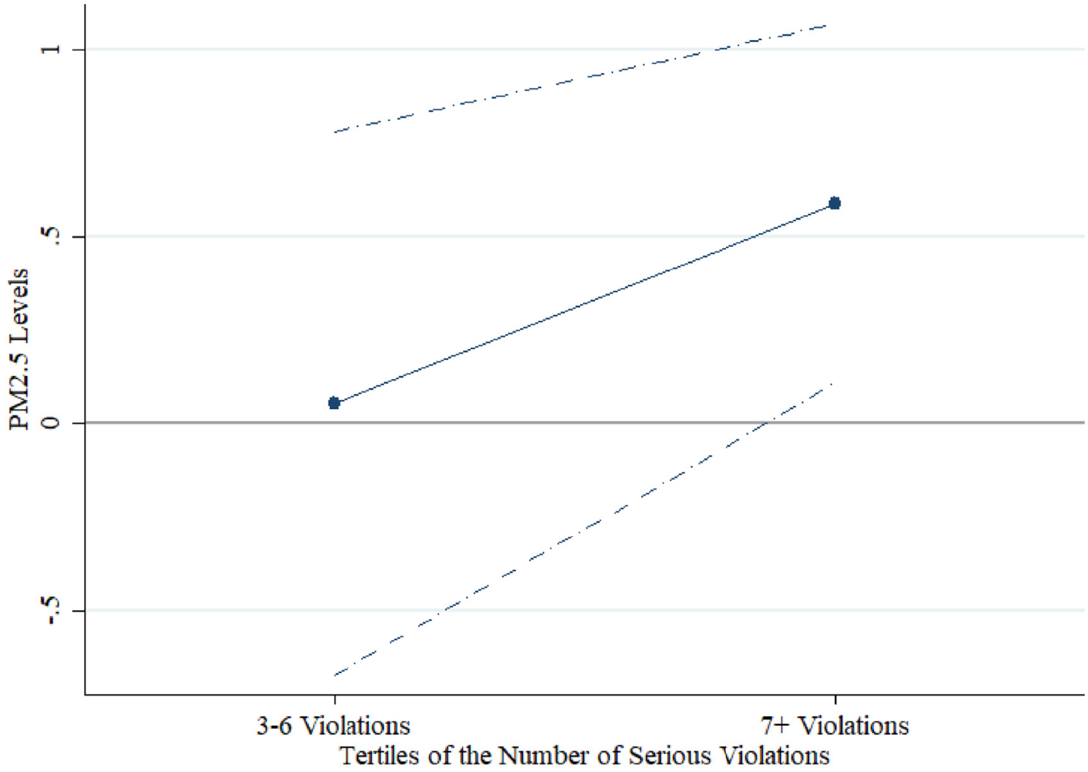
Fig. 4. Effect of Pollution on Log Deaths from COVID-19 by Number of TRI sites.

our results suggest that pollution might be a driving factor in this. In addition, COVID-19 mortality rates in treated counties after the rollback are worse in counties that had above-median unemployment according to the 2018 Census. Unemployed individuals might have less access to healthcare, making them more at risk of death from COVID-19. If polluting sites affect housing values, unemployed individuals might also be more likely to live nearer to sources of pollution. However, in our main sample, which includes only population dense counties in the control group, the outcomes of exposure to pollution are worse in counties that had below-median poverty rates according to the 2018 census. Thus, it does not appear that income is the main driver of these findings. As expected, the results are also larger for counties with above-median percentage of people over the age of 65, indicating that pollution is likely more harmful for older individuals.[22]

5.4. Additional robustness checks

If our results are driven by TRI pollution, we would expect COVID-19 deaths and cases to be worse in counties with more TRI sites. Fig. 4 presents results in which we estimate our main model nonparametrically by interacting our indicator for of being after the rollback ($POST_i$) with three different bins for the numbers of TRI sites counties have (3−5 TRI sites, 6 to 10 TRI sites, and 11 or more TRI sites). The omitted category is counties with 1 or 2 TRI sites. We include the indicator for being after the rollback as a control, as well as our daily controls. The estimates indicate that the effect of living in a county with up to 3 TRI sites on COVID-19 outcomes is near zero. However, as the number of TRI sites increases, the effects become much larger.

[22] Unfortunately, data on the age of residents by county is only available from the Census for a subset of counties.



Notes: Figure 5 shows how PM2.5 pollution after the rollback of environmental enforcement varied by counties based on the number of serious violations in that county. The Y-axis plots the coefficients on the three-way interaction between being after the EPA's rollback of civil enforcement with the stated bin for the number of violations and an indicator for being in a treated county. The omitted category is counties with 0-2 violations. This model includes stay at home orders, re-openings, mask mandates, temperature, precipitation, county fixed effects, month fixed effects and day of the week fixed effects. The dotted lines show 95% confidence intervals based on standard errors clustered on county. Treated counties with more violations show larger increases in PM2.5 pollution after the rollback, compared to control counties.

Fig. 5. Air Pollution Increases After the Rollback in Treated and Control Counties by the Number of Violating Facilities.

Overall, the main effects appear to be driven by counties with 11 or more TRI sites. Each additional TRI site a county has increases deaths from COVID-19 by 1.45%, though the effects are nonlinear.

One might also be concerned that the timing of the rollback could be endogenous if the reason companies polluted more was because there were more COVID cases. While we have already addressed this to some extent by limiting our sample to counties with no deaths (and few cases) before the rollback, we also show that the counties with the largest pollution increase after the rollback were the counties with the largest numbers of serious violators in the EPA's Enforcement and Compliance History Online (ECHO) database. The ECHO data includes a flag for whether each facility "is designated as a High Priority Violator under the Clean Air Act, designated in Significant Noncompliance under the Clean Water Act or Resource Conservation and Recovery Act, or designated as a Serious Violator under the Safe Drinking Water Act in the national systems of record." These facilities are considered "high priority violators" until they are in full compliance and all penalties are paid,[23] so the data reflects current conditions. Fig. 5 plots the coefficients on the three-way interaction between an indicator for being after the rollback, an indicator for being in a treated county, and the stated bin for the number of facilities with serious violations per county. We also control for stay-at-home orders, re-openings, temperature, precipitation, county fixed effects, month fixed effects and day of the week fixed effects. The omitted category is counties with 0−2 violations.

[23] Requirements for removal of the designation vary by program. These are the requirements for air pollution listed in the EPA literature accompanying the ECHO data.

Table 6
Additional robustness and validity tests for the log of deaths.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Log COVID-19 Deaths						
	Baseline Model	Limiting to Comparable Counties with 50%–70% Essential Workers	Limited to Counties with Population Density <2000 in the Treatment Group	Dropping States Near the Mexican Border With Possible Smoke Exposure	Limiting to Counties in States with Both Treated and Control Counties	Limiting to Only Essential TRIs	Limiting to Only TRIs Emitting Air Pollution
Treated Counties After the Rollback	0.1055***	0.1371***	0.0429*	0.1098***	0.0891***	0.2307***	0.1208***
	(0.0272)	(0.0377)	(0.0238)	(0.0298)	(0.0270)	(0.0293)	(0.0244)
With County, Month, and Day of Week Fixed Effects	X	X	X	X	X	X	X
Observations	84126	45236	79162	73155	82452	84126	84126

Notes: Columns 1–7 present the results for being in a county with 6 or more TRI sites after the EPA's rollback with the log of COVID-19 deaths as the outcome. Column 1 replicates our results from Table 3. Column 2 presents the results when limiting to counties with similar percentages of essential workers. Column 3 presents estimates in which we drop treated counties with population densities of more than 2000. Column 4 presents results when we drop counties with potential seasonal smoke exposure. Column 5 presents results when the sample is limited to states with both treated and control counties. The results in column 6 limit the analysis to essential TRI sites. Column 7 limits the sample to include only TRI sites that emit air pollution. All models control for being after the rollback, social distancing, stay at home orders, re-openings, mask mandates, days since the first COVID death, total tests administered, daily number of confirmed COVID-19 cases, weather, and day of the week, county and month fixed effects. Standard errors are clustered at the county level and are in parenthesis. Coefficients labeled as ***, **, and * are statistically significant at the 1, 5, and 10 percent levels, respectively.

Fig. 5 shows that treated counties with more serious violators increased pollution more after the rollback relative to control counties. However, this analysis comes with 2 important caveats. First, we do not know which set of laws was broken by a particular facility – we just know that they are a serious violator. Second, not all facilities in the ECHO data are TRI sites (though many are). That said, this analysis suggests that one important reason that pollution increased after the rollback of environmental enforcement is that facilities with a history of noncompliance with environmental laws might have released more pollution. If such facilities perceived that penalties were less likely to be applied during the pandemic, they might choose to release more pollution.

While our preferred model is a difference in differences design with county fixed effects, we have also estimated the effects of pollution exposure using several alternative approaches and samples. One concern is that treatment and control counties might differ in the percentages of essential workers as a fraction of the labor force, which might affect the results. Ideally, we would like to control for the percentage of essential workers by county as we do in our state fixed effects model, but unfortunately, there is no monthly within-county variation in the data on the percentages of these workers. Instead, we use data from the Bureau of Labor Statistics' 2019 Census of Employment and Wages by type of industry and guidelines from the state of Massachusetts on which industries are deemed essential to limit the counties in the sample to counties with a similar estimated percentage of essential workers.[24] The following industries are likely to contain significant numbers of essential workers based on guidelines released by the state of Massachusetts: agriculture, construction, manufacturing, utilities, education, health, social assistance, and public administration (local and federal government). Non-essential workers are roughly those in wholesale, retail, information, finance, professional and scientific, arts and entertainment, mining, and other services. Unfortunately, the data do not allow us to disaggregate the categories more.[25]

While the overall distribution of essential workers is roughly similar in treatment and control counties, the results in column 2 of Table 6 show the results when limiting the counties in the sample to counties with 50–70% of essential workers (as a percentage of the total workforce). Column 1 presents the results from our baseline model from Table 3 Column 3. These results trim the lowest 10 percent and the highest 25 percent of counties in terms of the estimated percentages of essential workers. In general, larger counties have lower percentages of essential workers, so this analysis effectively removes especially large or small counties. The results are slightly larger when limiting to counties with the same fraction of jobs that are likely to be essential by county, indicating that differences in the fraction of essential workers does not drive the main results.

Another concern is that especially population dense counties in the treatment group (with 6 or more TRI sites) might also be driving the results. So, in column 3 of Table 6 we also show that our results are robust to dropping treated counties with population density over 2000 persons/mi.[2] This analysis effectively drops all treated counties in the top 10th percentile of the distribution in terms of population density. However, the control group retains counties with high population density (above 2000). This is a strong test of the identification strategy because retaining dense control counties and dropping dense treatment counties should bias the analysis toward finding no result. As expected, the results are smaller, yet we observe that

[24] We have replicated these results using 2018 Census of employment categories instead of BLS categories and the results are very similar despite some differences in the categories.

[25] Additional details about how we applied the Massachusetts guidelines on essential workers to the BLS data are available in the data appendix.

being in a treated county after the rollback is associated with a 4.3 percent increase in daily deaths from COVID. We also estimate the effects on COVID-19 cases and deaths using the daily rate of deaths or cases per 10,000 individuals as the outcome instead of the log of daily deaths and cases. The results, presented in Table A2, are similar to those in our main specification. Being in a treated county after the rollback leads to a 14.5% increase in the daily death rate and an 15.9% increase in the daily case rate (per 10,000) above the mean.

It is also possible that smoke from seasonal agricultural burning in Mexico might increase the overall levels of pollution in certain states. The prevailing winds in late April and May were potentially blowing the smoke northeast according to Fig. A4 (The World Resources Institute 2020). Thus, column 4 of Table 6 presents the results when we drop all counties in Texas, Louisiana and Florida. The results are unchanged, suggesting that smoke from seasonal agricultural burning does not drive the effects of pollution on COVID-19 cases and deaths. To test whether states without control counties affect the results, column 5 presents the results when dropping states without control counties, including Massachusetts, Rhode Island, Delaware, Connecticut, and Washington DC.[26] The results are similar when dropping these states.

Another concern is that some TRI sites are not expected to be operating during the pandemic. Thus, column 6 presents the results when estimating only on a sample of TRI sites that have industry codes indicating that they are likely to be considered essential according to documentation from a variety of states, including Massachusetts. Such essential industries include oil, gas and coal, food and beverage, chemicals, computers, electrical equipment, hazardous waste management, machinery, wood/paper, plastics and rubber, and transportation. These constitute more than half of all TRI sites and 97 percent of the counties in the sample has at least one essential TRI site. As expected, the results when limiting to these essential TRIs are slightly larger than to the main results (but likely include some error), indicating that these TRI sites are likely to be driving the effects. Similarly, while most TRI sites emit air pollution, we also test whether TRI sites emitting air pollution drive the results by limiting to only TRI sites that report emitting air pollution. In this specification we compare counties with 6 or more TRI sites emitting air pollution compared to counties with 1–5 TRI sites emitting air pollution. The results when limiting to only those TRI sites emitting air pollution are somewhat larger, indicating that air pollution likely drives our main results. The results for daily cases are similar across all specifications in Table 6 as well.

In addition, health behaviors and hospital bed availability might vary over time. To account for this, we show the mortality results adding additional controls across columns in Table A3 using data from the University of Southern California's Center for Economic and Social Research's Understanding Coronavirus in America (UAS) tracking survey on mask wearing, the Department of Health and Human Services' COVID-19 Reported Patient Impact and Hospital Capacity by State Timeseries on hospital bed utilization, and the COVID Tracking Project on the numbers of people hospitalized and on ventilators. Column 1 shows our main specification, and columns 2 through 4 add additional controls for the daily percent of people who report wearing a mask by county,[27] daily reported hospital bed utilization by state, and the daily number of people who are hospitalized on a ventilator by state. We also control for the number of hospitals reporting data and missing data flags to account for missing data and reporting bias. Our point estimate becomes slightly larger as these controls are added, suggesting that, if anything, the omission of these variables biases our point estimates downward.

A final concern is that daily cases and deaths could suffer from serial correlation bias. Thus, Panel C of Table A1 depicts the daily results using Hausman-Taylor correlated random effects models to account for possible serial correlation. The results are all similar in magnitude to those in Table 3 and statistically significant at the $p < 0.01$ level. This suggests that the results are not being driven by serial correlation bias. In addition, Sloczynski (2020) shows that when treatment effects are heterogenous, the average effect for each group is inversely related to the proportion of observations in each group (where there is a binary independent variable). Thus, we re-estimate the effects using Sloczynski's (2020) methods in Table A4. The Average Treatment Effects (ATE) are much larger using this specification, but the $\hat{w}_0$ is 0.008, suggesting that OLS is expected to bias our estimates by only 0.8% of the difference between the Average Treatment effects on the Untreated (ATU) and Average Treatment effects on the Treated (ATT) (both of which are positive and statistically significant at the $p < 0.01$ level). Thus, OLS is a reasonable choice of model. Given the larger $\hat{\delta}$, our estimates should be interpreted as an ATT more than an ATE.

6. 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. This is the first paper to document that in the response to the rollback of environmental enforcement, counties with more TRI sites saw increases in pollution, suggesting that firms respond in the absence of regulatory incentives by increasing pollution. Second, and perhaps more importantly, our results show that increased pollution increases the daily COVID-19 death rate by 10.6 percent and the case rate by 53.0 percent. These results are stronger for counties with higher fractions of Black individuals, suggesting that the burden of pollution exposure is

[26] We also estimate a specification in which we drop states with substantial error in how the data on cases and deaths are reported by county in the JHU data, namely Utah, Missouri and Florida. The results are unchanged.

[27] Because county level data is only available for a subset of dates in each county in the UAS data, we impute the state-level average on each day for which data is missing in a county and control for the missing data using missing data flags. The results are robust to imputing zeros, rather than the state level average, and controlling for the missing data flags as well.

unequal. Pollution might have the largest impacts on the most vulnerable members of society who suffer from worse health, causing higher death rates and more severe cases of COVID-19.

This study also suggests that deregulation efforts may come with high costs in terms of human lives during pandemics. Using the increase in the daily death rate, our back of the envelope calculation suggests that the environmental rollback led to 7,046 additional deaths from COVID-19, and a net cost of at least $52.11 billion over 107 days in terms of mortality costs alone.[28] This represents a cost of nearly $487 million per day. These findings suggest that unequal pollution exposure might exacerbate preexisting inequalities in health and result in more COVID-19 deaths. This work also underscores the importance of continuing to enforce existing regulations during pandemics.

Our results are consistent with a broader literature that finds that pollution increases respiratory infections and mortality, as well as causing worse COVID-19 outcomes. For example, using short-term variation in the concentration of PM10 in Germany, Isphording and Pestel (2020) find that a one standard deviation (6.3 $\mu g/m^3$) increase in pollution increases COVID-19 deaths by 30—35 percent. Using the distance to the closest neighboring county in non-attainment under the Clean Air Act as an instrument, Furzer and Miloucheva (2020) find that a 1 $\mu g/m^3$ increase in PM2.5 resulted in a 41 percent increase in cases and a 43.5 percent increase in deaths. Austin et al. (2020) use variation in daily wind direction as an instrument for pollution and find that a 1 $\mu g/m^3$ increase in PM2.5 resulted in a 2 percent increase in cases and a 3 percent increase in deaths, though the results are larger over longer time horizons. In contrast, we find that a 0.8 $\mu g/m^3$ increase leads to a 10.6 percent increase in deaths, which is much larger than what Isphording and Pestel and Austin et al. (2020) find, but smaller than what Furzer and Miloucheva find on deaths. However, our results on COVID cases are comparable to Furzer and Miloucheva's findings.

However, this study has a few limitations. First, we do not have individual-level data on the people who died, so we cannot conduct a full heterogeneity analysis by race, age, gender, or socioeconomic status, and instead rely on data from the 2018 Census data as a proxy. In addition, we are limited by the number, quality, and placement of pollution monitors over time, so we must make inferences about pollution to the rest of the sample based on the number of TRI sites. This study also focuses on air pollution from TRI sites, so future work should investigate the consequences for health of water pollution and other types of industrial sites on COVID-19 outcomes.

Finally, this work also suggests several opportunities for intervention. For example, Castres et al. (2017) find that more than half of London's National Health Service (NHS) facilities (including hospitals and clinics) had measured indoor air pollution that exceeded legal limits. While air filters are usually employed in intensive care units and operating rooms in the United States, it is unclear the extent to which all hospitals and clinics in the United States use HEPA air filters in all areas to eliminate indoor air pollution.[29] Air purifiers could be employed in all facilities that treat COVID-19 patients and for patients at home 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 suggests 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.

Financial disclosure statement

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Declaration of competing interest

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

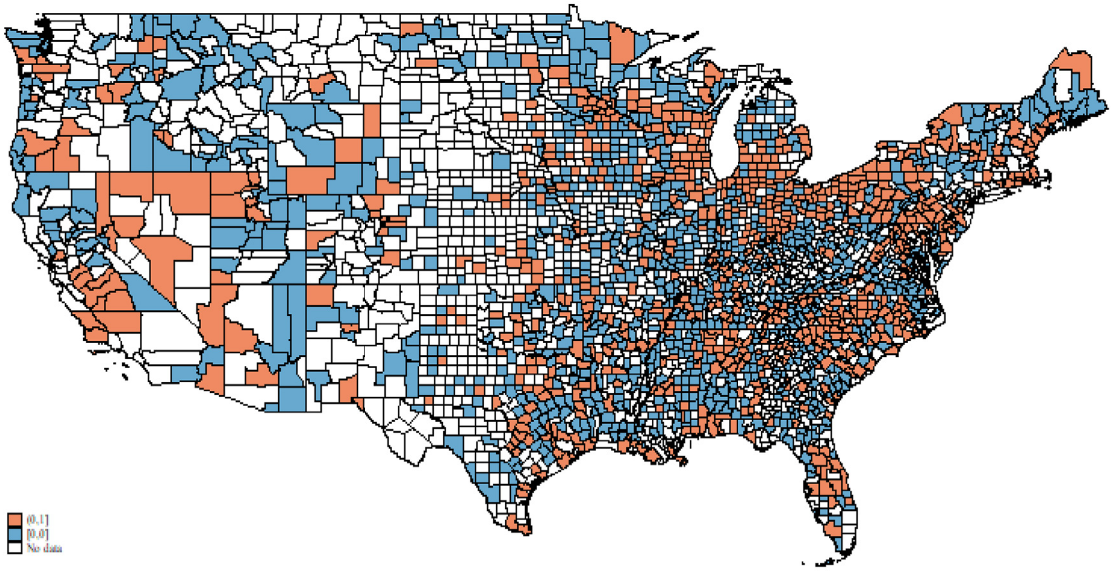
Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jeem.2021.102431.

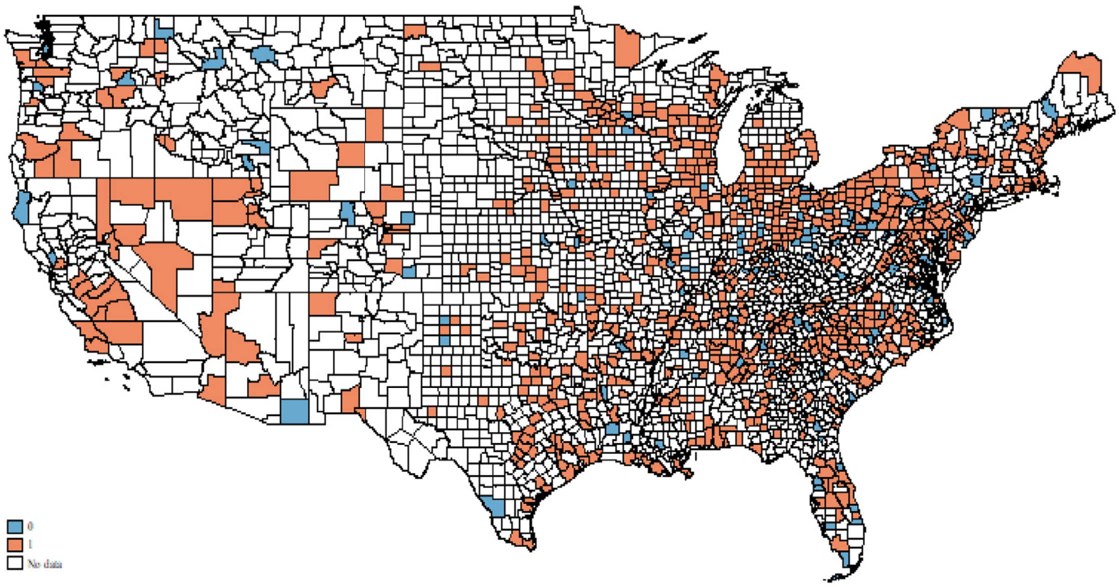
[28] We use the increase in the daily death rate of 0.0025 deaths/10,000 people multiplied by the 107 days in the post-rollback period (once deaths start to increase) to get 0.000027. We multiply this by the number of people living in treated counties (263,420,480) to get 7046 additional deaths. Blundell, Gowrisankaran, and Langer (2020) find that for plants in the ECHO data who are in the seven most polluting North American Industry Classification System (NAICS) industrial sectors, each inspection is equivalent to a $37,400 fine on average, largely because some violations require firms to make capital investments. If there was a decrease from 2019 of 953 inspections * $37,400 = $35,642,200. However, this likely overestimates the benefits in our sample because it is unlikely that all TRI sites are in the seven most polluting NAICS industrial sectors and because it is hard to know whether there would have been a decrease in inspections in the absence of the rollback. If the EPA's current value of statistical life is $7.4 million, and the environmental rollback led to 7046 additional deaths, this represents a cost of $52.14 billion. Subtracting the private savings of $35.64 million gives a net annual cost of $52.11 billion from the rollback.

[29] We were unable to find a single study conducted on this question in the United States, though studies in the United Kingdom, China and Taiwan all find that indoor air pollution exists in hospitals and varies with the type of ventilation system used (Chien-Cheng et al., 2015).

Panel A: Distribution of Treatment and Control Counties with All Counties with 1 or More TRI sites

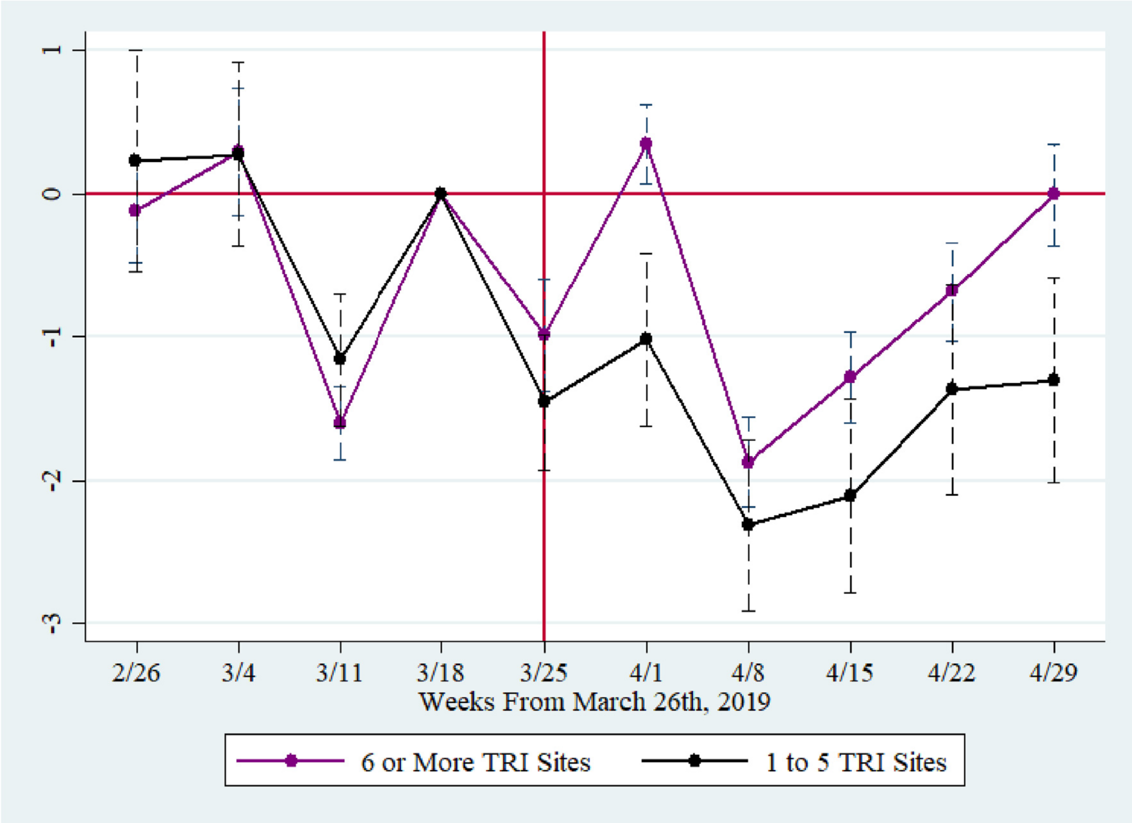


Panel B: Distribution of Main Specification Control Group, Limited to Population Density >250



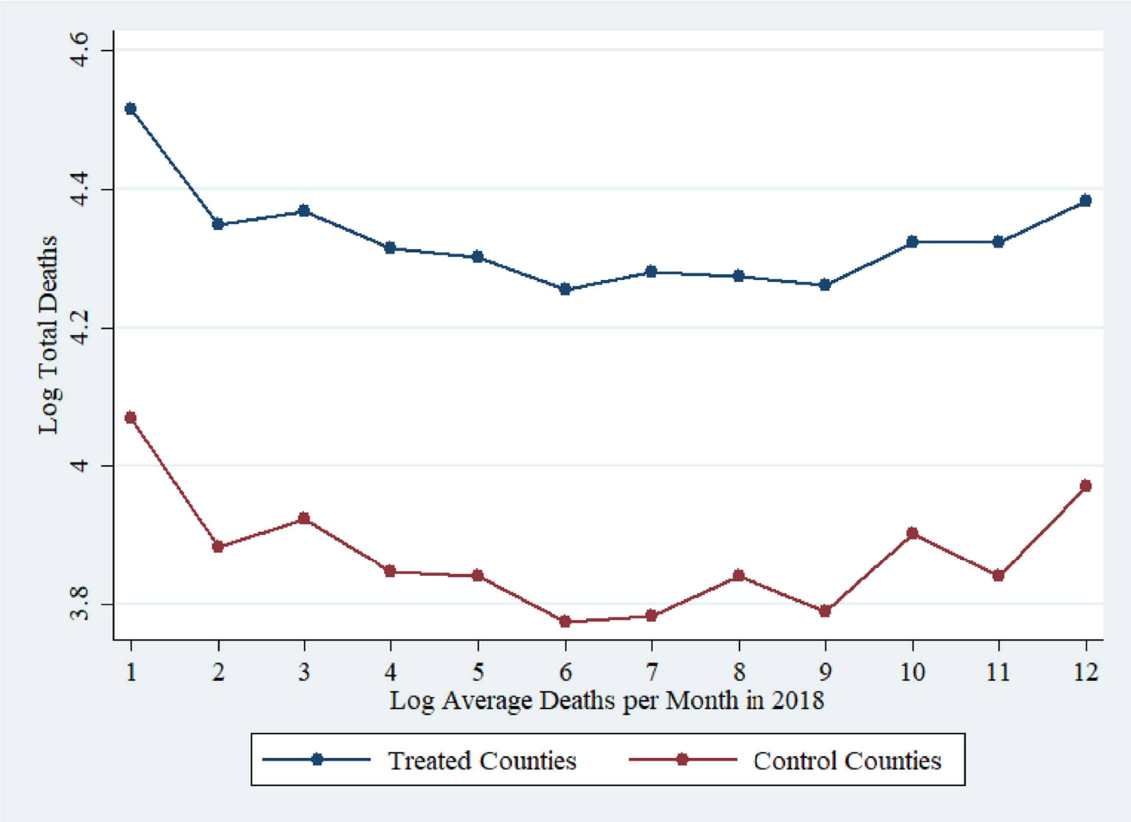
Notes: Figure A1 Panels A and B are a map of treated and control counties in our two main specifications. In both panels, treated counties are in orange and control counties are in blue. The white area includes counties that are dropped from the analysis because they have no TRI sites, had deaths in the pre-rollback period, or were not population dense enough to make good controls. Counties that had deaths in the pre-period or that are outliers in terms of population that were dropped from the main sample are also in white.

Fig. A1. Map of Treated and Control Counties.



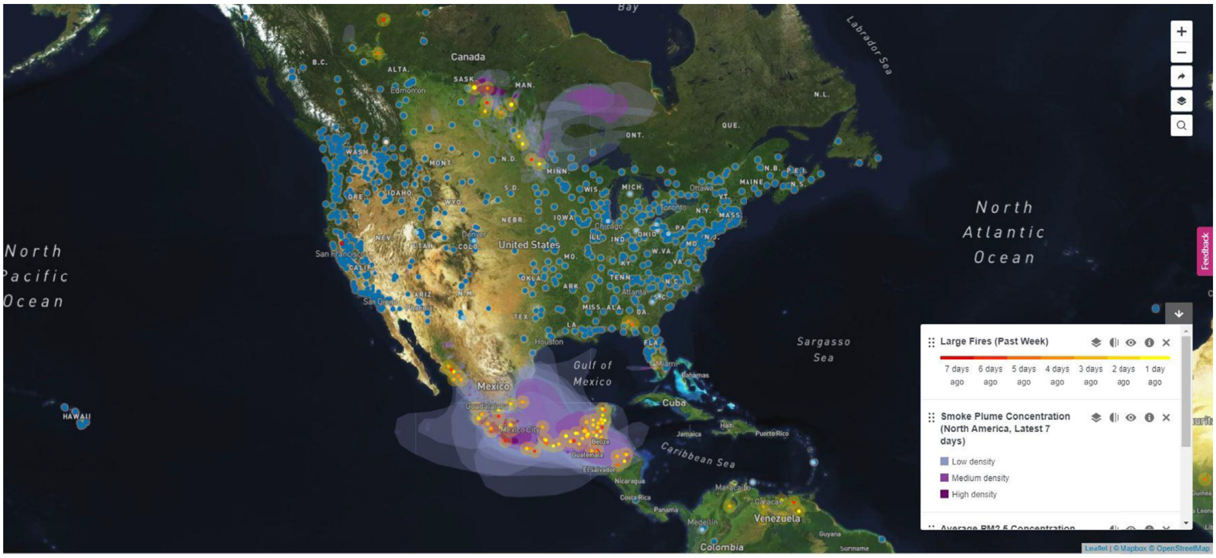
Notes: Figure A2 plots the coefficients from an OLS effects regression of weekly mean level of PM2.5 on leads and lags of time from March 26, 2019 using pollution data from January through May 2019 in all counties. The red line marks the week of March 26, 2019 and all coefficients are normalized such that the coefficient in the week prior to the rollback (3/18) is zero. Dotted lines represent 0.95 confidence intervals for the coefficients. The regression controls for weather and county fixed effects. Standard errors are clustered at the county level.

Fig. A2. Event Study for PM2.5 in Counties in 2019.



Notes: Figure A3 shows the logarithm of monthly deaths in treated (with 6 or more TRI sites) and control (with 1 to 5 TRI sites) counties in 2018. Treated and control counties show similar patterns of deaths in the time before the rollback of environmental regulations and COVID-19.

Fig. A3. Log of Average Deaths Per Month in 2018 in Treated and Control Counties.



Notes: Figure A4 shows the locations of fires in Mexico on May 18, 2020 and in the previous week according to The World Resources Institute (2020). Plumes of smoke are modeled according to wind direction.

Fig. A4. Fires in Mexico in as of May 18, 2020.

Appendix. Tables and Figures

Table A1
Results using All Counties, Including Counties with No TRI Sites and Estimates using PPML and Hausman-Taylor Correlated Random Effects.

	(1)	(2)
	Log COVID-19 Deaths	Log Confirmed COVID-19 Cases
	Panel A: Results using All Counties, Including Counties with No TRI Sites	
Treated Counties in Post Period	0.1758***	0.7766***
	(0.0183)	(0.0471)
Observations	159840	159840
	Panel B: Results using all Counties with 1 or More TRI sites	
Treated Counties in Post Period	0.1645***	0.7253***
	(0.0184)	(0.0490)
Observations	139117	139117
	Panel C: Hausman-Taylor Correlated Random Effects Estimates For Counties with 1 or More TRI Sites (Main Specification)	
Treated Counties in Post Period	0.1033***	0.4939***
	(0.0277)	(0.0951)
County Fixed Effects Regression	X	X
Observations	84126	84126

Notes: Panel A presents the results for the effects of being in a treated county after the rollback with the log of COVID-19 deaths or cases as the outcome using all counties in the United States, including those with no TRI sites, but still limiting to those without a COVID death before the rollback. Panel B presents the results of being in a treated county after the rollback for the full sample of counties with 1 or more TRI sites, except for those counties with a death before the rollback. Panel C presents results when using the Hausman-Taylor random effects panel data model accounting for possible serial correlation and uses the control group from our main specification. All models use county fixed effects and control for social distancing measures, stay at home orders, re-openings, mask mandates, days since the first COVID death, weather, and day of the week and month fixed effects. Column 1 additionally controls for daily confirmed COVID-19 cases. Standard errors are clustered at the county level are in parenthesis. Coefficients labeled as ***, **, and * are statistically significant at the 1, 5, and 10 percent levels, respectively.

Table A2
The Effects of Pollution on Deaths and Cases Using Daily Rates of COVID-19 Deaths and Cases per 10,000 People (per county).

	(1)	(2)
	COVID-19 Daily Death Rate Per 10,000	COVID-19 Daily Case Rate Per 10,000
Treated Counties in Post Period	0.0025**	0.0996***
	(0.0011)	(0.0225)
Main Specification Sample of Counties with TRIs using County fixed effects	X	X
Average of the dependent variable	0.0173	0.628
Percent increase above the mean	14.5%	15.9%
Observations	84181	84181

Notes: Column 1 shows the results of being in a treated county after the rollback on the daily COVID-19 death rate per 10,000 people. Column 2 shows the results of being in a treated county after the rollback on the daily COVID-19 case rate per 10,000 people. All models control for social distancing, stay at home orders, re-openings, mask mandates, days since the first COVID death, weather, and day of the week and month fixed effects. Column 1 additionally controls for daily confirmed COVID-19 cases. These regressions only include counties with 10,000 or more individuals. Standard errors are clustered at the county level and are in parenthesis. Coefficients labeled as ***, **, and * are statistically significant at the 1, 5, and 10 percent levels, respectively.

Table A3
Results with Added Controls for Mask Wearing, Utilization of Hospital Beds, and the Number of People Hospitalized and on Ventilators.

	(1)	(2)	(3)	(4)
	Log COVID-19 Deaths			
	Baseline Model Controlling for Mask Mandates	Controlling for Mask Mandates and Percent of People who Report Wearing Masks	Controlling for Mask Mandates, Mask Wearing, and Hospital Bed Utilization	Controlling for Mask Mandates, Mask Wearing, Hospital Bed Utilization, and the Number of People Hospitalized and on Ventilators
Treated Counties After the Rollback	0.1055***	0.1051***	0.1246***	0.1125***
	(0.0272)	(0.0272)	(0.0258)	(0.0256)
Controlling for Mask Mandates	X	X	X	X
Controlling for Percent of People who Report Wearing Masks		X	X	X
Controlling for Hospital Bed Utilization			X	X
Controlling for Number of People Hospitalized and on Ventilators				X
Observations	84,126	84,126	84,126	82,820

Notes: Columns 1–4 present the results for being in a county with 6 or more TRI sites after the EPA's rollback with the log of COVID-19 deaths as the outcome. Column 1 replicates our results from Table 3 that controls for mask mandates. Column 2 presents the results when additionally controlling for the daily percent of people who report wearing masks. Column 3 presents estimates when additionally controlling for the daily percent of people who report wearing masks and daily reported hospital bed utilization by state. Column 4 presents results when additionally controlling for the daily percent of people who report wearing masks, daily reported hospital bed utilization by state, and the daily number of people hospitalized or on ventilators by state. All models control for being after the rollback, social distancing, stay at home orders, re-openings, mask mandates, days since the first COVID death, total tests administered, daily number of confirmed COVID-19 cases, weather, and day of the week, county and month fixed effects. Standard errors are clustered at the county level and are in parenthesis. Coefficients labeled as ***, **, and * are statistically significant at the 1, 5, and 10 percent levels, respectively.

Table A4
Average Treatment Effect and Estimates for the Log of COVID-19 Deaths.

	(1) ATE Estimate for Log Deaths
Treated Counties After the Rollback	1.042***
	(0.110)
$\hat{w}_0$	0.0081
$\hat{\delta}$	−0.178
Observations	84126

Notes: Column 1 present the average treatment effect (ATE) for being in a county with 6 or more TRI sites after the EPA's rollback with the log of COVID-19 deaths as the outcome using Sloczynski's hettreatreg command and bootstrapped standard errors. All models control for being after the rollback, social distancing, stay at home orders, re-openings, mask mandates, days since the first COVID death, total tests administered, daily number of confirmed COVID-19 cases, weather, and day of the week, county and month fixed effects. Bootstrapped standard errors are in parenthesis. Coefficients labeled as ***, **, and * are statistically significant at the 1, 5, and 10 percent levels, respectively.

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