The Long Arm of the Clean Air Act: Pollution Abatement and COVID-19 Racial Disparities

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Abstract

This paper investigates the role of long-term exposure to fine particulate pollution (PM 2.5) on COVID-19 disparities. To isolate the effect of PM 2.5, we leverage pollution spillovers from neighbouring counties not meeting Clean Air Act-set maximums on acceptable pollution levels. We find a 1-unit increase in cumulative exposure to PM 2.5 increased COVID-19 deaths by 43.5%. PM 2.5 exposure carries an additional race-specific mortality effect of 6.8%-16% for counties with a high proportion of minority or Black residents. However, counties just above CAA pollution thresholds, which had significant pollution reductions over time, saw a full standard deviation reduction in COVID-19 deaths per 100,000. Counties with higher representation of minority or Black residents saw reductions in deaths by 1.50 and 1.15 standard deviations, respectively. Nevertheless, these protective effects insufficiently compensate for the still higher levels of pollution exposure in counties with more Black or minority residents and the more consequential impact of pollution for these communities.

Keywords: COVID-19, environmental pollution, racial inequalities

JEL Codes: I10, I14, Q52, Q53

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1 Introduction

COVID-19 has revealed stark health inequalities by race, with Black and Hispanic populations constituting a disproportionate number of cases and deaths, particularly in the United States (US) (Garg et al., 2020; Millett et al., 2020). Black individuals represent 13% of the US population, and approximately 40% of COVID-19 cases overall (U.S. Census Bureau, 2020; CDC, 2020). These disparities become more apparent at the state and regional level. For instance, Black individuals make up around one-third of the population in Georgia and Chicago, but over 70% of current COVID-19 hospitalizations (Gold et al., 2020; Yancy, 2020).

This disparity is linked to a complicated network of factors, including the disproportionate representation of people of colour in essential work (Rho et al., 2020), higher rates of transit use (Anderson, 2016), and muti-generational households (Schuetz, 2019) that all impact capacity to socially distance. Factors leading to COVID-19 exacerbation post-infection include unequal insurance coverage and access to care (Buchmueller et al., 2016), distrust of the medical system (Kennedy et al., 2007), and racial bias in current medical care (Hall et al., 2015; Hoffman et al., 2016). One's neighbourhood also likely bears impact on both spread and exacerbation based on factors like housing density (Diez Roux, 2001), and differential pollution exposure by race (Mikati et al., 2018; Tessum et al., 2019). Recent work shows a correlation between air pollution, specifically air particulate matter (PM), and COVID-19 deaths at the local-level (Wu et al., 2020; Setti et al., 2020; Conticini et al., 2020; Andree, 2020; Travaglio et al., 2020). However, no previous work has discerned the causal effect of long-term exposure to PM 2.5 on COVID-19 exacerbation in the US, with its considerably higher caseloads, or the differential impact of PM 2.5 by race. In this paper, we investigate the direct role of environmental pollution in exacerbating COVID-19 mortality, particularly in minority and Black communities.

Disparities in access to clean air by income and race are well-known (Mikati et al., 2018; Tessum et al., 2019). Indeed, US data suggests that counties with the highest PM 2.5 levels have an above-average representation of Black and minority residents (see Figure 1). Counties with the highest COVID-19 cases and deaths loads also have disproportionate representation of Black and minority residents. Over the short-term, rollbacks in enforcement by the Environmental Protection Agency (EPA) in the past three months have directly increased pollution and COVID-19 cases and deaths. Fine particulate matter (PM 2.5), which includes ammonium, carbon, nitrates and sulphates, drives this in particular: an increase in PM 2.5 by one $\mu g/m^3$ is correlated with a near doubling of COVID-19 death rates (Persico & Johnson, 2020). This effect size was larger for counties with a higher fraction of Black individuals. Nevertheless, the causal role of cumulative exposure to pollution on current COVID-19 health burdens and its effects by race, in terms of both differential exposure and differential effect, are not fully understood.

Our paper contributes to the growing literature on PM2.5 and COVID-19 in two main ways. First, we causally identify the effect of long-term exposure to fine particulate pollution in COVID-19 cases and mortality in the US, with a specific focus on Black and minority communities. Because PM 2.5 levels (and exposure to them) are likely endogenous, to understand their causal role on COVID-19 adjacent disparities, we employ an instrumental variables approach. To do this, we rely on two features of PM 2.5 and its regulation. First, PM 2.5 pollution regularly spills over across geographic boundaries. Second, counties faced strict regulation of their pollution levels, primarily beginning in 2005 (Currie et al., 2020). A county was deemed in non-attainment by the Clear Air Act (CAA) if their PM 2.5 levels were above 15 $\mu g/m^3$. We combine these two features to estimate marginal changes in PM 2.5 brought about by pollution spillovers from neighbouring counties using distance to closest neighbouring county in non-attainment in 2005.[1] Using this instrument, we find that a 1 $\mu g/m^3$ increase in PM 2.5 resulted in a 41% increase in cases and a 43.5% increase in deaths. This is an excess of 100 cases and 5 additional deaths per 100,000, on average. When accounting for race, at baseline, a 1 unit increase in PM 2.5 increases COVID-19 deaths by 26%. Counties with a higher than median proportion of Black residents then see an additional 16% increase in COVID-19 mortality due to PM 2.5. Counties with a high proportion of minority residents in general saw a 6.8% increase in COVID-19 deaths due to PM 2.5.

Our second contribution focuses on the fact that air pollution has substantially improved in recent years, in large part due to the Clean Air Act itself (Auffhammer et al., 2009). Air quality changes have been progressive in nature, with lower-income and racialized communities more likely to be deemed in non-attainment and thus seeing more considerable pollution reductions (Bento et al., 2015; Currie et al., 2020). As evidenced in Appendix Figure 1, the racial gap in PM 2.5 levels substantially declined across the PM 2.5 distribution from 2000 to 2016 for communities with a high proportion of minority or Black residents. This decline was especially large for those in non-attainment, whose states are required to draft detailed plans for pollution abatement and risk losing federal funding for air pollution control programs.[2] We exploit this strict threshold in a regression discontinuity design. Consistent with prior literature (i.e., Bento et al., 2015; Currie et al., 2020), we first demonstrate that the CAA regulation had an abatement effect. For counties just above the non-attainment threshold of 15 $\mu g/m^3$ in 2004, PM 2.5 levels in 2016 were over 2% lower on average, with the strongest results in counties with large minority populations. Next, we consider whether CAA-related air pollution reductions resulted in a downstream protective effect on current COVID-19 mortality. We compare COVID-19 outcomes for counties around the non-attainment cut-off in 2004 (the year prior to enforcement) and estimate that being in non-attainment resulted in 381 fewer cases and 32 fewer deaths per 100,000. For counties with a high proportion of minority or Black residents, the protective effect increased to 47 and 37 fewer deaths per 100,000, respectively.

With well-established literature showing links between pollution and respiratory health, it is not unexpected that long-term pollution exposure also increased COVID-19 health burdens. This relationship

[1] We show that our results are robust to multiple forms of this instrument in Appendix Table 5.
[2] A comprehensive review of the Clean Air Act can be found in Currie & Walker (2019).

is not isolated to the US. The most closely related paper to ours estimates the causal impact of multiple types of pollution on COVID-19 in the Netherlands and finds similar results (Cole et al., 2020). That our results show a more potent effect of PM 2.5 for US counties with a high proportion of Black or minority residents demonstrates how historical inequities in access to clean air compound long term, especially in the face of a global pandemic. This paper fills an identified evidence gap on racial disparities in COVID-19 outcomes beyond underlying health conditions (Williamson et al., 2020). The protective effect of pollution abatement long-term bolsters our understanding of environmental policy as both a health and an economic investment. The impact of pollution abatement policies to reduce health disparities, especially in Black or minority communities, underlines the importance of equity-improving environment policy to reduce race-based health inequalities.

2 Environmental Factors in COVID-19 Exacerbation

Prior to COVID-19, a robust literature has linked environmental pollution to health outcomes. Children in early life and older adults are the most at risk (Currie & Neidell, 2005; Currie et al., 2009; Currie & Walker, 2011; Schlenker & Walker, 2016; Bishop et al., 2018; Deryugina et al., 2019; Ward, 2015), with strong evidence that pollution reductions lead to reductions in asthma-related hospitalizations and attacks.[3] For adults over the age of 65 in particular, hospitalization for asthma, respiratory and heart-related problems increased due to pollution from airport congestion (Schlenker & Walker, 2016). Recent estimates also found that single day increases in PM 2.5 based on changes in wind direction increased emergency room visits, hospitalizations and excess mortality for older US adults (Deryugina et al., 2019). There is also evidence to suggest that pollution exposure directly increases cardio-respiratory issues (Newell et al., 2017) and diabetes (Bowe et al., 2018). Families from lower socioeconomic status are at particular risk, with both increased pollution exposure and more extensive negative outcomes conditional on exposure level (Neidell, 2004).

Recent work has shown a strong correlation between historical and recent pollution on current COVID-19 infection rates and deaths in the United States. In Italy, provinces with higher pollution saw higher infection rates and deaths (Setti et al., 2020; Conticini et al., 2020). PM 2.5 levels in 2016 also appear to have a significant impact on current confirmed caseloads and COVID-19 deaths in the US (Wu et al., 2020). These PM 2.5 effects compound by race and income (Persico & Johnson, 2020). Indeed, recent U.S. data shows higher rates of COVID-19 cases and deaths across the PM 2.5 distribution for high proportion minority or Black resident counties. We demonstrate in appendix Figure 2 that the

[3] Pollution reductions in California were found to reduce asthma-related hospitalization for children by 5-14%, for a total of $5.2 million in savings for 1 year (Neidell, 2004). Congestion taxes in New Jersey also helped to reduce acute asthma attacks (Simeonova et al., 2018). Similar results have also been found in the Canadian context, leveraging variation in pollution exposure from changing wind patterns (Ward, 2015). This effect may even begin *in-utero*, with pollution linked to low birth weight and pre-maturity (Sun et al., 2016) and resulting lung issues long term (Vollsæter et al., 2013). Going in the opposite direction, children's hospitalizations for respiratory issues increased by 11% on heavy traffic congestion days in Germany due to public transit strikes (Bauernschuster et al., 2017).

race gap in COVID-19 deaths appears to grow as we move along the PM 2.5 distribution. However, there are many endogenous factors at play in the relationship between pollution and COVID-19.

Firstly, many COVID-19 infections are based on capacity (or lack thereof) to socially distance, with more disadvantaged people potentially less able to evade exposure (Currie et al., 2020; Bhala et al., 2020; Papageorge et al., 2020). Essential work requirements, use of public transportation, and housing quality and density will all prevent risk avoidance for COVID-19 (Platt & Warwick, 2020). Persons of colour are more likely to be in an essential service roles and unable to work from home (Rho et al., 2020), making them more susceptible to transmission (Lewandowski, 2020). Higher public transportation ridership rates for communities of colour will also impact rates of COVID-19 infections (Anderson, 2016; Knittel & Ozaltun, 2020; McLaren, 2020). Poverty and density are additional risk factors for COVID-19 spread and exacerbation (Chin et al., 2020).

At the neighbourhood level, the role of segregation and redlining – where predominately Black neighbourhoods were systematically excluded from mortgage lending and other financial and governmental services – significantly impacted housing values and the current economic and health status of Black communities (McClure et al., 2019; Williams & Cooper, 2020). Chronic conditions like asthma have been linked to redlining, based on the proximity of highways and polluting industries (Nardone et al., 2020). Redlining also contributed to a decline in home-ownership rates, which may approximate stable housing, wealth, and the ability to control who and how many persons are in your living space (Schuetz, 2019). Directly, this will also be correlated with access to clean water for hand washing and inside air and other pollutants.[4] At the highest level, the location of residence is not exogenous, with significant segregation and corresponding disparities in these confounding variables (Williams & Cooper, 2020).

With a confirmed COVID-19 case, potential race-based drivers of COVID-19 death disparities include health care access, whether based on insurance rates (Buchmueller et al., 2016; Sohn, 2017), avoidance due to distrust (Kennedy et al., 2007), or racial bias in care (Hoffman et al., 2016). These factors will have an impact on both one's ability to treat underlying conditions and pose barriers to seeking early COVID-19 testing and treatment in the United States. Prevalence of co-morbidities like hypertension, diabetes, cardiovascular disease have all been cited as underlying risk factors for COVID-19 (Guan et al., 2020), with the potential for differing effects of these conditions on COVID-19 by ethnicity (Khunti et al., 2020). However, racial differences in these co-morbidities fail to explain a large part of the racial mortality gap (Williamson et al., 2020). Black patients with COVID-19 are no more likely, for example, to have diabetes, heart disease, or to be classified as obese than non-Hispanic White patients with COVID-19 (Gold et al., 2020). Due to these numerous confounding variables, identification of a causal PM 2.5 effect will isolate the precise role of cumulative PM 2.5 levels on current COVID-19 health burdens.

The CAA provides a useful policy intervention to help isolate the marginal effect of PM 2.5 on

[4] The virality of COVID-19 indoors in homes has been noted by Qian et al. (2020).

COVID-19 outcomes, and understand the role of the policy itself on current COVID-19 health burdens. While initially established in 1963, the CAA placed more stringent regulations around ozone and PM 2.5 in 1997. These rules defined different counties as non-attainment zones as per the National Ambient Air Quality Standards (NAAQS) if they had a measure of a PM 2.5 level above 15 $\mu g/m^3$. Non-attainment status is determined each year but was only enforced by the Environmental Protection Agency (EPA) after 2004 (Currie & Walker, 2019). Counties who were given non-attainment status risked losing federal funding if they failed to reduce their future PM 2.5 levels. Previous work has shown us that the CAA reductions were progressive in nature, in that they benefited lower-income and racialized communities to a larger degree (Auffhammer et al., 2009; Bento et al., 2015; Currie et al., 2020). Knowing this, we firstly investigate the role of neighbouring county non-attainment on own-county PM 2.5 levels. We focus on neighbouring counties in non-attainment status given that PM 2.5 can easily cross county borders to raise the PM 2.5 level of an individual county. Secondly, we estimate how this historical abatement policy impacted the current rate of COVID-19 cases and deaths at the county-level.

3 Data

To determine the effect of PM 2.5 and CAA regulations on current COVID-19 health burdens, we require three main data components. We first obtain data on mortality and other health outcomes for both our main analysis and placebo tests. We use daily cumulative COVID-19 cases and deaths by US county from the Johns Hopkins University Center for Systems Science and Engineering Coronavirus Resource Center. We use the most up-to-date case and death records, at which point the United States had over 1.4 million COVID-19 cases and over 87,000 deaths.[5]

The second main component of our data includes measures of air pollution levels, and the county linkages necessary to create our instrument. We use yearly county PM 2.5 levels from 2000 to 2016, along with summer and winter maximum temperature and humidity readings from Van Donkelaar et al. (2019). These data use satellite measurements of pollution, combined with statistical models using local characteristics, to produce more accurate, and spatially complete measures of PM2.5 chemical components.

Leveraging these PM2.5 measures, we next determine areas that were non-attainment zones as per the NAAQS-set PM 2.5 threshold of 15 $\mu g/m^3$ or higher.[6] We generate an indicator variable for being at or above the NAAQS threshold from 2000 to 2016. There were 208 counties deemed either non-attainment or in maintenance status in 1997. This total fell to 86 by 2006, and 18 by 2012 (Appendix Figure 3).

A crucial part of our identification strategy rests on identifying neighbouring counties and determining whether they met the EPA's criteria for non-attainment status. To construct our instrumental variable

[5] Data was last accessed May 16, 2020.

[6] In December 2012, the NAAQS was lowered to a threshold of 12 $\mu g/m^3$, but as we rely only on the thresholds as they were in 2004 and 2005 this does not impact our analysis.

on distance to nearest neighbouring county in non-attainment, we use the National Bureau of Economic Research (NBER) county distance database on the universe of all US counties. This data set contains measures of distance from the centroid of each county to the centroids of all other counties. For each county in our sample, we first measure if they were in non-attainment based on their 2005 PM 2.5 levels. We then select the closest county in non-attainment for all counties. The average distance to nearest neighbour in non-attainment is 293 miles. We generate alternative instrumental variables based on the inverse distance to nearest neighbour in non-attainment, the average PM 2.5 level across all neighbours within a 25-mile radius, and the proportion of all neighbours in non-attainment within a 25-mile radius. All instruments are calculated based on 2005 PM 2.5 values. We compare first and second stage results for each of these instruments in Appendix Table 5.

Finally, to control for confounding variables, we incorporate 2016 US Census data on county-level population, percent of the population over the age of 65, density, proportion of residents living under the poverty line, race statistics, including proportion of black, Hispanic, non-white or minority residents, and white residents. We calculate a measure of remoteness for a given county based on the number of other counties within a 25-mile radius. We additionally include controls for median household income, house value, percent owner-occupied, and the proportion of residents with only a high school degree. We exploit the 2018 5-year American Community Survey to measure public transit use to work. We include proportion of residents uninsured, as measured in 2010, from the Opportunity Insights county database and hospital beds per capita from the Homeland Infrastructure Foundation-Level Data. We incorporate average daily social distancing rate from Uncast to control for endogenous avoidance behaviours for at-risk populations (Uncast, 2020). Interestingly, early research on COVID-19 exacerbation suggests asthma and chronic obstructive pulmonary disorder (COPD) are not actually significant risk factors for COVID-19 exacerbation (Petrilli et al., 2020). Persons with underlying respiratory conditions are, however, more likely to practice avoidance behaviour in the face of risk (Neidell, 2004; Janke, 2014). Thus, the limited connection between asthma and COPD to COVID-19 exacerbation may be driven by higher rates of social distancing for persons with underlying respiratory or other conditions. We additionally incorporate days since any social distancing order, based on the COVID-19 US state policy database (CUSP) (Raifman et al., 2020). A value of zero is applied if there were not orders in place.

4 Methods

4.1 PM 2.5 and COVID-19

For estimating the effect of the PM 2.5 on current COVID-19 health burdens, our preferred OLS specification would indicate:

$$Y_{i,s} = \beta_0 + \beta_1 PM2.5_{i,s} + \rho X_{i,s} + \pi_s + \epsilon_{i,s} \tag{1}$$

where $Y_{i,s}$ measures the log of confirmed COVID-19 cases or deaths in county i and state s. The effect of PM 2.5 levels in 2016 is measured through β_1. The matrix $X_{i,s}$ measures county-level control variables including average temperature and humidity, social distancing rate, days since first case and social distancing orders, percent of county living below the poverty line, the logs of median household income and house value, percent owner occupied, average education level, percent uninsured, hospital beds per capita, racial demographics, percent of population over age 65, county remoteness, share of workers commuting using public transit, population and density. State fixed effects are incorporated in the term π_s and we use population weighting. We cluster standard errors at the county-level.

PM 2.5 levels are, however, not exogenous. Counties in with high PM 2.5 levels likely differ substantially from those with low PM 2.5 levels. Table 1 presents differences in key control variables by whether or not a county is in non-attainment. Counties in non-attainment have higher COVID-19 case and death rates, higher population and density, higher income, lower poverty, and fewer residents with only a high school education. They also have a higher proportion of Black residents. Counties with the highest PM 2.5 levels in general have above average representation of Black and minority residents (Figure 1). Aside from these observable factors, OLS estimates may be biased upwards if there are unmeasured or unobservable factors driving both PM 2.5 levels and COVID-19 health burdens. These could include governmental efficiency, types of local industry, commuting patterns, and the work available in given counties. To account for these factors we employ an instrumental variable strategy based on distance to nearest neighbouring county in non-attainment in 2005.[7]

We argue that the distance to the nearest non-attaining neighbour is a reliable instrument for several reasons. First, because air pollution is not confined to geographic boundaries, pollution in one county can spill over to its neighbour, and the ease with which it does so is mediated by distance. Indeed, evidence shows that even Canadian air pollution levels increase based on cross-border pollution wind drift from U.S jurisdictions, which have more lenient standards (Ward, 2015). We therefore expect that the shorter the distance to the nearest county in non-attainment, the more local PM 2.5 levels will be affected. Second, because we leverage non-attainment status in 2005, we avoid issues surrounding contemporaneous violations of the exclusion restriction. If a neighbouring county or entire state experiences a budget crisis that affects both their pollution abatement programs and their health care provision, for example, we might be concerned about a violation of the exclusion restriction. However, because we leverage non-attainment status in 2005 and include state fixed effects across all specifications, this is less of a concern. Nevertheless, we may still be concerned that non-attainment of a neighbouring county was somehow correlated with future health in a region (other than through PM 2.5). If this was the case, we could expect to also see effects on other non-COVID-19 causes of mortality that are not plausibly driven by

[7] In Appendix Table 5 we review alternative instruments based on the inverse distance to nearest neighbour in non-attainment, the mean PM 2.5 levels for neighbouring counties within 25 miles and the proportion of neighbouring counties within 25 miles in non-attainment prior to 2005.

pollution. We run a series of placebo tests showing that this is not the case. Finally, to the extent that local pollution is also driven by counties which are nearby but not above the non-attainment cutoff, our choice of specification for the instrument would underestimate the impact of neighbours' pollution, which we argue would subsequently bias our estimates downwards. We demonstrate in appendix Table 5 that our results are robust to using mean PM 2.5 levels of all nearest contiguous neighbours as an instrument. Our choice of distance to the nearest non-attainment neighbour as our main instrument of choice provides a more conservative point estimates of COVID-19 effects.

Key variable differences between counties by neighbouring county non-attainment are also shown in Table 1. We split these into two groups, whether the next nearest county in non-attainment was above or below the median of this measure. Counties with close neighbours in non-attainment do still have larger, more dense populations, and more neighbouring counties within a 25-mile radius. However, the differences in these and most other variables fall compared to own-county non-attainment differences. Those cities with close neighbours in non-attainment have higher rates of poverty and persons with only a high school-level education and higher proportions of Black residents. Those counties without a nearby neighbour in non-attainment have comparably higher Hispanic populations. These results demonstrate the own-non-attainment and distance to neighbouring county in non-attainment do not proxy for the same characteristics.

We provide evidence to support our instrument's validity in the last columns of Table 1. The β column presents coefficients from regressing our instrument on our outcomes, our PM 2.5 measures, and our main covariates. We note that our instrument predicts 2005 PM 2.5 levels, as is necessary for a first stage. After controlling for 2005 PM 2.5 levels, our instrument still minimally predicts deaths and population density, but no other control variables. When we perform the same exercise but control for 2017 levels of all covariates to predict log-deaths and population density, we retain a 0.1% increase in deaths due to our instrument, but this is no longer significant at traditional levels. Similarly, a 1-mile increase in distance to nearest neighbour in non-attainment has not effect on population density (the estimated coefficient is 0.017 (0.02)).

Using this instrument, our first stage in a two-stage least squares design is then:

$$PM2.5_{i,s} = \alpha_0 + \alpha_1 Dist_{i,s} + \rho X_{i,s} + \pi_s + \epsilon_{i,s} \tag{2}$$

Our instrumental variable is included in the equation as $Dist_{i,s}$. This is used to predict $PM2.5_{i,s}$ in 2016. Control variables are analogous to Equation 1. Using the predicted value of PM 2.5 induced by distance to nearest neighbouring county in non-attainment in Equation 1 generates a two-stage least squares estimate of PM 2.5 on COVID-19 outcomes. We then incorporate an interaction term between a race indicator and PM 2.5 levels to test for differences in PM 2.5 effects by county-level racial demographics.

These race indicators include whether a county has an above median proportion of minority residents and whether a county has an above median proportion of Black residents. Differences in PM 2.5 effects by these demographics will provide a first indication of whether pollution impacts communities of colour differently.

4.2 Protective Effects of non-attainment

To understand the relationship between historical pollution abatement policies and current COVID-19 exacerbation we exploit the CAA non-attainment threshold of 15 $\mu g/m^3$ to assess discontinuous changes in COVID-19 deaths based on being on the cusp of non-attainment directly before enforcement began in 2005.

We first demonstrate the effectiveness of the CAA threshold in 2004 in reducing future PM 2.5 emissions for counties just above the cut-off. Our estimating equation is:

$$PM2.5_{i,s}^{2016} = \alpha_0 + \alpha_1 I[PM2.5_{i,s} \geq 15] + g(PM2.5_{i,s}) + \rho X_{i,s} + \pi_s + \epsilon_{i,s} \tag{3}$$

We next demonstrate that this reduction in PM.25 emissions around the cutoff also affected deaths; our sharp regression discontinuity takes the form:

$$D_{i,s} = \alpha_0 + \alpha_1 I[PM2.5_{i,s} \geq 15] + g(PM2.5_{i,s}) + \rho X_{i,s} + \pi_s + \epsilon_{i,s} \tag{4}$$

Our outcome variable of interest $D_{i,s}$ is log COVID-19 cases or deaths in county i in state s. The local average treatment (LATE) effect of being in non-attainment in 2004 is measured through α_1. We use 2004 PM 2.5 levels to assess own attainment status in order to account for potential anticipatory county-level PM 2.5 changes in response to known policy changes occurring in 2005. We note that a county's ability to adjust their ambient PM 2.5 levels with precision to fall on either one or the other side of the cutoff are very limited, particularly given the important role of neighbouring county emissions.[8] We include an operator $g(PM2.5)$ to allow for differing effects of PM 2.5 above and below the attainment threshold. To maintain parsimony given the limited effective sample sizes utilized within the regression discontinuity bandwidth we include a limited set of county-level controls, including level of social distancing, remoteness, proportion of black and Hispanic residents, and proportion using public transit. State fixed effects are included through π_s. We employ stratified analysis by whether a county had above median representation of minority or Black residents to estimate the differential impact of this policy for communities of colour.

[8] Indeed, McCrary (2008) sorting test results in Appendix Figure 4, with p-values of 0.24 indicate that this is not a large cause for concern. We also show in appendix Table 7 that there are no discontinuous jumps in key control variables, including daily distance travelled during social distancing time for a given county.

5 Results

5.1 PM 2.5 and COVID-19 Outcomes

We present baseline estimation results in Table 2. A näive OLS specification, including only state fixed effects and temperature controls in column (1) estimates that an increase in cumulative exposure to PM 2.5 by 1 $\mu g/m^3$ approximately doubles the COVID-19 death and cases count. On average, this is 245 cases and 11 additional deaths per 100,000. Conditional on confirmed case loads, this baseline specification still finds a 15% increase in deaths. When accounting for census socioeconomic variables in column (2), we see a large decrease in effect sizes. Next we account for social distancing practices and policies and racial demographics in columns (3) and (4), and see another sizable drop in effect sizes for deaths and cases. These changes indicate an upward bias in estimated PM 2.5 effects driven by the fact that counties with high levels of PM 2.5 are disproportionately minority or Black (consistent with our findings in Figure 1). Column (4) additionally controls for a measure of public transit use to work. To the extent that we are concerned about commuting patterns as a mechanism for the disproportionate spread of COVID-19 which may also simultaneously affect PM 2.5 levels, we can directly control for the proportion of workers who commute to work primarily using public transit.[9] Doing so negligibly changes our point estimate.

To control for remaining unobservable selection that might increase both PM 2.5 levels and COVID-19 outcomes, we implement an IV strategy in column (5), instrumenting PM 2.5 with distance to nearest neighbouring county in non-attainment in 2005. First stage and reduced form results, as well as weak instrument and Wu-Hausman testing for IV estimation are found in Appendix Table 5. We argue our instrument acts only through own-county PM 2.5 in 2005 to impact cumulative PM 2.5 and, eventually, COVID-19 outcomes as, in Table 1 our instrument is not predictive of other county-level characteristics. Our IV estimates demonstrate that an increase in cumulative PM 2.5 exposure by 1 $\mu g/m^3$ increases the number of COVID-19 deaths by 43.5%. This is an additional 4 COVID-19 deaths per 100,000, on average. From Panel B, our results indicate an increase in case load by 41%, or 100 cases per 100,000, on average.

Incorporating an interaction term between PM 2.5 and race allows for differential impact of PM 2.5 by whether a county had a higher than median proportion of Black or minority residents. We see a particularly strong differential impact of PM 2.5 for counties with a high proportion of Black residents. At baseline, a 1 unit increase in PM 2.5 increases COVID-19 deaths by 26%. Counties with a higher than median proportion of Black residents then see an additional 16% increase in deaths. This differential is less stark for a general measure of minority residents, where the incremental effect of PM 2.5 by race is

[9] We can additionally investigate the effect of public transit use separately for Black and white residents for a subset of just over 2500 counties. Appendix Table 8 demonstrates that the results remain largely unchanged when doing this, suggesting that patterns of transit use that may differ by race are not driving underlying COVID or PM2.5 disparities.

6.8%. When accounting for differential effect of PM 2.5 on COVID-19 cases, similar baseline effect and incremental effects of PM 2.5 by race are present, though slightly lower –suggesting PM 2.5 impacts both spread and exacerbation beyond spread. Counties with a high proportion of Black residents again see a higher incremental effect of PM 2.5 over counties with a high proportion of minority residents in general. Conditioning the mortality rate on county-level case rate, we see that counties with a high proportion of Black residents specifically see an additional 2.8% increase in deaths conditional on infection rates. Minority counties do not see the same exacerbation effect.

To ensure that our results were not driven by the outlying case of New York state, which had the highest number of COVID-19 cases and deaths in the US, we also run this analysis excluding New York and it's 62 counties. Our results are robust to this sample specification.[10] Another potential cause for concern with this estimation strategy may be that neighbouring non-attainment status is also correlated with, in some way, a county's ability to effectively administer medical care, or with a less health-conscious population. If this was the case we would expect to find mortality effects for causes which are otherwise not directly affected by PM 2.5 levels. To verify that this is not the case, Table 3 presents a series of placebo tests using county-level data on 2018 annual mortality from infectious diseases, external causes and diseases of the circulatory system from the Center for Disease Control (CDC).[11]

In panel A, we present baseline placebo tests for these three cause of death. Because of small-sample suppression in the publicly available mortality data, the CDC does not publish death counts smaller than 10. In order to be conservative, we round all suppressed counties up to 10 deaths in Panel A.[12] Columns (1) and (2) present the reduced form and IV results for logged infectious disease deaths. Columns (3) and (4) present results for logged external causes of death, and columns (5) and (6) show results for logged deaths from circulatory conditions. Our instrument does not appear to be predictive of increased deaths from our placebo causes. Panel B limits our sample to counties which had more than 10 deaths each year, and for whom we do not have data suppression issues. Under this sample restriction, our instrument still does not predict effects for infections disease, external or circulatory disease deaths. Appendix Table 6 further extends these placebo tests to measures of death due to endocrine and digestive diseases, where we again find no effect of PM 2.5 on mortality. We interpret these results to suggest that our main results are not driven by underlying relationships between PM 2.5 levels and a county's health care provision or other co-morbidities.

[10] Results are presented in Appendix Table 9.

[11] 2018 is the most recent publicly available year of data for these causes of death. External causes are grouped broadly into: transport accidents, falls, exposure to inanimate mechanical forces, exposure to animate mechanical forces, accidental drowning and submersion, other accidental threats to breathing, exposure to electric currents, radiation, and extreme ambient air temperature and pressure, exposure to smoke fire and flames, contact with heat and hot substances, contact with venomous animals and plants, exposure to forces of nature, accidental poisonings by and exposure to noxious substances, overexertion, travel and privation, accidental exposure to other and unspecified factors, intentional self-harm, assault, event of undetermined intent, legal intervention and operations of war, and complications of medical and surgical care.

[12] Although in principal the true number of deaths in each of these cases can range between 0 and 10.

5.2 Distributional Racial Differences in PM 2.5 and COVID-19

Knowing the effect of PM 2.5 by race likely differs across the distribution of COVID-19 case burdens, we estimate the PM 2.5 effect by race across the distribution of COVID-19 deaths using a Re-centered Influence Function (RIF) regression. We first estimate raw racial gaps in COVID-19 deaths via:

$$D_{i,s} = \alpha + \beta M_{i,s} + \gamma_i \tag{5}$$

COVID-19 deaths $D_{i,s}$ are estimated using a RIF for each quantile of the COVID-19 death distribution. Here, $M_{i,s}$ is an indicator for a county having a Black (minority) population greater than the U.S. median. The raw racial gap in COVID-19 deaths is shown first in Figure 5. This plot suggests that the racial gap in COVID-19 deaths for both high proportion Black and minority counties is concentrated in very high caseload counties. For counties with a high proportion of Black (minority) residents in the 95^{th}-percentile of COVID-19 deaths, we estimate 127 (126) excess deaths and 200 (265) cumulative excess deaths due to race. We next estimate our fully specified model, controlling for PM 2.5 and county-level socioeconomic factors like poverty, median household income, education level, social distancing practices, and all other main control variables. Controlling for all confounding factors, a 1 unit increase in PM 2.5 lead to 52 additional deaths at the 95^{th}-percentile of COVID-19 deaths and 92 cumulative deaths across the distribution in either figure. Finally, interacting this PM 2.5 effect by an indicator for Black (minority), we find a 1 unit increase in PM 2.5 leads to an additional 42 (32) excess deaths for counties in the 95^{th} percentile of COVID-19 deaths and who have a higher representation of Black (minority) residents. Cumulatively, this is 65 (47) excess deaths due to PM 2.5 in counties with a high proportion of Black (minority) residents.

5.3 Protective Effect of non-attainment

We next present estimates of long-term effects of non-attainment status, as deemed by the CAA, on COVID-19 outcomes. We can see in Appendix Figure 1 that the racial gap in PM 2.5 levels fell significantly from 2000 and 2016 across the PM 2.5 distribution.[13] When we plot coefficients from county non-attainment status before 2005 interacted with racial demographic indicators, we see that non-attainment appears to play a strong role in improving the racial gap in PM 2.5 over time. This result is especially so for high PM 2.5 communities.

Because treated counties risked losing federal funding if they did not reduce future PM 2.5 levels, we hypothesize that counties just above the non-attainment threshold in 2004 (the year prior to strict enforcement) would have lower PM 2.5 levels in 2016. Results in Panel A of Table 4 support this

[13] Panel A shows the estimated coefficients produced from a RIF regression of minority status across the distribution of PM 2.5 in both 2000 and 2016. Panel B plots the same coefficients but using an indicator for a high proportion of Black residents.

hypothesis. Whether or not we condition on covariates (columns 2 and 1, respectively), we find a negative LATE of non-attainment status, suggesting a reduction in PM 2.5 levels by 2016 (although these results are not significant at conventional levels). We find the largest effect when we restrict our sample to counties with an above-median representation of minority groups in column (3). Those counties just above the threshold had, on average, 0.39 lower PM2.5 $\mu g/m^3$, consistent with findings in Currie et al. (2020). Finally, in column (4), we restrict the sample to counties with above-median proportions of Black residents. We find similar results in above-median Black communities, although these results are smaller than the estimates for minority status and not precisely estimated.[14]

Panel B exploits this same threshold rule to investigate the effects of non-attainment on deaths per 100,000. We find a LATE of approximately 28.5 fewer deaths per 100,000 in non-attainment counties, relative to counties just below the threshold. This effect increases to 47 fewer deaths per 100,000 in counties with an above-median representation of minority residents (column 3), and 37 fewer deaths in counties with an above-median proportion of Black residents. Importantly, while communities of colour appear to see the most significant benefit from the protective effects of past non-attainment, we note that these are also the communities most negatively impacted by PM 2.5 in the first place. While non-attainment benefited these communities, it was not enough to offset their disproportionate representation among high-pollution and high COVID-19 regions.

6 Conclusion

COVID-19 has shone a spotlight on already present economic and health inequalities. This study investigates the role of historical inequities in air pollutants, and the policies employed to combat current inequities in COVID-19 morbidity and mortality for communities of colour. Using an IV approach, we first estimated the precise effect of PM 2.5 on COVID-19 caseloads and deaths outside of the many potential confounding factors. Our results demonstrate a near 50% increase in both cases and deaths with a 1 unit increase in cumulative PM 2.5 exposure. Nevertheless, we find that 15 to 39% of this effect is born specifically by counties with a higher representation of minority or Black residents. While not observable at the county level, if this effect is predominantly driven by the health outcomes of minority and Black residents, we expect the effect size to be larger. Using distributional analysis, we find much larger effects of PM 2.5 and PM 2.5 by race for counties with very high COVID-19 caseloads.

We next causally identify differences in COVID-19 outcomes based on being in non-attainment of the EPA PM 2.5 standards. We find being in non-attainment reduced deaths per 100,000 by a full standard deviation. For high minority counties, this was nearly a 1.5 standard deviation reduction. For counties

[14]We note that non-attainment for counties with a high proportion of Black residents has a more substantial impact on PM 2.5 reductions compared to counties below the non-attainment line and with a minority of Black residents, over a within-group comparison of non-attainment status. We estimate a decline in PM 2.5 (2016) of -0.991 (0.244) for higher proportion black counties just above the non-attainment threshold compared to lower proportion black counties just below the threshold.

with a high proportion of Black residents, this was a reduction by 1.15 standard deviations. We find similar results for cases. To the best of our knowledge, this paper is the first to identify protective effects of the CAA on current COVID-19 health outcomes.

These results underline how environmental inequities give rise to downstream health inequalities and the role of environmental policies in reducing both. The significant protective effect of the CAA on reducing COVID-19 cases and lives lost due to COVID-19 also suggests long-term cost-savings. Yet, pollution effects, underlying co-morbidities and many of the socioeconomic factors included in this analysis cannot account for the entirety of the racial gap in COVID-19 outcomes. Structural racial inequities in access to quality health care (Gee & Ford, 2011; Bailey et al., 2017; Bhala et al., 2020) and direct racism likely also contribute (Krieger, 2014; Paradies et al., 2015). This work can inform targeted resource allocation for community-level interventions for the most at risk based on current pollution levels, but also other confounding health inequities. The implications of this work also go beyond the pandemic period, as these communities will likely experience widened health and economic gaps after COVID-19 has come under control. Targeted pollution abatement policy-making would help to mitigate these gaps long term.

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Figures

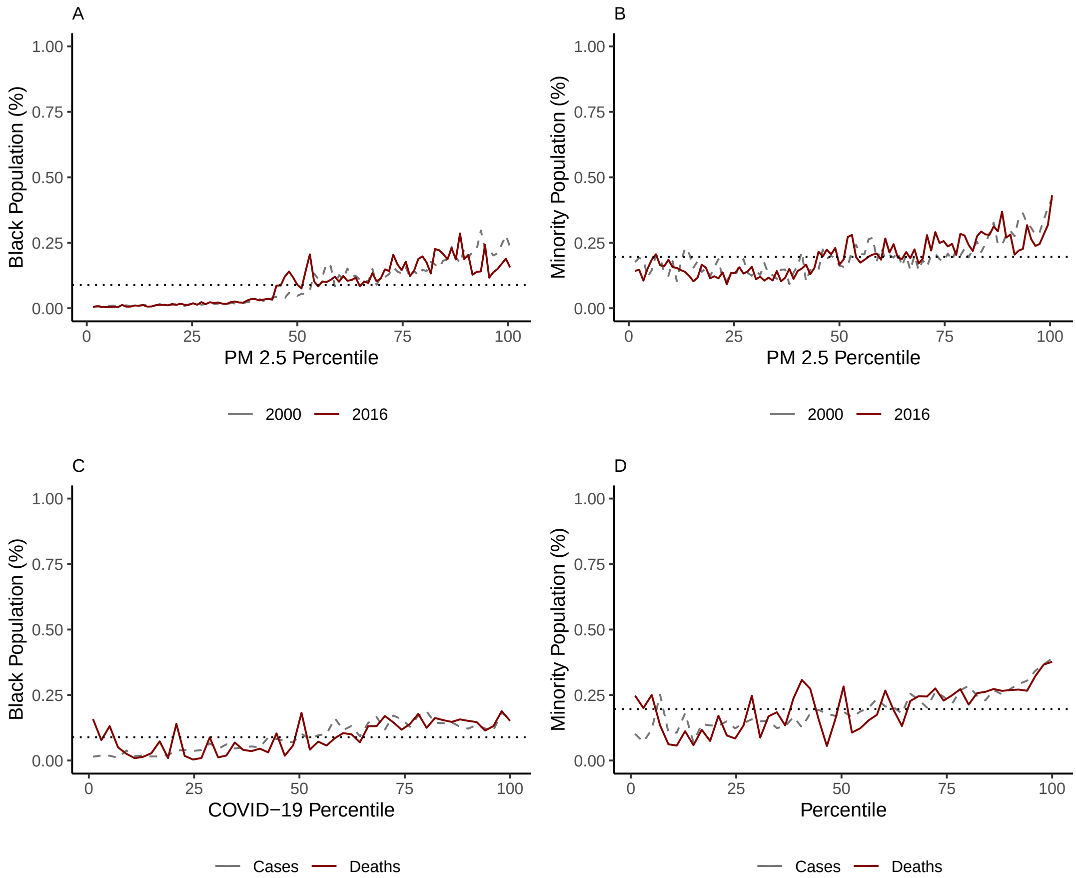

Figure 1: Racial Demographics by PM 2.5 and COVID-19 Distributions

Note: Top panels plot the average county-level proportion of Black (A) and minority (B) residents by the percentile distribution of PM 2.5 levels, measured in 2005 (grey) and 2016 (red). The bottom panels plot the same county-level racial proportions by the percentile distributions for COVID-19 cases (grey) and deaths (red).

Tables

Table 1: Descriptive Statistics by Nearest Neighbour in non-attainment

	Own County Non-Attainment (NA)			Neighbouring County in Non-Attainment			Predictive Power of Instrument
	$NA_i = 0$	$NA_i = 1$	Δ	Close	Far	Δ	β
Outcomes							
Log Cases	3.270	5.842	2.572***	4.050	2.632	-1.418***	0
Log Deaths	-0.199	2.687	2.886***	0.479	-0.720	-1.199***	0.001*
PM2.5							
PM 2.5 (2005)	10.028	15.635	5.607***	12.644	7.719	-4.925***	-0.013***
PM 2.5 (2016)	6.017	9.196	3.179***	7.232	4.977	-2.255***	0.001
Covariates							
Pop. Density	220	2,310	2,090*	430	120	-310***	-0.254***
Population	92,500	561,300	468,800**	124,830	85,740	-39,090**	23.373
Med. HH Income	51,289	57,911	6,623***	50,833	52,105	1,271*	0.044
Non-remote	2.163	4.598	2.435***	3.401	1.059	-2.342***	-0.002
Days Since First Case	46.119	52.780	6.661***	49.564	43.039	-6.525***	0.001
Days from SD Order	34.707	44.524	9.817***	42.924	27.031	-15.893***	0
% Black	0.089	0.153	0.064***	0.124	0.057	-0.067***	0
Prop. Public Transit	0.140	0.155	0.015	0.150	0.131	-0.019***	0
Education	0.207	0.190	-0.017***	0.214	0.199	-0.015***	0
Poverty	0.157	0.143	-0.014**	0.164	0.149	-0.015***	0
% Over 65	0.159	0.133	-0.026***	0.152	0.165	0.013***	0
% Hispanic	0.079	0.063	-0.016·	0.048	0.110	0.062***	0
% Uninsured	0.002	0.002	0	0.002	0.002	0	0
N	2,928	82	3,010	1,505	1,505	3010	3010

Note: This table presents descriptive statistics across the main comparison groups presented in the analysis. Columns 2-4 compare mean characteristics for counties by non-attainment status. Columns 5-7 compare characteristics for counties with either close or far neighbouring counties in non-attainment, as determined by being below (above) the median distance to the nearest neighbour. The final column provides a test of the validity of our main instrument. We regress each covariate used in the analysis on the instrument and the the remaining covariates, to determine how predictive our instrument is of underlying county characteristics. $***p < 0.001$, $**\ p < 0.01$, $*p < 0.05$, $.\ p < 0.10$

Table 2: PM 2.5 Levels and COVID-19 Outcomes

	OLS				IV		
					Overall	Black	Minority
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Panel A: COVID-19 Deaths			
PM2.5	1.063***	0.751***	0.493***	0.442***	0.435***	0.258***	0.377***
	(0.112)	(0.112)	(0.077)	(0.074)	(0.111)	(0.095)	(0.110)
PM 2.5*Race						0.164***	0.068***
						(0.018)	(0.021)
Adjusted R^2	0.52	0.66	0.77	0.79	0.79	0.79	0.78
				Panel B: COVID-19 Cases			
PM2.5	1.016***	0.706***	0.387***	0.339***	0.409***	0.266***	0.355***
	(0.106)	(0.108)	(0.054)	(0.053)	(0.085)	(0.068)	(0.082)
PM 2.5*Race						0.133***	0.064***
						(0.013)	(0.016)
Adjusted R^2	0.45	0.63	0.85	0.86	0.86	0.87	0.86
				Panel C: COVID-19 Deaths | Cases			
PM2.5	0.151***	0.129***	0.091***	0.096***	0.006	−0.017	0.004
	(0.041)	(0.037)	(0.034)	(0.033)	(0.059)	(0.058)	(0.059)
PM 2.5*Race						0.028**	0.002
						(0.011)	(0.012)
Adjusted R^2	0.9	0.91	0.92	0.92	0.92	0.92	0.92
Census	-	x	x	x	x	x	x
Social Distancing	-	-	x	x	x	x	x
Race	-	-	-	x	x	x	x
N	3009	3009	3009	3009	3009	3009	3009

Note: This table presents OLS and 2SLS estimates of the impact of PM 2.5 (2016) on log COVID-19 deaths (panel A), cases (panel B), and deaths conditional on cases (panel C). We instrument using distance to nearest neighbour in non-attainment in 2005. Baseline specifications include mean winter and summer temperatures and humidity, state fixed effects and population weights. We incorporate census controls (poverty, population density, median household income, median house value, percent owner occupied, average education, percent insured, hospital beds per capita, percent of population over 65), average rate of daily social distancing, days from state social distancing date and date of first case, county-level race demographics (percent Black, Hispanic, and white and public transit use) . Alternative specification controlling for smoking, average BMI, and other infectious and external deaths, testing positivity rate, as well as including lags of all control variables do not impact estimated coefficients but are not included in main specification due to reduction in sample size (results available upon request). The final two columns incorporate interactive effects by whether a county has a higher than median proportion of Black or non-white residents. Standard errors are in parentheses and clustered at the county level. $***p < 0.001$, $**\ p < 0.01$, $*p < 0.05$, . $p < 0.10$

Table 3: PM2.5 Levels and Placebo Outcomes

	Infectious		External		Circulatory	
	Red. Form	IV	Red. Form	IV	Red. Form	IV
	(1)	(2)	(3)	(4)	(5)	(6)
			Pane A: Baseline Placebo Tests			
PM 2.5	−0.001		0.001		−0.001	
	(0.001)		(0.001)		(0.001)	
NA Neighbour Distance		0.064		−0.076		0.100
		(0.063)		(0.082)		(0.066)
Mean Y	2.95	2.95	4.21	4.21	5.47	5.47
N	3,010	3,010	3,010	3,010	3,010	3,010
Adjusted R^2	0.27	0.27	0.15	0.14	0.1	0.08
			Pane B: Excluding Suppressed Outcomes			
PM 2.5	0.000		0.001		−0.001	
	(0.001)		(0.001)		(0.001)	
NA Neighbour Distance		−0.013		−0.094		0.097
		(0.071)		(0.084)		(0.065)
Mean Y	3.90	3.90	4.75	4.75	5.56	5.56
N	1,225	1,225	2,352	2,352	2,931	2,931
Adjusted R^2	0.15	0.15	0.12	0.1	0.1	0.08

Note: This table presents the reduced form and 2SLS estimates of PM 2.5 on other log health outcomes as a placebo check. We estimate the effect of PM2.5 on deaths from infectious disease, external causes, and circulatory system conditions. Each specification includes all main controls and population weights. County level death counts are suppressed for counts of less than 10. Panel A results include suppressed outcome counties, replacing suppressed values with a count of 10 deaths to be conservative. Panel B excludes suppressed data points. $***p < 0.001$, $**\ p < 0.01$, $*p < 0.05$, $.\ p < 0.10$

Table 4: Non-Attainment Status and COVID-19 Outcomes

	Unconditional (1)	Conditional (2)	Minority (3)	Black (4)
		Panel A: PM 2.5 (2016)		
LATE	-0.361	-0.115	-0.387*	-0.040
	(0.286)	(0.209)	(0.162)	(0.189)
Bandwidth	2.590	2.590	2.451	3.365
Effective N	417	417	293	595
		Panel B: COVID-19 Deaths		
LATE	-28.445**	-32.600**	-47.158*	-36.684**
	(10.726)	(10.518)	(20.111)	(14.045)
Bandwidth	5.173	5.173	4.288	4.295
Effective N	1,385	1,385	649	868
		Panel C: COVID-19 Cases		
LATE	-312.938*	-381.355**	-626.681**	-408.63*
	(143.907)	(132.161)	(236.994)	(196.759)
Bandwidth	4.019	4.019	3.578	3.301
Effective N	994	994	510	578

Note: This table presents regression discontinuity estimates of non-attainment status in 2004 on PM 2.5 measured in 2016 and COVID-19 deaths per 100,000 people. Unconditional models control for state fixed effects only. To maintain estimation power and parsimony, conditional models control for poverty rates, racial demographics, average summer and winter temperatures and state fixed effects (Panel A). Conditional models in Panel B control for social distancing, remoteness of a county, racial demographics and state fixed effects. Additional specifications controlling for population and density increased both the effect sizes and the standard errors specifically when sub-setting for Black counties. Standard errors are in parentheses and clustered at the county level. $***p < 0.001$, $**\ p < 0.01$, $*p < 0.05$, $.\ p < 0.10$

Appendix A: Supporting Figures

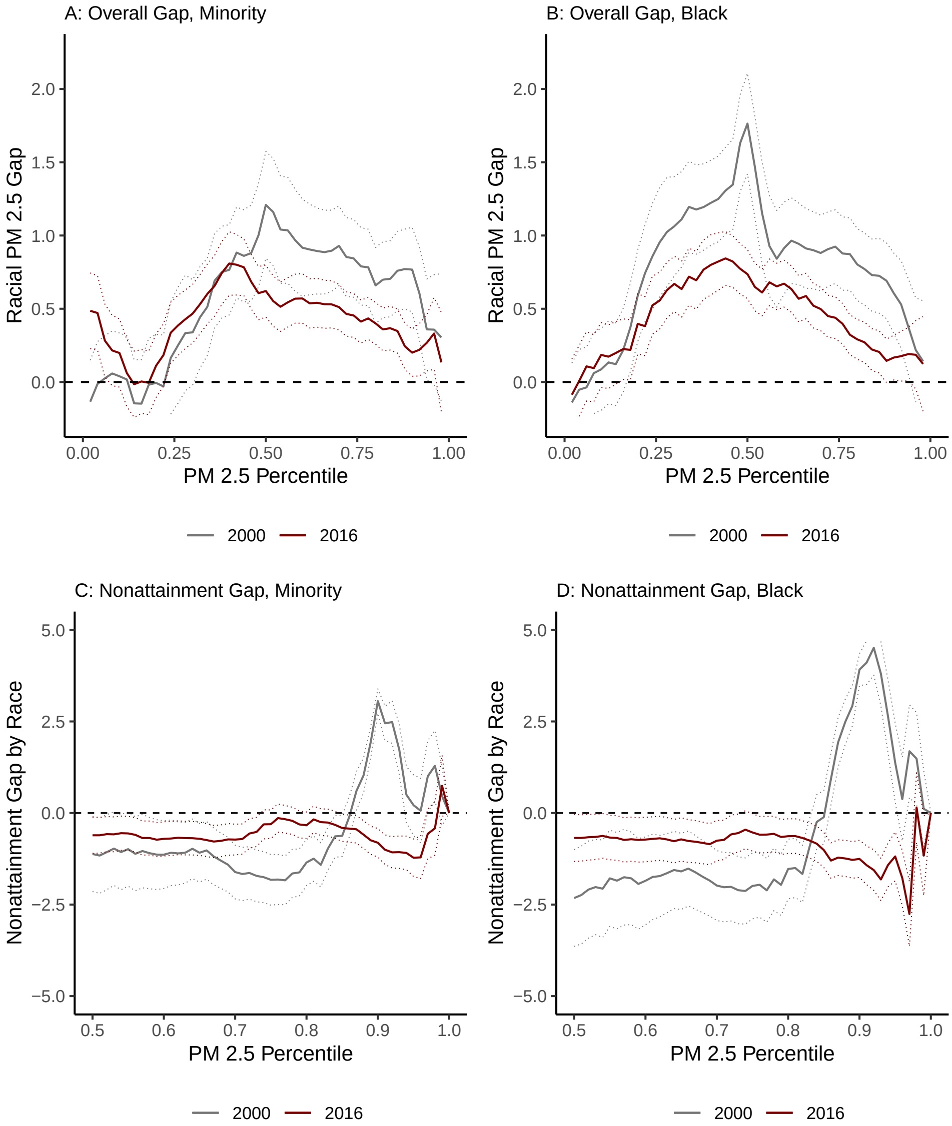

Figure 1: Changes in Racial Gap in PM 2.5 from 2000 to 2016

Note: Panels A and B show show coefficients and confidence intervals from an indicator of whether a county had an above median proportion of minority (A) or Black (B) residents across the PM 2.5 distribution, as generated by an RIF regression. Panels C and D show coefficients and confidence intervals across the PM 2.5 distributions for these same race indicators, interacted by whether the county was in non-attainment before 2005. All regressions control for population, average winter and summer temperatures and state fixed effects.

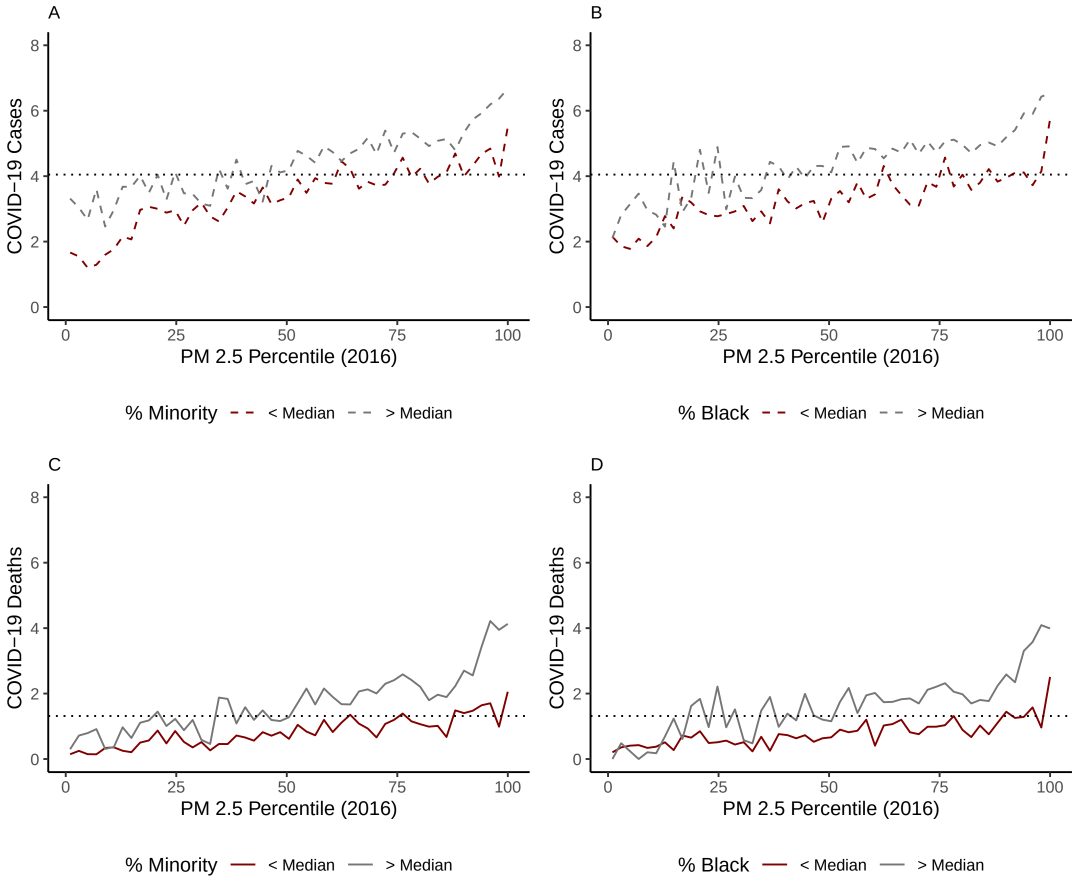

Figure 2: COVID-19 outcomes by PM 2.5 Distribution, by County-level Racial Demographics

Note: The top panels plot binned average log of county-level COVID-19 deaths by percentile of PM 2.5 distribution as measured in 2016. We plot lines separately for counties with above median proportion of minority residents (grey) and below median (red). The bottom panels plot the same outcomes, separated by whether a county's proportion of Black-identifying residents is above (grey) or below (red) the overall median levels.

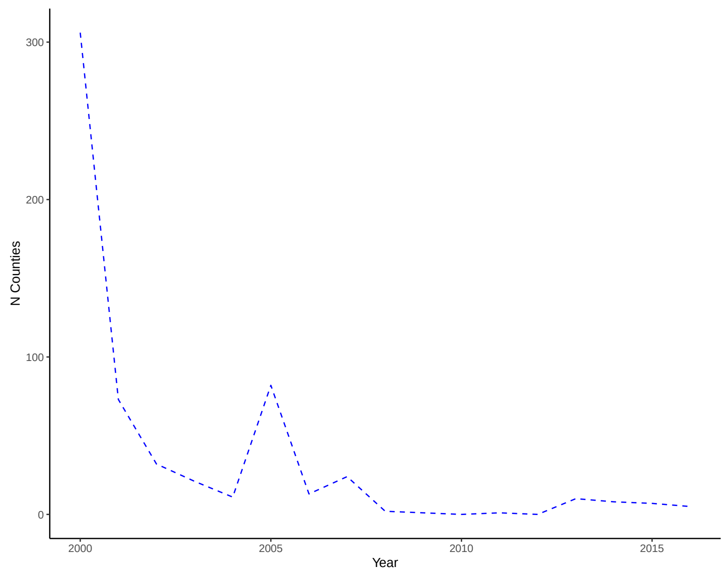

Figure 3: Number of Counties in non-attainment, 2000-2016

Note: Appendix Figure 3 shows the number of counties in non-attainment of the Clean Air Act emissions standards from 2000 to 2016 using authors' own calculations. A county was in non-attainment if their PM 2.5 levels were above 15 $\mu g/m^3$. This threshold changed in 2012 to 12 $\mu g/m^3$. Standards enforcement largely began in 2005.

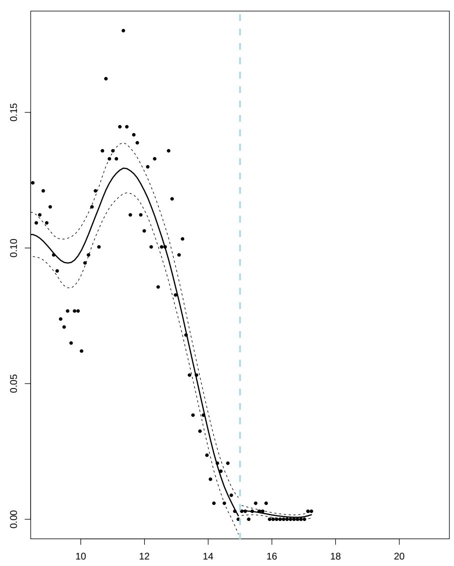

Figure 4: McCrary Sorting Test

Note: This plot shows the results of a McCrary (2008) sorting test. There appears to be no heaping around the Clean Air Act threshold of 15 $\mu g/m^3$, confirmed by a p-value of 0.24.

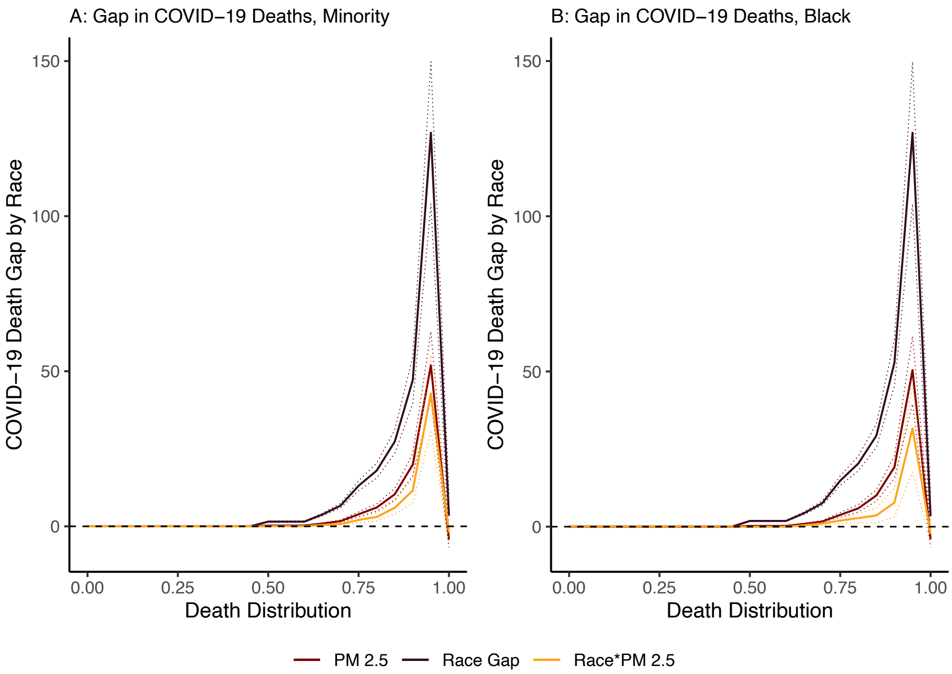

Figure 5: Racial Gap in COVID-19 Deaths

Note: Plots A and B show coefficients and confidence intervals for the raw race gap, PM 2.5 controlling for all other confounding variables, and an interaction between race and PM 2.5 across the COVID-19. Black lines show raw race gap for counties with a high proportion of minority residents (A) or Black residents (B). Red lines show PM 2.5 effects, controlling for social distancing practices, population, poverty, median household income, average education, state fixed effects and all other baseline controls. The yellow line plots the interaction between race and PM 2.5, while further controlling for PM 2.5, race and all other controls.

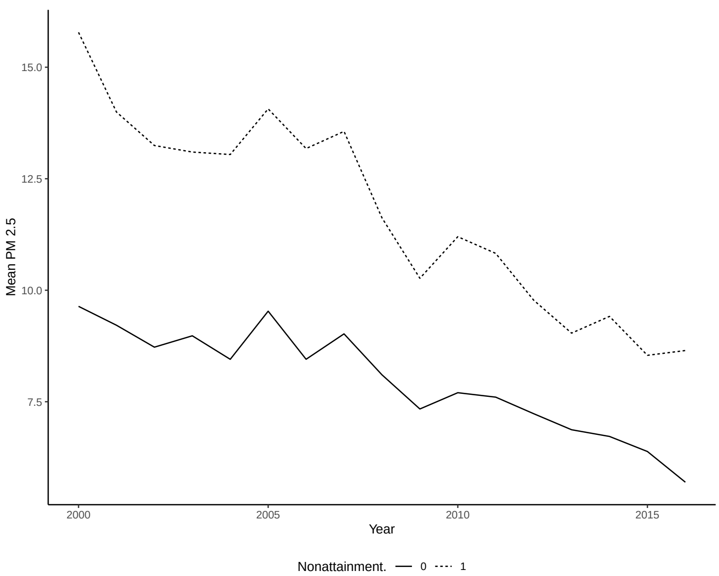

Figure 6: Mean PM 2.5 by Non-attainment Status

Note: Figure shows the downward trend in PM 2.5 for counties from 2000 to 2016 by non-attainment status. Non-attainment was estimated as having a PM 2.5 level above 15 $\mu g/m^3$ from 2000 to 2011 and 12 $\mu g/m^3$ from 2012 on wards.

Appendix B: Supporting Tables

We present alternative IV specifications compared to our baseline specification of distance to nearest neighbour in non-attainment in Table 5. Comparator IV specifications include the inverse distance to nearest neighbour in non-attainment (2), the average PM 2.5 levels of all neighbouring counties within a 25-mile radius (3), and the proportion of all neighbouring counties in a 25-mile radius who are in non-attainment (4). All measurements are based on 2005 values, the year non-attainment enforcement largely began. Table 5 presents first stage results and weak instrument testing and Wu-Hausman tests for endogeneity across all specifications. We select distance to nearest neighbour in non-attainment based on first stage results, its plausibly exogenous impact on own-county PM 2.5 levels and its more conservative estimated effect on COVID-19 outcomes.

Table 5: Instrument Variable Comparisons

	(1)	(2)	(3)	(4)
Mean (Std. Dev.)	292.908 (262.065)	0.012 (0.017)	11.284 (2.724)	0.124 (0.275)
	Panel A: First Stage (PM 2.5)			
Distance to NA Neighbour	-0.008^{***} (0.001)			
Inverse Distance to NA Neighbour		12.498^{***} (3.405)		
Mean Neighbour PM 2.5			0.390^{***} (0.024)	
Proportion NA Neighbours				0.739^{***} (0.117)
F-Stat	235	175	218	148
Weak Inst. P-val.	0.000	0.000	0.000	0.000
Wu-Hausman P-val.	0.979	0.359	0.867	0.032
N	3,010	3,010	2,204	2,122
R Sq	0.84	0.80	0.87	0.83
	Panel B: Second Stage (Log Deaths)			
PM 2.5	0.435^{***} (0.111)	0.184 (0.147)	0.700^{***} (0.067)	1.132^{***} (0.168)
N	3,010	3,010	2,201	2,119
Adjusted R^2	0.84	0.8	0.87	0.83

Note: Table presents instruments calculated based on the distance to nearest neighbour in non-attainment, the inverse distance, mean neighbouring county PM 2.5 and the proportion of neighbouring counties in non-attainment. All instruments based on 2005 PM 2.5 data. Controls in both stages include mean winter and summer temperatures and humidity, state fixed effects, poverty, population density, median household income, median house value, percent owner occupied, average education, percent insured, hospital beds per capita, percent of population over 65, average rate of daily social distancing, days from state social distancing date and date of first case, and county-level race demographics and population weights.. $***p < 0.001$, $**\ p < 0.01$, $*p < 0.05$, . $p < 0.10$

Table 6: PM2.5 Levels and Additional Placebo Outcomes

	Endocrine		Digestive	
	Red. Form	IV	Red. Form	IV
	(1)	(2)	(3)	(4)
PM 2.5	0.001		−0.000	
	(0.001)		(0.001)	
Distance to NA Neighbour		−0.121		0.017
		(0.090)		(0.064)
Mean Y	4.32	4.32	4.27	4.27
N	1,915	1,915	1,730	1,730
R Sq	0.16	0.13	0.11	0.11

Note: This table presents the reduced form and 2SLS estimates of PM 2.5 on other log-health outcomes as an additional placebo check. Each specification includes all main control variables and population weights. Standard errors are in parentheses and clustered at the county level. Results exclude suppressed data points. $***p < 0.001$, $**\ p < 0.01$, $*p < 0.05$, $.\ p < 0.10$

Table 7: Testing for Discontinuity of the Controls

	Daily Distance Travelled	Remote	Prop. Black	Prop. Hisp	Prop. White	Mean Summer Temp.	Mean Winter Temp.
LATE	0.003	-2.4	-0.163	-0.016	0.149	-1.558	-1.433
	(0.035)	(2.124)	(0.127)	(0.073)	(0.188)	(1.791)	(2.215)
Bandwidth	2.415	1.479	1.175	1.540	1.433	1.422	2.720
N	365	102	60	105	94	92	469

Note: This table presents regression discontinuity estimates of non-attainment status in 2004 on the control variables used in our RD analysis. Standard errors are in parentheses and clustered at the county level. $***p < 0.001$, $**\ p < 0.01$, $*p < 0.05$, $.\ p < 0.10$

Table 8: PM 2.5 Levels and COVID-19 Outcomes : Accounting for Race-Specific Public Transit Use

	OLS				IV		
					Overall	Black	Minority
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: COVID-19 Deaths						
	1.043***	0.725***	0.480***	0.453***	0.428***	0.288***	0.363***
	(0.114)	(0.114)	(0.078)	(0.074)	(0.109)	(0.095)	(0.107)
PM 2.5*Race						0.143***	0.075***
						(0.019)	(0.022)
Adjusted R^2	0.51	0.65	0.77	0.79	0.79	0.79	0.78
	Panel B: COVID-19 Cases						
PM2.5	0.989***	0.671***	0.373***	0.353***	0.413***	0.298***	0.351***
	(0.108)	(0.109)	(0.054)	(0.050)	(0.082)	(0.069)	(0.078)
PM 2.5*Race						0.117***	0.071***
						(0.014)	(0.016)
Adjusted R^2	0.9	0.91	0.92	0.92	0.92	0.92	0.92
	Panel C: COVID-19 Deaths | Cases						
PM2.5	0.152***	0.129***	0.089***	0.089***	−0.009	−0.026	−0.011
	(0.042)	(0.038)	(0.034)	(0.034)	(0.059)	(0.059)	(0.060)
PM 2.5*Race						0.022**	0.002
						(0.011)	(0.012)
Adjusted R^2	0.9	0.91	0.92	0.92	0.92	0.92	0.92
Census	-	x	x	x	x	x	x
Social Distancing	-	-	x	x	x	x	x
Race	-	-	-	x	x	x	x
N	2542	2542	2542	2542	2542	2542	2542

Note: This table presents OLS and 2SLS estimates of the impact of PM 2.5 (2016) on log COVID-19 deaths (panel A), cases (panel B), and deaths conditional on cases (panel C). We instrument using distance to nearest neighbour in non-attainment in 2005. Baseline specifications include mean winter and summer temperatures and humidity, state fixed effects and population weights. We incorporate census controls (poverty, population density, median household income, median house value, percent owner occupied, average education, percent insured, hospital beds per capita, percent of population over 65), average rate of daily social distancing, days from state social distancing date and date of first case, county-level race demographics (percent Black, Hispanic, and white). Unlike Table 2, in this specification, we use measures of race-specific public transit use to work for Black and white residents. Alternative specification controlling for smoking, average BMI, and other infectious and external deaths, testing positivity rate, as well as including lags of all control variables do not impact estimated coefficients but are not included in main specification due to reduction in sample size (results available upon request). The final two columns incorporate interactive effects by whether a county has a higher than median proportion of Black or non-white residents. Standard errors are in parentheses and clustered at the county level. $***p < 0.001$, $**\ p < 0.01$, $*p < 0.05$, $.\ p < 0.10$

Table 9: PM 2.5 Levels and COVID-19 Outcomes : Excluding New York State

	OLS				IV		
					Overall	Black	Minority
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Panel A: COVID-19 Deaths			
PM2.5	0.941***	0.560***	0.471***	0.451***	0.463***	0.326***	0.395***
	(0.097)	(0.082)	(0.076)	(0.069)	(0.104)	(0.094)	(0.103)
PM 2.5*Race						0.141***	0.076***
						(0.018)	(0.023)
Adjusted R^2	0.61	0.73	0.76	0.78	0.78	0.78	0.77
				Panel B: COVID-19 Cases			
PM2.5	0.864***	0.477***	0.374***	0.358***	0.459***	0.350***	0.396***
	(0.079)	(0.059)	(0.052)	(0.045)	(0.077)	(0.068)	(0.073)
PM 2.5*Race						0.113***	0.071***
						(0.013)	(0.017)
Adjusted R^2	0.62	0.78	0.82	0.85	0.85	0.85	0.84
				Panel C: COVID-19 Deaths | Cases			
PM2.5	0.046	0.066*	0.062*	0.068*	−0.047	−0.061	0.395***
	(0.036)	(0.036)	(0.035)	(0.035)	(0.062)	(0.061)	(0.103)
PM 2.5*Race						0.020*	0.076***
						(0.011)	(0.023)
Adjusted R^2	0.9	0.9	0.91	0.91	0.9	0.91	0.91
Census	-	x	x	x	x	x	x
Social Distancing	-	-	x	x	x	x	x
Race	-	-	-	x	x	x	x
N	2480	2480	2480	2480	2480	2480	2480

Note: This table presents OLS and 2SLS estimates of the impact of PM 2.5 (2016) on log COVID-19 deaths (panel A), cases (panel B), and deaths conditional on cases (panel C). We instrument using distance to nearest neighbour in non-attainment in 2005. Baseline specifications include mean winter and summer temperatures and humidity, state fixed effects and population weights. We incorporate census controls (poverty, population density, median household income, median house value, percent owner occupied, average education, percent insured, hospital beds per capita, percent of population over 65), average rate of daily social distancing, days from state social distancing date and date of first case, county-level race demographics (percent Black, Hispanic, and white). Unlike Table 2, in this specification, we exclude New York State from the sample. Alternative specification controlling for smoking, average BMI, and other infectious and external deaths, testing positivity rate, as well as including lags of all control variables do not impact estimated coefficients but are not included in main specification due to reduction in sample size (results available upon request). The final two columns incorporate interactive effects by whether a county has a higher than median proportion of Black or non-white residents. Standard errors are in parentheses and clustered at the county level. $***p < 0.001$, $**\ p < 0.01$, $*p < 0.05$, . $p < 0.10$