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Did the Clean Air Act Improve Environmental Justice Disparities?

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Abstract

This paper analyzes the differential impacts of the 1990 Clean Air Act Amendments (CAAA) on the racial pollution exposure gap, also known as the Environmental Justice (EJ) gap. Using recently developed, Census tract-level satellite data of PM2.5 pollution, I test whether CAAA non-attainment status and resulting State Implementation Plans decreased pollution in high-percentage Black and Hispanic areas more than in non-high percentage Black and Hispanic tracts. My results confirm that the CAAA reduced overall pollution concentrations in the U.S. and decreased the absolute level of the Environmental Justice gap. A heterogeneity analysis provides evidence that the results are primarily driven by air quality gains in Black communities in California and the Rust Belt.

Keywords: Environmental Justice, Air Pollution, Clean Air Act, State Implementation Plans, Public Economics

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1. Introduction

Regulating pollution is among the government's most important and controversial undertakings. On the one hand, regulations have immense importance in preventing adverse human health impacts. They are especially important for historically disadvantaged communities, where pollution can interact with other systemic problems to compound harm and create disparities. On the other hand, regulations can disrupt capital investments, jobs, and other economic activities and decision-making. This dichotomy makes the design and analysis of environmental policies of the utmost importance for public welfare.

This paper evaluates one of the most prominent air pollution enforcement mechanisms in the U.S., State Implementation Plans (SIPs), on pollution disparities across racial and demographic characteristics. Under the Clean Air Act (CAA) and its 1990 Amendments (CAAA), the Environmental Protection Agency (EPA) regulates the release of criteria air pollutants, setting maximum permissible pollution limits known as National Ambient Air Quality Standards (NAAQS). While the EPA sets NAAQS and deems whether areas meet those standards, the Agency leaves enforcement to the states. When an area is deemed out of compliance, state, tribal, or local governments develop State Implementation Plans (SIPs), which lay out specific plans for bringing the area into compliance with NAAQS (EPA 2021a). The stricter regulation in non-attainment areas versus all other counties provides a convenient and useful source of variation to examine the effects of CAA regulations. Given the staggered implementation of policies over time (attainment status can "turn on and off" every year based on concentrations), there is ripe opportunity for experimental quantitative research methods to examine the impacts of these regulations.

Figure 1

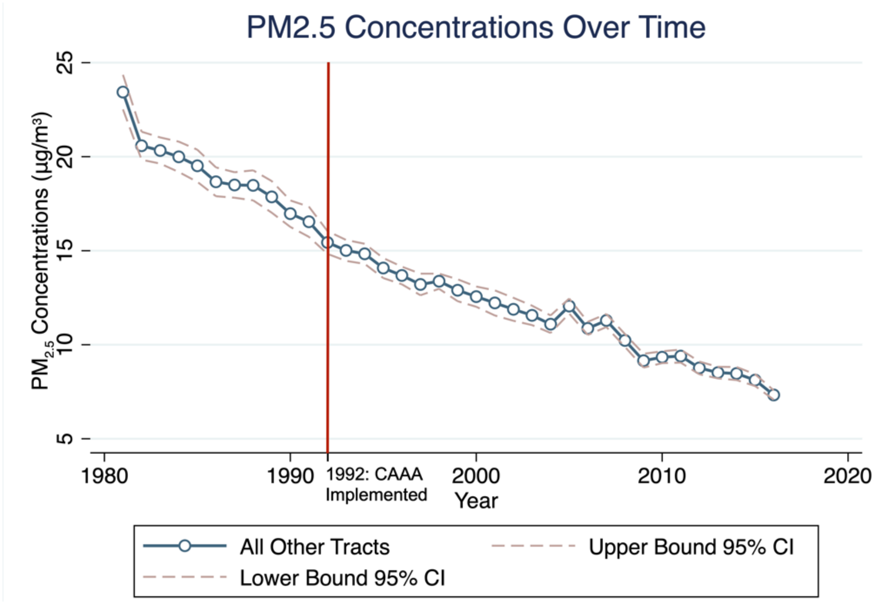


Figure 1 shows that pollution concentrations of Particulate Matter (PM)[3] 2.5 have fallen significantly since 1980. Prior research shows SIPs almost certainly played an important role in that progress (McKitrick 2007, Currie et al. 2020). However, gains are not evenly spread. Of particular concern are violations of Environmental Justice (EJ), defined as differential pollution or other environmental hazards faced by marginalized people, which continue to be documented in the popular press and peer-review literature (Shaw and Younes 2021, Cushing et al. 2018, Hernandez-Cortes and Meng 2021). These disparities fluctuate depending on demographics, economics, and policy changes. As EJ concerns increase in importance in the minds of policymakers, it is worth examining what impacts historic Clean Air Act Amendments' SIP rules have had on pollution exposure for disadvantaged communities. To get at this question, I ask whether the Clean Air Act Amendments decreased the quantitative pollution exposure gap between EJ-impacted communities and the rest of the population. I extend previous work, exploring both national trends in policy impacts across

[3] The 10 and 2.5 in PM10 and PM2.5 mean x micrometers or smaller. See Section 2.2 for further definition.

minority[4] and non-minority communities and conducting heterogeneity analysis of individual SIPs to ask where the most progress and EJ improvements have been made. My results confirm that the CAAA reduced pollution concentrations and that the EJ gap has narrowed since 1981. A heterogeneity analysis provides evidence that my results are driven by the significant gains experienced by Black communities and in the Rust Belt, Tri-State area, and Southern California.

2. Background: Air Pollution

2.1 Clean Air Act History and Policy

The Air Quality Act of 1967 was the country's first air pollution control program.[5] It established the NAAQS, specifying maximum allowable concentrations for six criteria air pollutants. The 1970 CAA and the 1977 CAAA shaped air policy into what we know today. The CAA requires states to develop SIPs that outline specific steps of how they will meet the NAAQS. SIP requirements are much stricter for regions in non-attainment, regions where a criteria pollutant exceeds the allowed NAAQS concentration (42 U.S.C. 7401). SIPs are designed by a committee of the local regulatory body, elected officials, and representatives of local organizations and must be subsequently approved by the EPA (EPA 2020). The plans are approved or denied solely on emissions reductions criteria ("Revisions to Appendix…" 2018). As a result, neither justice-based concerns about disproportionate or cumulative impacts nor economic burdens are factored into the decision. The 1977 CAAA introduced the first technology-based performance standards on particulates from fossil-fuel fired power plants (Aldy et al. 2022). Other examples of SIP policies include quantitative progress

[4] Throughout this paper I will use the terms "minority," "people/communities of color," and "POC" interchangeable depending on circumstance to refer to Black and Hispanic individuals. Furthermore, while I would prefer to use the term "Latino" or "Latinx," it is standard practice in the literature to use "Hispanic" due to Census Bureau classifications. This nomenclature is not ideal, but I come to this research with the utmost deference to those communities who have experienced years of environmental racism and other forms of hidden oppression.
[5] The regulatory details are summarized from: (Reitze 2004) and (EPA 2020).

milestones, increased ambient monitoring, the application of emissions control technology subject to economic and technical feasibility, and emissions offsets (EPA 2022). Regarding offsets, the EPA initially prohibited the construction of new major polluting stationary sources[6] for non-attainment regions. However, they later adopted an offset policy where a new facility could be permitted by paying another facility in the same region to reduce emissions permanently (Reitze 2004). The policy has drawn scrutiny from EJ advocates, who fear that local governments permit new facilities to be built in disadvantaged communities, while allowing pollutant concentrations to decrease in affluent areas within the same county.

After the first ten years of the program, over 60 regions with a population of nearly 100 million remained in non-attainment of the 1977 NO2 and Ozone NAAQS (Reitze 2004). In response, the 1990 CAA Amendments divided attainment status by pollutant into classifications like moderate, serious, and severe. The classifications in some cases trigger a SIP policy mechanism like an offset market, inspection/maintenance program, or command and control requirements. As CAA regulations have been revised, technology evolves, and economic conditions change, states may submit revisions to their SIPs subject to approval by the EPA. One such regulatory change was the adoption of two separate standards for PM10, annual and 24-hour (EPA 2021b). The long-term measure protects against chronic respiratory conditions, while the daily measure protects against respiratory irritation and decreased cognitive function (Shehab 2019).

[6] Defined as facilities with 100+ tons pollution/year, i.e. power plants, manufacturing. This is in contrast to mobile and non-point sources of pollution such as automobiles and wildfires, which are more difficult to regulate.

2.2 Air Pollution Types and Sources

The six main categories of criteria air pollutants regulated by the NAAQS are sulfur dioxide (SO2), nitrogen dioxide (NO2), carbon monoxide (CO), particulate matter (PM10 and PM2.5), photochemical oxidants measured as ozone (O3), and lead (EPA 2021c).[7]

The main pollutant of interest for this paper is PM2.5, as it is the most studied within the EJ literature due to its adverse health impacts. Many sources contribute to PM, including direct sources such as smokestacks and fires and indirect sources such as power plants, industrial manufacturing, and automobiles. Unlike the other criteria pollutants, which are chemicals, PM is composed of solid particles and airborne liquid droplets. These particles are 30 times smaller in diameter than a human hair and manifest as dust, soot, and smoke that is inhaled and penetrates the lungs, posing a health risk at high exposure levels and in interaction with other health conditions (EPA 2021d).

2.3 Air Pollution Health and Economic Impact

Pollution negatively affects health outcomes in the short- and long-term, which causes economic harm due to resulting respiratory and cognitive ailments such as low birth weight and reduced educational outcomes. Researchers have documented these impacts across several pollutants and settings (Bell et al. 2010, Stingone and McVeigh 2016). For example, ozone harms individuals

[7] SO2 is a component of sulfur oxides that is primarily generated by power plants and other industrial facilities and causes respiratory issues in humans, haze in the sky, and chemical reactions that form PM.
The sources and environmental effects of NO2 are largely the same as SO2, though it also reacts with other chemicals in the atmosphere to cause Acid Rain. (Continued on the next page of footnotes)
CO primarily comes from fossil-fuel combustion such as vehicles and home heating and causes oxygen limitation in the body and long-term risk of heart conditions.
Ground level Ozone is the main ingredient in smog. It is formed by reactions with nitrogen oxides and volatile organic compounds (VOCs) after emission from vehicles, refineries, chemical plants, and other industrial facilities. Those with asthma are at highest risk from ozone, typically on hot summer days. It also has adverse ecological effects.
Lead gets in the air primarily through smelters like metals processing operations and waste incinerators. It has significant adverse health impacts, especially in children who experience negative neurological effects. The EPA's regulation of leaded gasoline was a major success, as air lead levels dropped almost 100% over 30 years.

with asthma and negatively affects worker productivity, even at levels below NAAQS standards (Zivin and Neidell 2012). Similarly, PM2.5 has constrained the Chinese GDP through reduced labor hours and higher medical expenses (Wu et al. 2017). If pollution reduces productivity, as these findings show, abatement can be seen as a form of human capital investment, boosting productivity and growth. Combined with improved health outcomes, these economic impacts provide a strong motivation for the government to pursue pollution control, as they can strengthen local markets (Chakrabarti and Mitra 2005) and the macroeconomy (Leeves and Herbert 2007).

2.4 Disparate Health Impacts of Pollutions

Communities of color are disproportionately susceptible to pollution's harms due to compounding social/economic factors that correlate with race and income. Recent epidemiological literature links long-term PM2.5 exposure to worsened COVID-19 mortality outcomes (Wu et al. 2020). The EJ literature also correlates higher COVID vulnerability to co-dependent social factors like urban/industrialized areas, low household income, low educational attainment, and Black population share (Hooper et al. 2020). This problem extends beyond COVID and lung cancer. Populations can be vulnerable to death from PM exposure alone. Whether you examine direct mortality or correlated illnesses, fine particulate matter is undoubtedly a health crisis. Pope et al. (2009) estimate a 0.61-year reduction in life expectancy for each 10 μg/m3 increase in sustained exposure to PM2.5. Deryugina et al. (2020) find that higher PM exposure correlates with worse health outcomes and lower socioeconomic status. EJ disparities are pronounced in this context, though positive welfare gains in this century demonstrate that pollution abatement has made a difference. With the Black-White life expectancy gap closing by 1.5 years over a 15-year span (Arias et al. 2019), Currie et al. (2020) calculated that 4% of this improvement could be explained by just a 1 μg/m3 closure of the Black-White pollution gap.

3. Literature Review

3.1 Historical Environmental Justice Literature

The EJ field is interdisciplinary and was spurred by a grassroots social movement. Its first literature was published in the 1980s (Banzhaf et al. 2019). The field's most famous paper was published in 1987 by the Commission for Racial Justice, which documented a correlation between race and proximity to hazardous waste facilities. Since then, scholars have rigorously shown that low-income and people of color are disproportionately exposed to environmental hazards (Evans et al. 2002, Hsiang et al. 2019, Tessum et al. 2021). Disparities are examined across numerous socioeconomic variables- including income/poverty (Hsiang et al. 2020), and age (Gray et al. 2010). The field, closely intersecting with epidemiology, links pollution exposure to a myriad of maladies. Pope (1991) presented the first seminal work, studying PM10 pollution from steel production in the Utah and Salt Lake Valleys and associated increases in respiratory-related hospital admissions.

A common theme across the EJ literature is that the location and intensity of polluting facilities depend on local economic and demographic factors (Ringquist 2005; Mohai and Saha 2007). Communities of color are more likely to house polluters (Bullard et al. 2008). Some authors have offered lower political participation as an explanation of this phenomenon, relying on findings from political science that race, income, and health all impact political participation and clout (Michener 2017). In a hypothetical scenario where a new coal plant is opening down the road, who is more likely to comment against it at a city council meeting - a wealthy homeowner or a renter working two jobs? Research suggests the former. Cicatielo et al. (2015) find across 47 countries that wealth is positively linked to conventional political participation. On the environmental side, Hamilton (1995) finds that race, educational attainment, and homeownership predict a community's ability to mobilize against the entry of polluting facilities into an area, raising the expected costs to firms of locating in particular areas. Confirming this point with data, Gray et al. (2010) find that polluting plants in higher voter-turnout-areas face greater regulatory activity. This hypothesis motivates the location-specific costs described in my theory section.

3.2 Economic and Pollution Impacts of the Clean Air Act

State Implementation Plans' efficacy and their responsibility for overall pollution declines are disputed. Reitz (2004) classifies them as a "failure" due to uneven implementation costs, increasing population and manufacturing, and overly optimistic abatement projections. Greenstone (2004) finds that non-attainment status only played a minor role in the impressive 80% drop in sulfur dioxide (SO2) pollution since 1970. However, Greenstone (2002) also pins specific declines in polluting industrial activities to non-attainment status designation: 590,000 jobs, $37 billion in capital stock, and $75 billion (1987$) of output over the first 15 years of the first CAAA. Shapiro and Walker (2018) hypothesize and assert that the large decrease in manufacturing emissions is largely a result of environmental regulation, making pollution more costly, though this is not directly on SIPs. Auffhammer et al. (2009) estimate the effects of non-attainment status on PM10 concentrations at ground-level monitors. They find a treatment effect of -12.5% and that the treatment effect occurred independently of SIP implementation, indicating a regulatory anticipation effect is present. I address this in my model in Section 7.1. In an overarching CAA literature review, Alby et al. (2022) find consistent evidence that pollution declines more rapidly at air monitors in non-attainment counties than those in attainment.

3.3 Environmental Justice Outcomes of the Clean Air Act

While national impacts of the CAA are well-investigated, the EJ literature related to the Act is burgeoning and informs my research. As previously mentioned, firms can trade pollution permits to offset their emissions when in a non-attainment area. These markets are one abatement method that areas can use in their SIPs under the circumstance that they want to permit a new polluting facility to be built. EJ advocates have criticized permit trading programs for potentially allowing pollution to move into minority/low-income areas (Cushing et al. 2016). Shapiro and Walker (2021) analyze the criteria pollutant offset markets legislated through the CAA. They find no substantial effects on pollution movement to communities based on race or income in twelve prominent offset markets. A study of one specific NOx market in the heavily polluted South Coast Air Basin found pollution reductions that do not vary significantly across demographics (Fowlie et al. 2012). Ringquist (2011) studies the SO2 allowance trading program and finds that communities with high percentages of Black and Hispanic residents experience fewer imports of SO2. So, the evidence is inconclusive on the overall efficacy of SIPs, but strongly suggests that new facilities under non-attainment do not harm the EJ gap individually.

In an important nationwide study, Colmer et al. (2020) find that though particulate pollution levels have dropped overall, the most and least polluted areas in 1981 remain so today. They examine non-attainment status as a predictor variable and find that Census tracts in PM2.5 non-attainment before 2016 are associated with an average decrease of 7.09 percentile rank points against all other tracts between 1981 and 2016, i.e., SIPs are associated with declining pollution levels. They also observe a general, though not universal, narrowing of the pollution exposure gap in disadvantaged communities. This is a timid quantification, and my study explores it further. My paper is most closely related to Currie et al. (2020). The authors study differential impacts of the CAA on pollution exposure. The authors find that the Black-White pollution exposure gap has closed since 2000. They attribute 60 percent of the racial convergence in PM2.5 exposure to the CAA. To help explain this phenomenon, Konisky (2009) finds that following updated federal guidance in the mid-1990s to address EJ concerns, there was evidence of increased CAA enforcement in Black communities and lowered enforcement in Hispanic and poor communities.

3.4 Contribution to the Literature

The EJ literature examines disparities as a determinant of interest across numerous socioeconomic variables- including race (Bullard et al. 2008), income/poverty (Hsiang et al. 2019), education (Colmer et al. 2020), age (Gray et al. 2010), and others (Hausman and Stolper 2020). As explained in Section 6.2, race is the most important dimension of heterogeneity in PM2.5 outcomes. My data analysis shows that racial concentrations are much more predictive of pollution than income or poverty. As such, I focus on disparities across race. Regarding disparities across varying racial/ethnic groups, most authors have studied pollution and health outcomes for Black and Hispanic communities (Konisky 2009; Ringquist 2011; Shapiro and Walker, 2021; Mansur and Sheriff 2021), due to the risk factors recounted in Section 2.4. In states where EJ policy accounts for additional socioeconomic and health factors, vulnerable groups are often referred to as "disadvantaged communities," and studies such as Hernandez-Cortes and Meng (2021) examine changes in pollution on those communities defined in statute. The foundation for my paper, Currie et al. (2020), studies the Black-White pollution gap over time. To build on findings in the literature and bring the conversation in line with previous papers, I approximate the Currie et al. research design, but study the heterogenous effects of the CAAA on the EJ gap for Black and Hispanic Americans.

Another avenue of my contribution is in the data. Researchers have used many methods to analyze air pollution outcomes. These include using facility-level data (Shapiro and Walker 2018) and pollution dispersal models (Hernandez-Cortes and Meng 2021) to approximate where pollution is experienced. Other analyses utilize ground-monitor data from government-run stations (Auffhammer et al. 2009) combined with Census and geographical data (Pope et al. 2002). A recent innovation in the field is satellite remote sensing, which provides broad measurements going back decades. My dataset (explained fully in Section 5) is drawn from Colmer et al. (2020) and Meng et al. (2018), which combines all three of the methods above to create annual, Census Tract level pollution measures.[8] Additionally, my data contributes to the literature by connecting the findings of treatment effects across PM10 regulations (Auffhammer et al. 2009) and PM2.5 regulations (Currie et al. 2020) on PM2.5 outcomes.

My basic structure of difference-in-differences and event studies mimics the design of Currie et al. (2020), though it diverges in a few features. Currie's policy variables are aggregated by "Commuting Zones" (clustered at the local labor market level) to replicate how the regulations work in practice. Their dependent variable is pollution exposure at the individual level. For simplicity and data limitations, I analyze policy at the county and pollution at the tract level. Furthermore, Currie combines difference-in-differences with unconditional quartile regression to estimate counterfactual pollution distributions. They define 19 PM concentration cutoffs using re-centered influence function regressions, then for each, estimate the effect of non-attainment on the probability of moving above the cutoff. This technique is advantageous as it provides stronger backing for causality. However, such an approach is beyond the scope of this paper, though my regression results across multiple specifications are in line with Currie's results. Other methods in the literature include Shapiro and Walker (2021) who use a similar difference-in-differences model to test pollution and permit trading activity across Black and Hispanic communities, but do not find significant results. Colmer et al. (2020) use rank-rank correlations to effectively analyze distributional changes over time, though they are correlated findings and do not robustly control for confounders to prove an EJ causation claim. I utilize their data to attempt to extend those findings. With an "EJ gap" as an outcome of interest, Hernandez-Cortes and Meng (2021) use trend breaks of emissions to examine the impacts of California's Cap and Trade program. As explained in Section 7.1, my model incorporates elements of these studies to attempt to draw a causal picture of the CAAA.

[8] There are numerous advantages to this approach, which are laid out in Section 5.

Last, I conduct a novel heterogeneity analysis. The findings illustrate which non-attainment areas drive my average treatment effect and suggest substantial heterogeneity across the U.S. Future work may link this heterogeneity analysis to specific SIP features to better understand the policy mechanisms and local relationships that shape environmental outcomes drive my results.

4. Theoretical Framework

This section summarizes my theoretical framework, documenting economic theories on firm and individual location decisions that may give rise to observed EJ gaps.

4.1 Consumers' willingness-to-pay for clean air

A central concept in environmental economics is willingness-to-pay (WTP) for clean air. Economists use consumer purchases in a variety of settings, for example, purchases of indoor air purifiers can estimate individuals' WTP for clean air (Ito and Shuang 2020). Housing is a key market where economists study these issues. When looking at residential housing, more polluted neighborhoods generally have lower property values, ceteris paribus. Economists use heterogeneity in housing characteristics and pollution to estimate WTP for cleaner air based on consumers' locational choices (Bazhaf et al. 2019).

Coase (1960) first hypothesized that firms might locate in poor neighborhoods due to lower potential compensation by the firm to residents (an evaluation of WTP). Following this logic, poorer populations may sort into polluted areas if they prioritize other essentials rather than environmental quality. This process, broadly referred to as Tiebout sorting, links environmental and other social inequalities as a function of wealth and preferences (Banzhaf and Walsh 2013). While observed pollution differences across neighborhoods can cause such exposure gaps to emerge in theory, recent evidence to suggests disadvantaged communities may also have lower WTP for environmental quality due to "hidden" pollution driven by disparities in information about air quality (Hausman and Stolper 2020).

When applying these concepts to PM2.5 pollution in the United States, the data do not support the theory. My statistical analysis in Section 6 demonstrates that the main delineation of PM2.5 pollution inequality in the U.S. is race, not income. It is a finding supported by Currie et al., who statistically show that income differentials explain almost none of the pollution exposure disparities between Black and White populations. While income disparities still persist on many other forms of pollution, additional theory is needed in this research context. To examine outcomes, I draw upon a broader definition of welfare.

4.2 Defining Welfare Beyond Income

In economic theory, social outcomes and expected utility are often modeled as a function of income, with worse outcomes assigned to the poor (Atkinson 1999). However, the Nobel Prize winning economist Amartya Sen pushed the field of Welfare Economics to quantify a multifaceted, humanist approach. One of Sen's notable contributions was to analyze a person's "capability," rather than their utility when assessing their welfare. Capability refers to their freedom of choice and ability to achieve (Sen 1982). For example, a person's ability/freedom to ride a bicycle is not just determined by their income, but their physical health, knowledge, and environmental endowment.[9] Any of those commodities enhances one's capability to bike. Heavy air pollution, on the other hand, would deteriorate the performance of a child's lungs, their biking capability, and overall welfare. While I do not specifically model capability, it is a useful framework of welfare when examining EJ outcomes.

To explain racial pollution disparities, Sen might assert that, rather than minorities having lower WTP for clean air, we should look to the complex structural factors and endowments

[9] Based on a similar hypothetical presented by Sen (1979).

determining welfare outcomes beyond income. Key among those factors is a racial wealth gap that exceeds the income inequality gap in the United States (Williams 2017). The racial wealth gap literature diagnoses this problem and frames this paper's link between race and welfare. There are several proposed explanations. Williams (2017) introduces a Wealth Privilege model where wealth is easily transferred down through generations, a process dominated by Whites and furthering economic stratification. Intergenerational wealth transfers are a consensus cause in the literature of the racial wealth gap (McKernan et al. 2014, Darity et al. 2018, Ashman and Neumuller, 2020). In analyzing the impacts of a lack of generational wealth, Herring and Henderson (2016) study "wealth characteristics." They find Black Americans lag behind Whites in ownership of homes, stock, and businesses, as well as receive lower wealth returns to income, education, age, and the previously mentioned assets.

A lack of these wealth characteristics has translated to communities of color being disadvantaged in terms of economics, health, environment, education, housing, and other compounding factors. But why must there be "communities of color" in the first place? Here, the racial wealth gap manifests as residential segregation by race. There are also multiple explanations in the literature for residential segregation. Historically, White government officials and developers used racist policies such as redlining and racial covenants to exclude Black people from their neighborhoods (if not outright intimidation and violence) (Boustan 2013). Recent studies have demonstrated the long-lasting impacts of these policies. Aaronson et al. (2021) show that 1930's redlining maps led in the following decades to racial segregation and wrought reduced homeownership rates, housing values, and credit access. Whipple (2021) finds that homes with racial covenants in the early 20th century were significantly less likely to be foreclosed during the Great Recession and redlining. In the second half of the 20th century, Logan and Parman (2017) show increasing rates of residential sorting were caused by a combination of White flight, urbanization, and deindustrialization, and increased racial sorting at the household level. Then, as explained in the following section, pollution disparities occur as industrial activity moves into segregated neighborhoods.

4.3 Pollutions Havens vs. the Porter Hypothesis

A key question in environmental economics is how polluters choose their sites. As summarized in Shadbegian and Wolverton (2010), early location theory papers identified natural resource abundance, labor availability, local wages/unionization, market size/proximity, transportation costs, and various production costs as key criteria for firm location based on the principle of profit maximization. More recent literature has turned its attention to EJ questions such as regulation and community welfare. If individuals in disadvantaged communities have a lower WTP for environmental quality (Bazhaf et al. 2019), firms have lower marginal costs from building facilities in those areas. The theory behind this phenomenon dates back to Olson (1965), who connected it to the free-rider dilemma of public goods. He hypothesized it is cheaper for firms to locate in areas where collective action against expected pollution is less likely. A basic economic model considers this as allocatively efficient, as pollution is produced equal to the value society places on it and the government regulates it as an externality. However, governments often do not properly price the externalities of pollution, resulting in a market failure. Furthermore, EJ scholars advocate for policymakers to integrate the cumulative impacts of pollution on marginalized populations into the social cost of pollution, which is used in cost-benefit analyses. While the CAA does not consider disparate impacts, it attempts to enforce that social cost of pollution.

"Pollution havens" are an idea that firms locate where environmental regulations are laxer and hypothesizes a negative impact on firms' competitiveness from increased regulations when they are already sited (Dechezleprêtre and Sato 2017). While the theory is typically applied on an inter-country scale, it has relevancy for intra-country analysis. The hypothesis that environmental regulations, all else being equal, will reduce a firm's economic competitiveness was first raised by McGuire (1982). Pollution havens have been rigorously debated, and their empirical evidence is far from conclusive due to issues of endogeneity (Levinson and Taylor 2008). There is, however, a competing hypothesis, The Porter Hypothesis, that implementing a stringent policy on a firm will trigger the economic incentive for them to invest in pollution abatement technologies. The authors hypothesize further that adopting clean technologies can raise productivity and costs savings to the point where the firm profits from the change in the long run (Porter and van der Linde 1995). This theory and academic conversation provide a narrative of the possible causal relationship around the closing EJ gap. If the Porter Hypothesis holds and the Pollution Havens hypothesis lapses, communities of color will have experienced disproportionate gains in clean technology (and possibly industrial productivity). My data exploration and regression results provide quantitative backing for this story, while the heterogeneity analysis introduces additional possibilities.

5. Data

This paper investigates whether the Clean Air Act Amendments decreased pollution exposure disparities, and if so, to what extent were SIPs and non-attainment status responsible for the change? To answer this question, it is necessary to have historical measurements of air pollution that are trustworthy and precise enough to mitigate concerns of environmental fallacy.

Much of the publicly available pollution data in the United States comes from the EPA's monitoring stations. While they are the foundation for much of the country's air quality enforcement, the network is notoriously flawed. First, there are not enough monitors to ensure every American can know their exposure. Not only does monitoring vary by race and income in dense areas (Stuart 2012), there are large swaths of rural America that are not covered at all (Garcia et al. 2016). Perhaps the most significant issue in air monitoring, however, is intermittency. Due to resource limitations, some monitors only collect data once every 6-12 days. With this schedule being public knowledge, some polluters have strategically adjusted their emissions to stay within attainment on those days (Zou 2021).

Herein lies the importance of a recent innovation: satellite data on pollution. Zou (2021) uses such data to show that air quality is significantly worse on unmonitored days due to arbitrary measurement techniques. The most relevant study using these methods is Meng et al. (2019), who estimated ambient fine particulate matter concentrations across North America from 1981–2016 through chemical transport modeling, satellite remote sensing, and ground-based measurements. This provides a much more accurate picture of PM2.5 distribution than previously available to researchers, which has since strengthened the corollary claims able to be made.

My pollution data source is the Colmer et al. (2020a) replication files. The authors use satellite data of PM concentrations across the U.S. from Meng et al. to construct annual PM measures at the Census tract level. The authors construct the measures using satellite data, a chemical transport model, and ground station measurements of PM2.5 and PM10. PM2.5 and PM10 are highly correlated[10] (Colmer 2020), so one can reasonably be used to estimate the presence of the other. For this reason, while I primarily study impacts of CAAA PM10 regulations, my main outcome of interest is mean annual PM2.5 ($\mu g/m^3$) at the tract level. My non-attainment data comes from the EPA Green Book.

6. Descriptive Statistics

6.1 Variable Description

Table 1(a) examines average, tract-level statistics for my variables of interest in 1992. I split the data based on whether their tracts were in attainment of the 1990 EPA PM10 standards. 1992 is

[10] Colmer et al. notes that "prior to the year 2000, data on PM10 were used in place of ground station and satellite data on PM2.5, when PM2.5 records were unavailable. All estimates indicate that there is very high persistence in rank over time, irrespective of which base year is used." Many studies have examined this correlation, with it ranging from R=0.64 (Munir et al. 2016) to R=0.95 (Janssen et al. 2013). For my purposes, this evidence is sufficient.

significant because it is the year that I specify 90th percentile P.O.C. tracts (1990 Census), and the first year of EPA's PM enforcement. Table 1(b) maintains 1990 Census data while including mean PM concentrations for all years in my sample and splits the data based on whether the tracts were ever in non-attainment.

Table 1
Variable Description

(a) When PM10 Nonattainment in 1992 = 0		**When PM10 Nonattainment in 1992 = 1**	
N = 53,969 tracts/observations		N = 10,728 tracts/observations	
Variable	Mean	Mean	t-test: Mean(0) - Mean(1)
Mean PM2.5 µg/m3	15.08	17.27	-2.190***
Population	3,825.58	3,773.41	52.169***
Proportion 90th Percentile Minority Tracts	0.09	0.17	-0.088***
Share Population Minority	0.19	0.31	-0.116***
Share Population Black	0.12	0.13	0.00
Share Population Hispanic	0.07	0.18	-0.115***
Share Population in Poverty	0.13	0.14	-0.009***
Income per Capita	14,145.02	15,059.87	-914.849***
(b) When PM10 or PM2.5 Nonattainment = 0 (1981-2016)		**When PM10 or PM2.5 Nonattainment = 1 (1981-2016)**	
N = 37,455 tracts/observations		N = 27,250 tracts/observations	
Mean PM2.5 µg/m3	12.43	15.66	-3.239***
Population	3,783.47	3,862.55	-79.087***
Proportion 90th Percentile Minority Tracts	0.07	0.15	-0.082***
Share Population Minority	0.17	0.26	-0.090***
Share Population Black	0.11	0.14	-0.034***
Share Population Hispanic	0.06	0.12	-0.056***
Share Population in Poverty	0.14	0.12	0.021***
Income per Capita	12,961.74	16,129.01	-3167.263***

The value displayed for t-tests are the differences in the means across the groups.
***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

High (90th percentile) minority tracts comprise around 8% more of total non-attainment tracts than attainment tracts. This relatively small figure confirms that the EJ disparity is driven by high minority tracts being on the upper tail of PM distribution rather than by a significantly higher number of communities of color being in non-attainment. Furthermore, across both splits, income is notably higher in non-attainment tracts. Compared to the data on racial groups in non-attainment, income seems relatively insignificant as a predictor of PM.

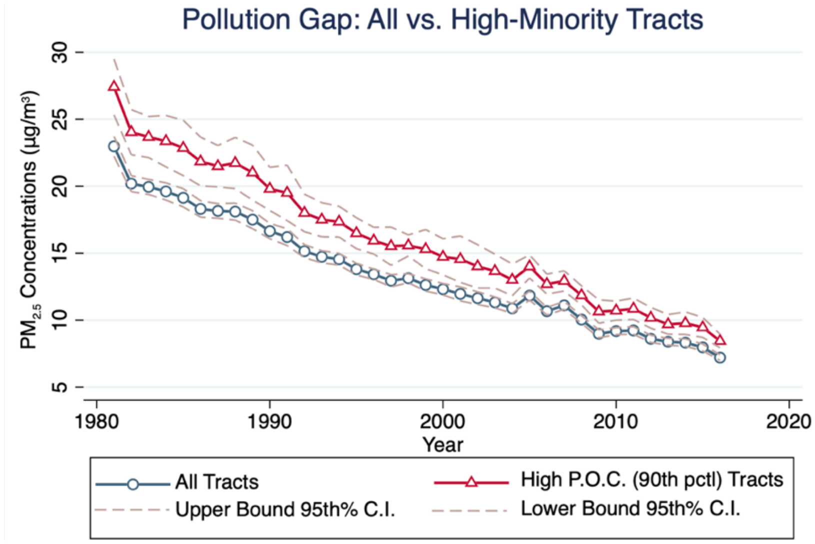
6.2 Nationwide net pollution changes

Figure 2 shows key trends that provide a basis for my hypothesis. They display mean PM2.5 concentrations from 1981 through 2016. Subfigure (a) displays concentrations in high-minority tracts against all tracts, where I observe a perceptible shrinking of the racial pollution exposure gap from roughly 4.5 μg/m3 to 1.5 μg/m3.[11] It supports the key finding of Currie et al. (2020) over an expanded time frame. This is a highly important finding, because Schwartz et al. (2021) finds an increase in life expectancy of 0.29 years when a population was exposed to 7 μg/m3 versus 12 μg/m3 of PM2.5. This is a drop similar in means to my EJ gap finding, so a gap closure is likely improving disparities in health and life expectancy outcomes. Something must be driving the gap closure, whether policy, demographic change, or an omitted variable. Subfigure (b) motivates my model specification. Pollution trends of high and low minority tracts cluster together *independent* of poverty levels. Moreover, the heterogeneity based on poverty status disappeared around 1998. These two observations tell us that, while everyone experienced cleaner air over time, people of color experienced environmental inequality and exposure changes in the past 40 years. As such, I leave the discussion of income here to solely focus on race.

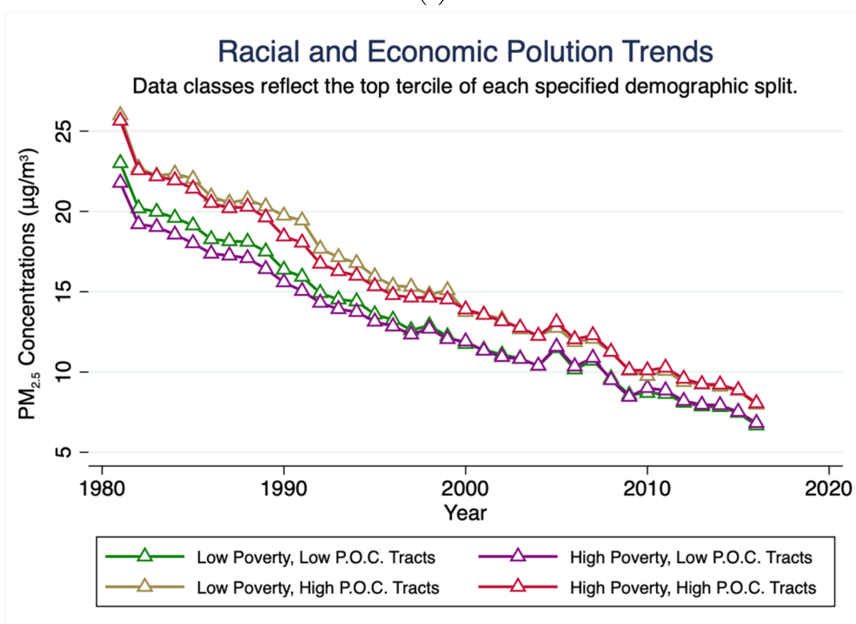
[11] One may reasonably observe that while the level change of the gap is negative, the gap in percentage terms of overall pollution is has not significantly changed. Many examine inequality in percentage terms. But for pollution, negative health impacts occur at high concentrations, so I define my EJ gap in level terms to reflect low marginal impact at low concentrations.

Figure 2

(a)



(b)



6.3 Maps

Figure 3 maps pollution and attainment status across the country in 1992, the first year of enforcement of the first nationwide Particulate Matter standards (PM10), and in 2005, the first year of the PM2.5 standards. PM2.5 concentrations in 1992 were highest in industrialized areas like the Rust Belt, the Southeast, and Southern California (Figure 3a). Those spatial patterns held, but overall concentrations fell over time (Figure 3b). Non-attainment status with PM10 standards, on the other hand, was primarily concentrated on the West Coast (Figure 3c). Counties in non-attainment for PM2.5 were concentrated in the Rust Belt, the Tri-State Area, and Southern California in 2005 (Figure 3d). There was a disparity between pollution concentration patterns and PM10 non-attainment status in 1992 due to the different particle composition. Despite this, examining the concentrations in 2005 relative to the PM2.5 non-attainment map, it appears the PM10 regulations were successful in reducing pollution.

Figure 3

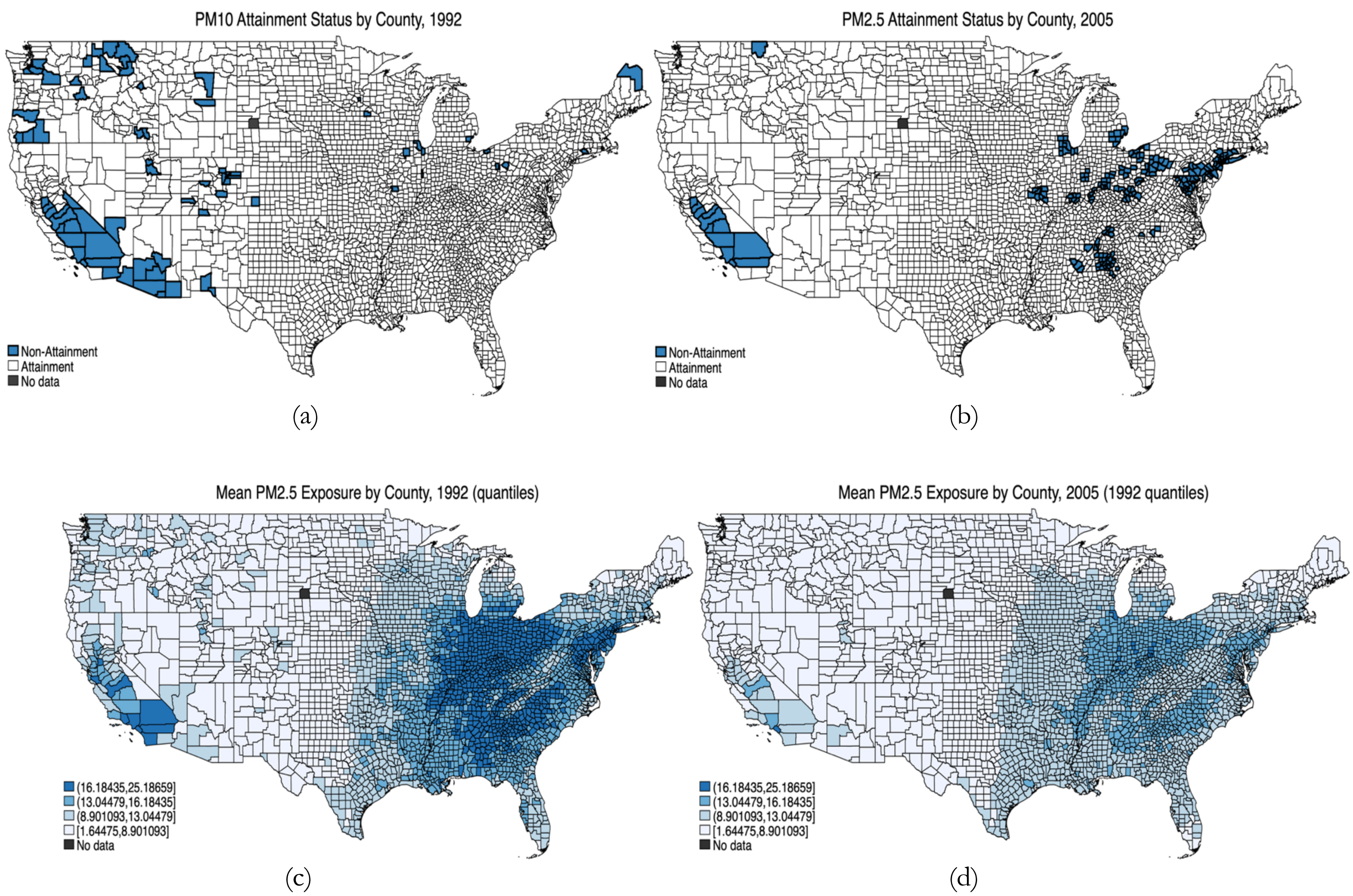
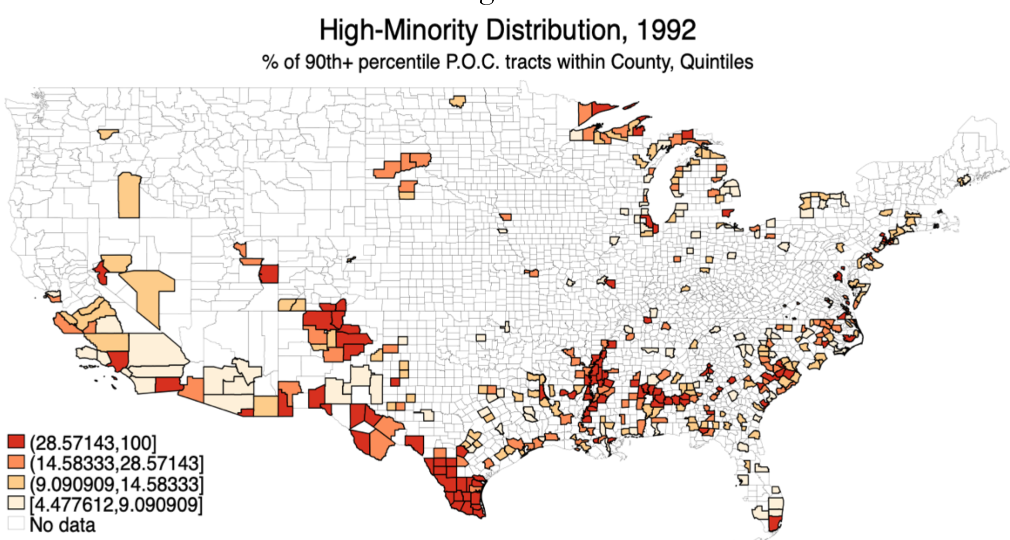


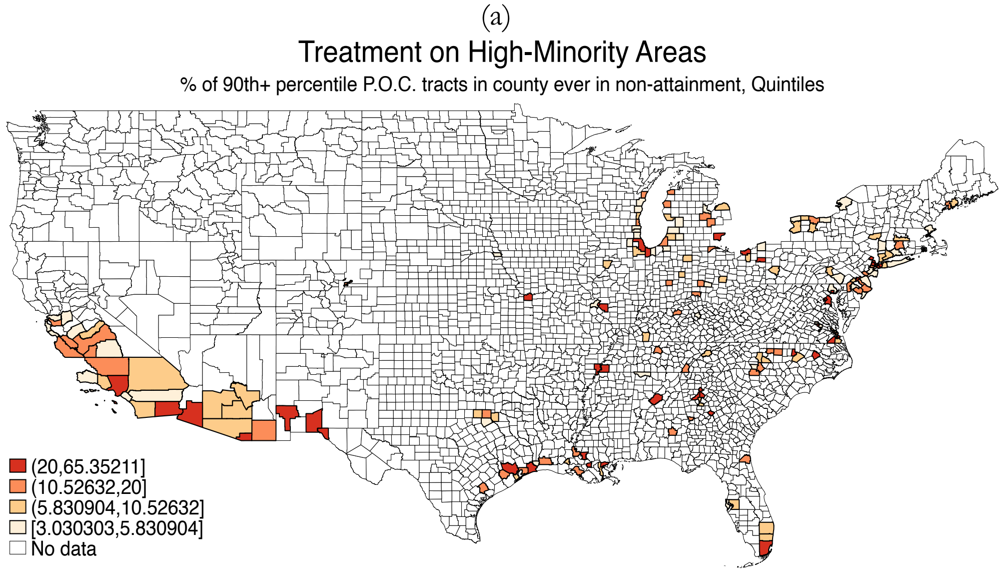
Figure 4 examines the geographic dispersion of my key demographic variable of interest, high-minority tracts. The maps show the percentage of high-minority tracts within each county.

Communities of color are densely concentrated around each coast, with other clusters in the Great Lakes region, the inland southwest, and the inland southeast. Cross-referencing with the PM maps, correlations between race and pollution are highest in the Southeast and Southern California. Figure 4(b) overlays the location of high-minority tracts with non-attainment status. I observe more instances of treatment for communities of color in the Southwest and the Northeast. Figures 4(a) and 4(b) shows that high-minority areas were covered by both the PM10 and PM2.5 rounds of the CAAA regulation.

Figure 4



(a)



(b)

7. Findings

7.1 Model

I use difference-in-difference (DiD), stacked DiD, and event study models to study the impact of a county being designated as non-attainment on PM2.5 pollution. I estimate my DiD model using two-way fixed effects (TWFE), evaluating the average treatment effect of county non-attainment status T_c on PM2.5 concentrations in tract i in county c and year t (Y_{ict}) after the county was designated as being in non-attainment ($Post_{ct}$). I use tract and year-level fixed effects to account for unobserved geography-specific and time-specific confounders such as other environmental policies and technological advancement. In each regression, all standard errors are clustered at the county level, which allows for tracts located in a single county to have correlated errors. My regression equation is:

$$Y_{ict} = \beta_0 + \beta_1(Post_{ct} * T_c) + \gamma_i + \gamma_t + \varepsilon_{\text{ict}} \qquad (1)$$

Recent literature raises concerns with the TWFE model in staggered treatment contexts (Borusyak and Jaravel 2016). Attainment status differs over time for some counties, with counties entering non-attainment status as early as 1992 and as late as 2009. TWFE models estimate a weighted average of treatment effects, which may be problematic when treatment effects are heterogenous over different groups or time (Goodman-Bacon 2021). This is likely the case in my study since we would expect heterogeneity in treatment effects due to technological advancements, updated legal code, and the anticipation effect of impending regulatory approval and enforcement (Malani and Reif 2015). Further bias may be introduced from previously treated counties serving as controls for recently treated counties.

To address these concerns, I first use an event study, exploiting within county variation in treatment status in "event time," or time since each treated county was placed into non-attainment status.[12] This approach has a further advantage since the visualization of the event study regression allows me to investigate parallel trends in the years leading up to treatment. While maintaining the TWFE, I study heterogeneous policy impacts through the event-year indicator j and collinear time indicators $[t = \tau]$. I estimate the equation:

$$Y_{ict} = \sum_{j=-\tau}^{\tau} \beta_j 1[t = j] + \gamma_i + \gamma_t + \varepsilon_{\mathrm{ict}} \qquad (2)$$

After the basic event study, I then interact all event study terms with indicators for high-P.O.C. tracts in a regression to evaluate heterogeneity.

I also implement a 'stacked' difference-in-differences model. This model addresses concerns of time variation in controls by creating 'clean controls' in an event-specific panel dataset (Cengiz et al. 2019; Beatty et al. 2021). For each year where treatment occurs, a dataset is created with 10 years pre- and post-treatment of event time and never-treated counties as the controls. All those datasets are merged ('stacked') to create a dataset where previously treated tracts do not serve as controls for tracts entering non-attainment years in the future. The regression equation is identical to equation (1) with the alternatively constructed data.

I test for differential outcomes from treatment for EJ communities using a triple Difference-in-Differences (DDD) model (Olden and Møen 2020; Gruber 1994; Cunningham 2021). In this case, the initial treatment split is on attainment status (county level), while the additional split is high-minority tracts H_i versus non-high-minority tracts. The outcome Y_{ict} of the DDD model, specified below, denotes PM2.5 levels by year t, tract i, and county c.

$$Y_{ict} = \beta_0 + \beta_1 H_i * Post_t + \beta_2 T_c * Post_t + \beta_3 T_c * H_i * Post_t + \gamma_i + \gamma_t + \varepsilon_{\mathrm{ict}} \quad (3)$$

The parameter of interest is $\beta 3$, the coefficient estimating the difference in pollution for high-minority tracts in non-attainment after the policy.

[12] For counties that enter, exit, then re-enter non-attainment, the treatment is measured at the first occasion.

7.2 Regression Results

Table 2 presents my regression results for the impact of attainment status on average PM2.5 concentrations across all counties. Both columns present model results adjusting for tract and year TWFEs, while column 2 implements the stacked regression dataset. Across both specifications, I confirm prior research and find that the CAAA were responsible for the lower pollution in non-attainment tracts relative to never-treated tracts. This result indicates that non-attainment status can explain around 10% of the ~16 μg/m3 drop in nationwide mean PM2.5 concentrations (Figure 1).

Table 2
Difference-in-Difference Results

	(1) TWFE DiD	(2) Stacked DiD
	Mean PM2.5 μg/m3	
Nonattainment (Treatment)	-2.025***	-1.599***
	(0.237)	(0.220)
Constant	14.19***	12.60***
	(0.0473)	(0.00615)
R-squared	0.939	0.935

Robust std. errors in parentheses   *** p<0.01, ** p<0.05, * p<0.1

Figure 5 presents my event-study model results. In the 'before' period, pollution does not appear to follow any identifiable trend, supporting my research design though the parallel trends assumption. I observe an immediate drop in pollution though year four, then again after year ten. This indicates the presence of a composition effect, where all regulations are reflected in the short term, while older PM10 regulations are driving further decreases in the later event time. I decompose these year-over-year trends in greater detail in the Appendix (Figure 8) and raise the possibility of PM10 SIPs having secondary policy impacts on PM2.5.

Figure 5

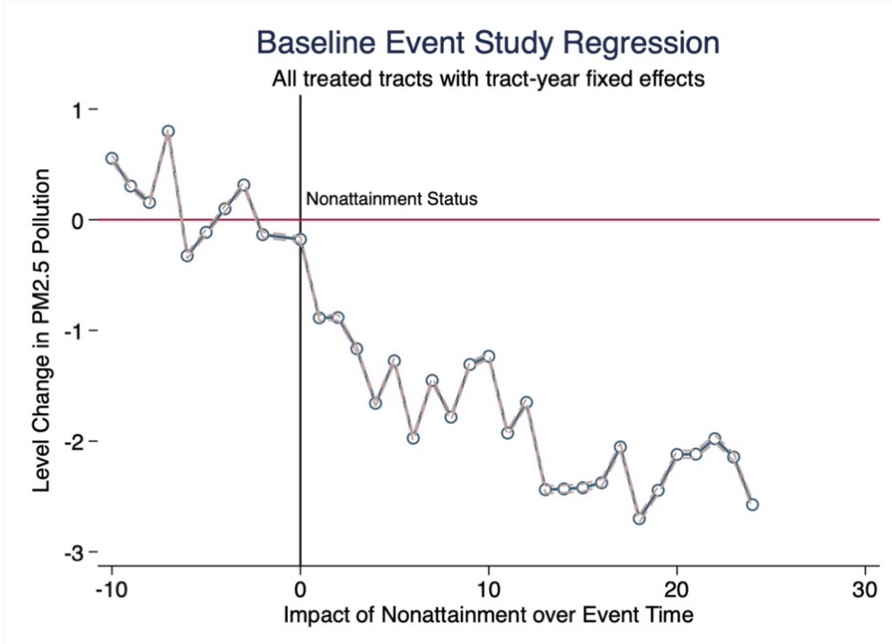


Table 3 is my main regression table. Like before, I specify TWFE and stacked regression models. The DDD controls for the heterogeneity of non-attainment status and high-minority status. The key interaction term in column 2 highlights that high-minority tracts saw a -0.89 μg/m3 greater drop in PM2.5 on average than non-high-minority tracts after entering non-attainment status. This indicates that non-attainment status can explain around 25% of the 3.5 μg/m3 decrease in the EJ gap (Figure 2a) over the last 35 years.

Table 3

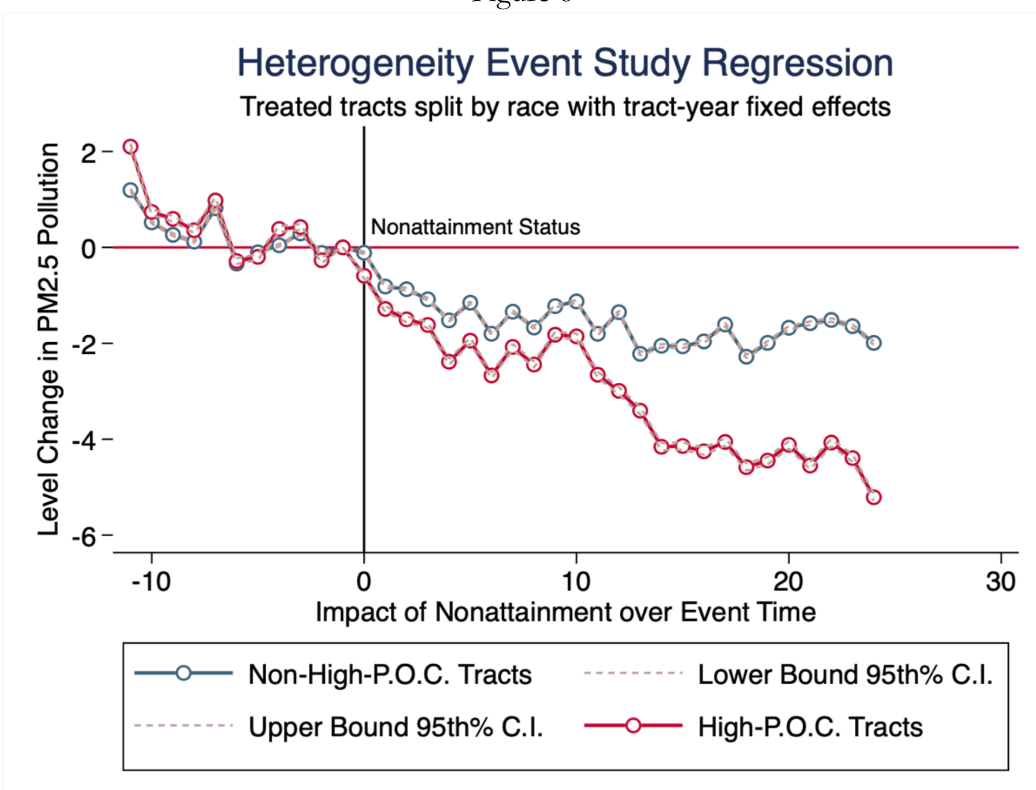
Triple Difference Regression Results

	(1) TWFE DDD	(2) Stacked DDD
	Mean PM2.5 μg/m3	
Nonattainment (Treatment)	-1.815***	-1.464***
	(0.212)	(0.198)
High-P.O.C. Treatment Interaction	-1.383***	**-0.889*** **
	(0.286)	(0.211)
Constant	14.19***	12.60***
	(0.0442)	(0.00582)
R-squared	0.939	0.936

Robust std. errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Lastly, Figure 6 is an additional event study. Treatment groups are split between high and low minority tracts, allowing me to examine differential treatment effects by race (control groups are excluded). In the 'before' period, the change in racial pollution gap does not appear statistically different as evidenced by clustering around zero and overlapping Confidence Interval (C.I.) lines.[13] Parallel trends are again confirmed, this time for the DDD heterogeneity analysis. Following year zero of event time, it becomes clear that high-minority tracts experienced a greater decrease in PM2.5 than non-high-minority tracts. The policy effect appears to grow stronger over time, with the gap of pollution change expanding rapidly around the 10th year of event time. Again, it appears a composition effect is present, as a majority of the gap closure is likely attributable to PM10 regulations when PM2.5 non-attainment disappears from the data.

Figure 6



[13] In each regression, all errors are clustered at the county level which allows for tracts located in a single county have correlated errors.

Under all specifications and coefficients, the results indicate that the CAAA were successful both in their stated goal of cutting air pollution and the EJ objective of narrowing the racial pollution gap. As the models increase in complexity, the coefficients shrink, but maintain significance, indicating the fixed effects and stacked treatment groups are capturing unobserved variance while leaving a meaningful signal. This result allows me to reject the null hypothesis that the CAAA did not reduce the racial pollution gap and provides casual evidence that the CAAA were responsible for the change.

7.3 Discussion and Implications

These results and the validity of the model are conditional on a few factors. First, endogeneity bias is a risk in any observational study, so the causality of my results is conditional on non-attainment status being exogenous. While the pre-trends of the event studies support this, it is impossible to prove. Furthermore, as previously discussed in Section 7.1 and elaborated upon in the Appendix, this analysis faces heterogeneity in treatment effects due to some counties being treated much later than the initial treatment round. As such, it is possible that the early rounds of SIPs and non-attainment designations induced second- or third-hand behavior impacts or policy changes. The event study results indicate that non-attainment status resulted in near-immediate pollution cuts, but it is still possible that an omitted variable responsible for some of the signal, or non-attainment is associated with confounders.

The findings of Currie et al. and the confirmation and expanded validity of this study provide macro-level good news for advocates of environmental quality and EJ. The concerns of pollution permit trading markets resulting in higher inequality should be further allayed. In taking a federalist approach to air, it appears that SIPs were broadly effective in cutting pollution and smoothing out disparities. Despite being repeatedly plagued by legal battles and political uncertainty, the Clean Air Act is a success story.

8. Heterogeneity Analysis

Decomposing these regression results allows me to examine the heterogeneous impacts of the CAAA. I re-run my DiD for each county placed under non-attainment status, comparing average PM2.5 concentrations over time to all non-attainment counties to obtain county-specific treatment effects. Figure 7 maps the results. Results vary from -7 μg/m3 in the South Coast Air Basin[14] and the East Coast to an increase of 6 μg/m3 in other areas of the Southwest. Areas that saw increases in pollution are a minority of the county treatment effects but demonstrate that SIPs do not universally decrease pollution immediately.

Figure 7

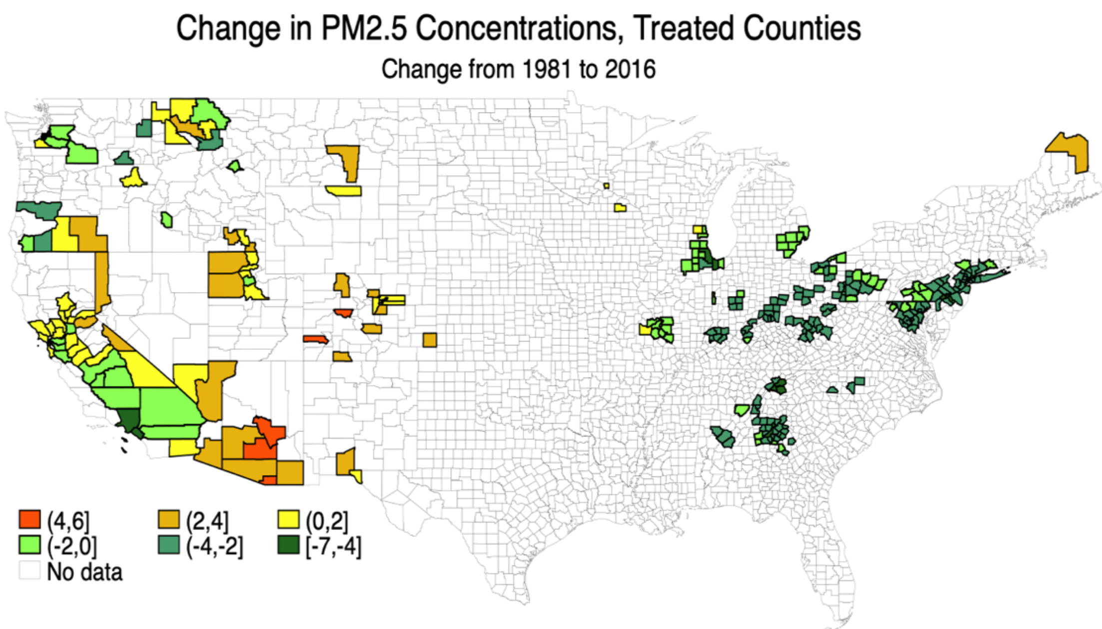


Table 4 presents correlations between my county-level treatment effects and county demographics (Table 5 in the appendix shows all correlations). Higher PM2.5 reductions correlate with a higher Black population and negatively correlate with the Hispanic population. The latter is a surprising finding given the regression results but makes sense if we compare Figure 4(b) to Figure 7.

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[14] Comprised of Los Angeles and Orange County, California

The treated counties with the greatest increases in pollution overlap some areas with the greatest concentrations of Hispanic population, such as Arizona[15], New Mexico, and Imperial County, California. The negative coefficients on income per capita and percentage population with a high school degree indicate that, consistent with my discussion in Section 4, wealthier and better-educated counties saw more pollution reductions on average.

Table 4

variable	correlation with beta
Share White	-0.0126
Share Black	-0.391
Share Hispanic	0.3296
Share < 18y/o	0.2455
Share > 60 y/o	-0.0149
Share P.O.C.	-0.0404
Income	-0.097
Share High School Degree	-0.2659
Share manufacturing	-0.313
Share poverty	0.0967

Another interesting result is the positive correlation between high PM reductions and county share of manufacturing employment. Using the same variable, Colmer et al. (2020) found that lower manufacturing shares led to higher tract percentile rank points of PM2.5 from 1981 to 2016. These two results suggest that PM2.5 SIPs effectively regulate direct source pollution and potentially are less effective in reducing non-point source pollution. Direct sources such as power plants, smokestacks, and construction sites are less mobile and easier to regulate. Non-point sources include wildfires and automobiles, whose emissions interact with NO2, SO2, and VOCs[16] in the atmosphere to form PM2.5. Using Arizona as a case study, the state had multiple counties in non-attainment for years and saw PM2.5 increases over time. Primary sources of PM2.5 in Arizona include automobiles and cross-

[15] Cochise, Pinal, Gila, and Santa Cruz Counties in Arizona saw 4 out of the 6 greatest PM2.5 increases in my treated counties dataset.

[16] See Section 2.2

border pollution spillovers from Mexico (ADEQ 2022). Located in a valley, Phoenix, AZ has the 7th worst air in the country, with PM2.5 building up from auto traffic, wood fire pits, and fireworks (Stone 2020). So, with manufacturing not a major source of PM2.5 in Arizona, it seems that the state's SIPs have been ineffective in tackling air pollution problems, which manifests as an EJ disparity given the state's significant Hispanic population.

Conversely, there are significant Black populations in the major metropolitan areas of formerly industrial states like Pennsylvania, California, Ohio, Tennessee, and Georgia. These are the states with counties that saw the greatest pollution drops. Thus, the SIPs targeting manufacturing likely had a strong clean-up effect in these areas, which drove the closure of the EJ gap. However, it is important to remember that the CAAA is only statistically attributable to a portion of pollution reductions (as evidenced in this paper and Currie et al. 2020). Deindustrialization was well underway during the CAAA and was accelerated in the 1990s by the signing of NAFTA. Furthermore, as explained in Section 4.3, the Porter Hypothesis leads me to believe that high-POC areas experienced disproportionate gains in clean industrial technology, reducing pollution. Clearly, there were multiple mechanisms at play that make it difficult to pinpoint a counterfactual. These findings are not causal but demonstrate that policy had heterogeneous impacts across different communities.

9. Conclusion

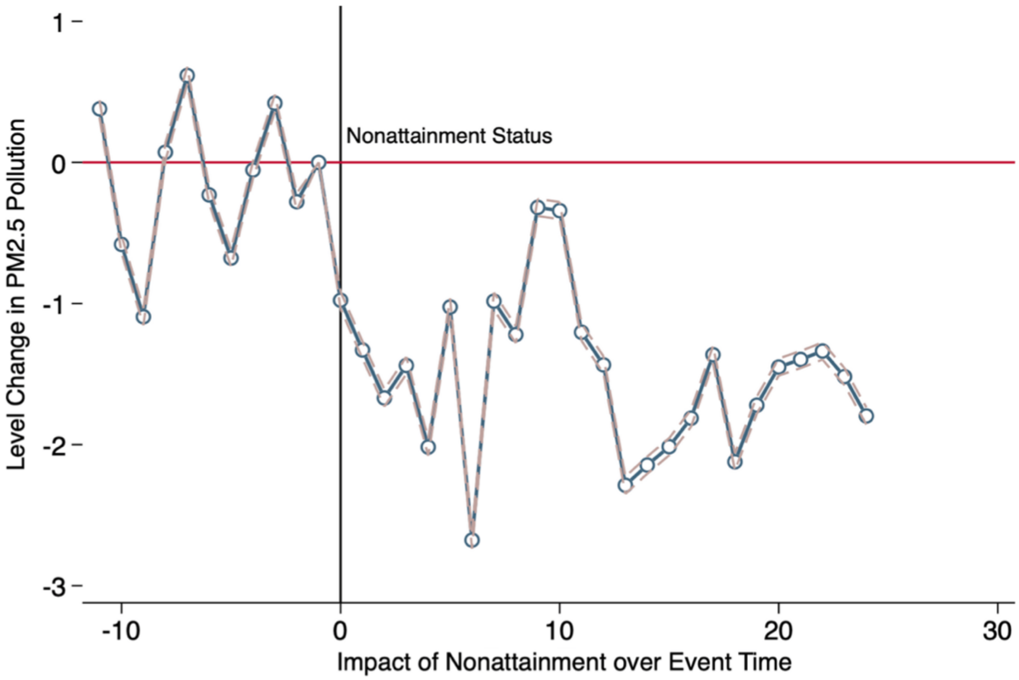
My research robustly finds a decrease in the racial pollution gap and causal evidence that the Clean Air Act was responsible. In summary, I contribute to the literature on several fronts: I add to the burgeoning utilization of satellite PM data in the Meng, Colmer, and Currie papers. I attempt to replicate and extend the results of Currie et al. (2020) who found CAAA's causal reduction in the Black-White gap of PM2.5. I extend the analysis to include PM10 attainment's impact on PM2.5, which brings in 11 years of extra observations. Event study results suggest that a composition effect is present in the results, with PM10 significantly contributing to the EJ gap closure in the long run. I also extend the analysis to Hispanic communities, confirming similar statistical trends and causal identification. I do so by situating this research within the ongoing empirical debate about observational design using Difference-in-Difference. To prevent bias from heterogeneous treatment effects, I confirm my results using a diverse range of specifications: traditional Difference-in-Difference, Triple Difference, Event Study, Two Way Fixed Effects, and Stacked Regression. My research robustly finds a decrease in the racial pollution gap and causal evidence that the Clean Air Act Amendments were responsible. Lastly, I conduct a heterogeneity analysis, decomposing earlier results and showing that air pollution decreases in heavy manufacturing counties were a primary driver of the EJ gap closure over time, while stagnating or worsening air quality in predominately Hispanic communities remains.

Disparate contributions of Black versus Hispanic populations to the EJ gap and its closures are worth future consideration. The results of Currie et al. and this paper suggest that gains in Black communities are driving the closure, while Hispanic communities have seen inconsistent outcomes. Future research should examine this question through decomposition and investigate the roles of residential sorting and PM pollution source types (point versus mobile) on these outcomes. It would also be valuable to extend the heterogeneity to more groups contained within regulators' definition of EJ groups, such as Asian and Indigenous populations. Additional next steps in the research should address the dearth of literature examining SIPs. While specific county/regional policies have been analyzed, I have not found a paper that comprehensively summarizes different regulatory structures of SIPs. Such research would allow comparative examination of effective plans to cut pollution, reduce EJ disparities, or improve public health.

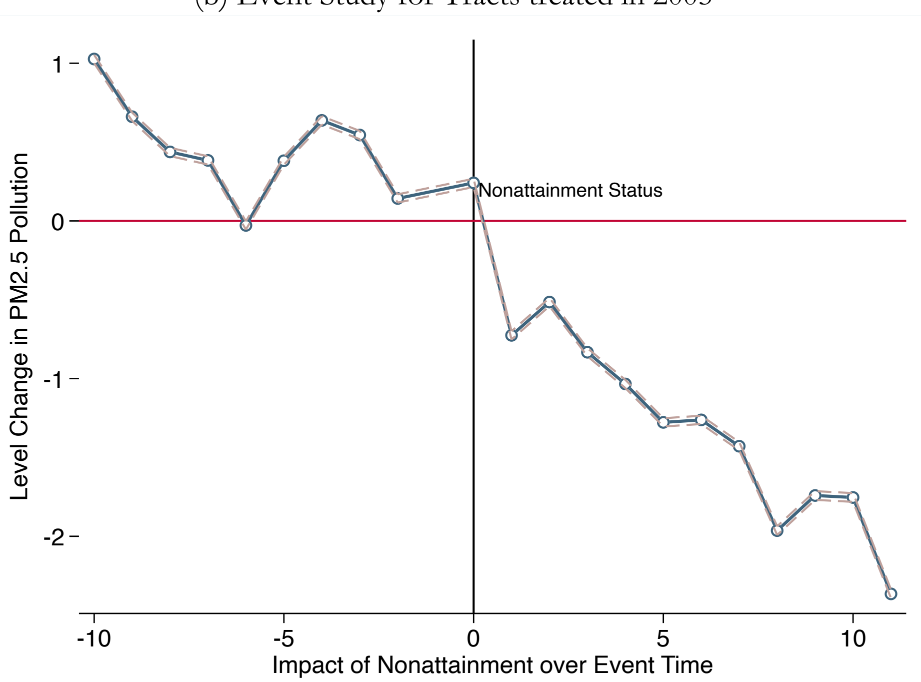
As a final contribution, I note that this positive finding does not universally reflect the reality on the ground in communities suffering from environmental injustice and systemic racism. Environmental Justice outcomes can improve for a family on the margin without seeing their quality of life improve. We still have significant progress to make in improving outcomes for those whom policy has been oppressive, rather than liberatory. Researchers and policy makers should seek out and integrate those voices into this work.

Appendix

Figure 8
(a) Event Study for Tracts treated in 1992



(b) Event Study for Tracts treated in 2005



Here I decompose the event study regression into tracts that entered non-attainment in 1992 and 2005, the first years of the PM10 and PM2.5 policies. In the former, I observe random distributions prior to the policy, then a noisy but discernable signal of the treatment effect. The original set of SIPs appears to have an immediate, strong treatment effect that is consistent over time. This is supported by Figure 5, the primary event study of all treated tracts, where the signal increases in strength after 10 years of event time (the only tracts remaining after 11 years of event time are those from PM10 regulations). This is likely due to a composition effect of PM2.5 and 10 policies which disappears once PM2.5 data runs out. In the 2005 round, the pre-trends appear to show non-zero effects on pollution. This raises the possibility that PM10 regulations had secondary policy impacts on the areas soon to enter PM2.5 non-attainment. There is still a significant post-policy treatment effect from PM2.5 SIPs that is smaller than PM10 initially but grows over time. Further research should investigate this relationship between PM2.5 and 10 regulations.

Table 5

variable correlations	beta	% White	% Black	% Hispanic	% < 18 y/o	% > 60 y/o	% P.O.C.	income	% GED	% manu-facturing	% poverty
beta	**1.000**										
% White	**-0.013**	**1.000**									
% Black	**-0.391**	**-0.626**	**1.000**								
% Hispanic	**0.330**	**-0.718**	**-0.044**	**1.000**							
% < 18 y/o	**0.246**	**-0.085**	**-0.124**	**0.270**	**1.000**						
% > 60 y/o	**-0.015**	**0.177**	**-0.091**	**-0.145**	**-0.506**	**1.000**					
% P.O.C.	**-0.040**	**-0.989**	**0.685**	**0.697**	**0.108**	**-0.171**	**1.000**				
income	**-0.097**	**-0.067**	**0.064**	**-0.070**	**-0.363**	**-0.272**	**-0.005**	**1.000**			
% GED	**-0.266**	**0.189**	**0.026**	**-0.168**	**-0.122**	**0.597**	**-0.104**	**-0.656**	**1.000**		
% manufacturing	**-0.313**	**0.381**	**-0.106**	**-0.330**	**0.082**	**0.087**	**-0.316**	**-0.227**	**0.413**	**1.000**	
% poverty	**0.097**	**-0.391**	**0.241**	**0.336**	**0.008**	**0.377**	**0.418**	**-0.612**	**0.450**	**-0.195**	**1.000**

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