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Racial Disparities in Environmental Auditing

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Abstract

This paper investigates the role of the U.S. Environmental Protection Agency in advancing environmental justice through monitoring and enforcement efforts mandated by the Clean Air Act. Our analysis relies on a comprehensive dataset encompassing auditing information from all environmentally relevant plants between 2000 and 2018. Leveraging county-level variation in racial composition and environmental auditing, we find a substantial and persistent reduction in the proportion of inspected plants following increases in the share of non-White population. This decline coincides with a decrease in political activism, particularly among entities typically advocating for more stringent environmental protection.

JEL Classification: J15, K32, P18, Q52, Q53, Q58.
Keywords: Environmental auditing; Racial demographic shifts; Environmental justice; Political activism.

Around the world, Environmental Protection Agencies (EPAs) are central governmental institutions in charge of controlling environmental damages from industrial activity and keeping firms from breaching legal pollution levels. In the United States, federal laws, such as the Clean Air Act (CAA), provide the constitutional framework for these objectives. A prolific literature agrees on the CAA's crucial contribution to better air quality in the U.S. over the last decades. Blundell et al. (2020), for instance, estimate that the CAA cost the taxpayers approximately $831 billion between 1970 and 1990. However, its benefits in the form of prevented air pollution damages exceed this amount and accumulate to over $35 trillion.

Besides the overall mitigation of pollution, one of the EPA's central goals is to reduce prevalent (racial) exposure inequalities in the U.S. (Environmental Protection Agency, 2002). Most recently, Currie et al. (2023) show evidence consistent with the fact that the CAA contributed to this goal, achieving an ongoing racial convergence in ambient air pollution exposure between African-American and White communities. The paper argues that higher pollution levels in African-American neighborhoods led to increased scrutiny, which reduced the racial pollution exposure gap by over 60 percent since 2000. Despite this progress in reducing absolute gaps, Colmer et al. (2020) show that relative differences in exposure prevail.

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This paper offers novel insights into EPA's contribution to environmental justice by examining its environmental auditing efforts mandated under the Clean Air Act. Specifically, we delve into the procedural aspect of environmental justice, focusing on the inclusivity of the environmental auditing process. With this focus, we aim to shed light on potential disparities in the enforcement of environmental regulations, thereby contributing to a deeper understanding of environmental justice practices. To the best of our knowledge, our paper is the first to provide direct evidence on the procedural justice of environmental auditing in the U.S.

To answer the research question, we compile the most comprehensive dataset to date on environmental auditing, air quality, and socio-demographic factors. Our dataset integrates auditing information from 251,829 environmentally relevant plants across the contiguous United States with data on racial demographics, population size, income, $PM_{2.5}$ concentrations, and indicators of political engagement. The final dataset forms a balanced county-year panel covering 3,014 counties from 2000 to 2018.

Our empirical strategy exploits variation in the racial composition of U.S. counties over time. While the overall U.S. population remains predominantly white, there has been a notable trend towards increased racial and ethnic diversification (Perez and Hirschman, 2009). Between 2000 and 2018, about one-third of the counties in our dataset saw annual increases of 0.5 percentage points or more in their non-White population share. We leverage these temporally and spatially dispersed demographic shifts by employing an event study nested within a staggered difference-in-differences design to examine changes in the EPA's auditing of all environmentally relevant plants in the USA. Following Sun and Abraham (2021), we estimate dynamic changes in the annual share of inspected plants after a positive jump in non-White population share. This involves comparing outcomes in counties that experience such a jump with those that have not yet or never experienced such a shift during our study period while controlling for county and year-fixed effects.[1] The methodology effectively addresses biases from period contamination and treatment effect heterogeneity, as discussed in Goodman-Bacon (2021) and Baker et al. (2022).

Although our empirical approach may not address all potential endogeneity concerns related to the occurrence of racial shifts across different counties, its validity is reinforced by several factors. Firstly, we observe no discernible spatial or temporal clustering of demographic shifts, suggesting the absence of systematic bias in their occurrence across counties. Secondly, we demonstrate the consistent adherence to the parallel trends assumption, essential for validating the selection of counties that have not yet experienced a jump or never do as the counterfactual. Thirdly, our analysis reveals that the timing of observed changes in outcomes corresponds closely with the occurrence of the demographic shift and continues over the years following its onset. This observation indicates that the shift was not anticipated and furthermore brings suggestive

[1] Various studies utilize staggered DiD approaches, leveraging county-level variation across the United States. Callaway and Sant'Anna (2021), for example, assess the impact of variations in county-level minimum wage policies on teen employment rates. Similarly, Deryugina (2017) quantifies the economic costs counties bear due to hurricanes.

evidence that the shift itself directly influenced the observed outcomes. Finally, we demonstrate that the Stable Unit Treatment Value Assumption (SUTVA) holds within our framework, ensuring that the jump in one county neither influences the outcomes nor the likelihood of jumps in another. Collectively, these elements strengthen the validity of our approach, supporting the reliability of the estimated effects in light of possible endogeneity.

We find robust evidence that the annual share of inspected plants decreases following an increase in the share of the non-White population. Relative to the year preceding the racial demographic shift, the share of inspected plants experiences an average reduction of about 9%. This decrease aligns with the timing of the demographic shift and endures throughout the initial decade following its occurrence.

Racial demographic shifts vary in intensity across counties and over time. To capture this variation, we explore a comprehensive range of jump magnitudes in the share of the non-White population. Our analysis demonstrates that our main findings remain robust across this variation. Furthermore, we observe that larger shifts in the non-White population correspond to more pronounced reductions in the share of inspected plants, underscoring the significance of demographic changes in influencing environmental monitoring outcomes.

We demonstrate the robustness of our findings through a series of additional tests. These include excluding counties without demographic shifts and accounting for instances of multiple demographic jumps, utilizing estimators proposed by De Chaisemartin and d'Haultfoeuille (2020). Furthermore, by examining increases in the share of the White population, we establish that the observed effects are specific to shifts in the non-White population rather than a general response to demographic changes.

To further assess the validity and robustness of the relationship between racial demographic shifts and changes in the extent of environmental auditing, we investigate several potential mechanisms. Firstly, we find that both average pollution levels and the compliance of polluting facilities with official standards remain unchanged following the demographic shift, suggesting that alterations in air quality do not explain the shift in inspection behavior.

A second mechanism we pursue is that of political activism. Prior studies have highlighted persistent procedural injustice in economically disadvantaged areas (Konisky, 2009; Konisky et al., 2021), often linked to limited political mobilization within low-income and minority communities (Hamilton, 1995). Despite the absence of changes in average income levels following the demographic shift, our analysis reveals a significant decrease in political engagement. Notably, there is a substantial 35% decline in the number of political donors following an increase in the non-White population share. We show that this decline is driven by left-leaning individuals while the number of right-leaning donors increases. Furthermore, we find a 28% reduction in the number of public protests subsequent to the demographic shift. In alignment with this trend, the number of newspaper articles covering protest-related topics also diminishes, suggesting a decrease in public visibility of potential social justice issues within affected communities.

This decline in media coverage may contribute to limited awareness and discussion surrounding important societal concerns among the broader population. Overall, the decline in political activism among groups that traditionally advocate for stricter environmental protection emerges as a potential mechanism to explain the reduced monitoring activity of the EPA.

This paper makes two key contributions to the existing literature. Firstly, our paper directly contributes to the literature on environmental justice and disparities in air quality exposure between White and non-White populations in the United States (Currie et al., 2023; Colmer et al., 2020). In particular, Currie et al. (2023) demonstrate that the implementation of the $PM_{2.5}$ National Ambient Air Quality Standards (NAAQS) under the Clean Air Act, which encompassed new areas of monitoring characterized by higher concentrations of African Americans, played a significant role in mitigating racial disparities in air pollution exposure. While nonattainment designation according to NAAQS is a largely objective outcome determined by ground-level measurements of $PM_{2.5}$ concentrations,[2] the EPA has greater flexibility in implementing other aspects of the environmental monitoring and enforcement process. One such aspect is the selection of plants for environmental inspection. Our study provides robust evidence that the proportion of inspected plants decreases following an increase in the share of the non-White population. Our findings thus challenge the overall equity and inclusivity related to CAA implementation, shedding light on persisting disparities. With this, we contribute to the thin literature that points to discriminatory aspects within the EPA's regulatory framework, such as substantial differences in fines imposed under the Resource Conservation and Recovery Act between White and minority areas (Lavelle and Coyle, 1992). Additionally, existing literature suggests that regulatory enforcement is less rigorous in proximity to disadvantaged communities (Gray and Shadbegian, 2005; Shadbegian and Gray, 2012).[3]

Our second main contribution involves exploring specific mechanisms that elucidate the changes in environmental auditing stemming from racial demographic shifts. We provide robust evidence indicating that a pivotal element in this process is the notable decrease in political activism subsequent to demographic shifts. This aspect of our research aligns with existing literature that emphasizes the diversity in political activism across racial groups. Historically, African American and Latinx communities have exhibited comparatively lower levels of political engagement when contrasted with their White counterparts, as highlighted by Bobo and Gilliam (1990) and Holbrook et al. (2016). This reduced political activism is crucial, as it potentially predicts discrepancies in environmental policy enforcement. Charnley and Engelbert (2005) supports this hypothesis by demonstrating how active participation in environmental matters significantly impacts EPA's effectiveness in managing environmental issues.

[2]Zou (2021) finds evidence suggesting that local governments engage in suppressing air pollution monitoring during high-pollution periods to reduce the risk of being designated as nonattainment areas.

[3]A notable limitation of existing research is their narrow focus: Lavelle and Coyle (1992) focuses on comparing lawsuit outcomes concerning Superfund waste sites between 1985 and 1992. Gray and Shadbegian (2005) examine data limited to 409 U.S. pulp and paper mills spanning 1985 to 1997. Shadbegian and Gray (2012) restrict their analysis to four major U.S. cities.

Our findings have significant implications for procedural environmental justice. Firstly, our study reveals the presence of racial disparities in environmental auditing under the Clean Air Act, emphasizing the need to revise EPA's auditing mechanisms for impartiality and equity. With a broader interpretation, our results underscore the importance of integrating environmental justice principles more effectively into the core framework of environmental policy-making. Secondly, our findings emphasize the role of political activism in shaping environmental justice outcomes, especially in areas undergoing demographic changes. This highlights the necessity for policy reforms aimed at strengthening civic engagement and participation. Such reforms may entail enhancing transparency, fostering public consultation, and ensuring community representation in environmental policy-making entities.

I. Monitoring Compliance under the Clean Air Act

This section sheds light on the methods and criteria employed by the EPA in selecting, monitoring, and auditing companies of environmental significance under the CAA. Understanding these processes is essential for comprehending the EPA's administrative mechanisms and the complexities inherent in enforcing air pollution standards. A particular emphasis is placed on the discretionary aspect of the EPA's decision-making process, examining how the agency exercises its autonomy in determining the targets of its inspections. This examination is especially relevant in the context of environmental justice, as it offers insights into how the EPA's choices can influence equitable environmental enforcement and protection across regions.

The US EPA is a federal agency mandated by federal legislation to mitigate environmental hazards. While the legislation is passed on the national level, a large part of the regulatory enforcement process is conducted through ten regional EPAs, often composed of states with geographic similarities.[4] These regional EPA offices conduct inspections, issue sanctions, and assist states with major violation cases (Environmental Protection Agency, 2023).

To enforce CAA regulations, the EPA employs a dual approach to gather pollution data. Primarily, the agency relies on self-disclosed information from companies. This self-reported data provides a direct insight into the individual pollution profiles of various facilities. In practice, facilities are required to submit snapshots of pollution at specific points in time or aggregated summaries over a longer period, each detailing emissions at the pollutant-point source level. Complementing this self-disclosure, the EPA operates ground-level monitoring sites across different regions. These monitors are crucial in continuously measuring ambient pollution levels, serving as an independent and objective method of verifying the accuracy of the data reported by companies (Shimshack, 2014).

Given that companies may have incentives to underreport their emissions (Harford, 1987; Oestreich, 2015) and the fact that monitor coverage is neither comprehensive nor immune to spatial variability and adjustments by polluters (Hu et al., 2009; Grainger and Schreiber, 2019;

[4]How states nest within the superordinate EPA regions is shown in Appendix B.

Zou, 2021), direct inspections of companies are crucial. Besides ambient air pollution levels, the frequency of these inspections is influenced by several factors: (i) varying enforcement budgets and priorities across different states and regions, (ii) facility characteristics and compliance history, (iii) the facility's location in a NAAQS nonattainment area, and (iv) environmental justice considerations (Environmental Protection Agency, 2016).

Furthermore, the scope and scale of evaluations may differ across facilities, industries, statutes, states, and over time. Inspections range in intensity and can be performed on- or off-site. Low-intensity inspections might include visual checks of emissions and abatement equipment, medium-intensity inspections might review operational, maintenance, sampling, and reporting procedures. In contrast, high-intensity inspections often involve detailed sampling by the regulator (Shimshack, 2014).

While budgets and priorities might differ across regions, Shimshack (2014) points out that the reasons for EPA inspections can generally be categorized into two types: "for cause" and "neutral selection." "For cause" inspections are initiated based on specific triggers such as a facility's compliance history, complaints from citizens or anonymous employees, and facility characteristics that typically indicate a higher likelihood of violations or significant environmental impact. Conversely, "neutral selection" inspections are more routine. They are scheduled based on factors like the time that has elapsed since the last inspection and logistical considerations, such as the geographic proximity to other facilities due for inspection. While the EPA has monitoring guidelines that suggest frequency targets for both types of inspections, these are usually advisory rather than mandatory. As such, both "for cause" and "neutral selection" inspections are grounded in deliberate criteria rather than being purely random (Environmental Protection Agency, 2011; Blundell, 2020).[5]

The history of a facility's compliance plays another significant role in determining the frequency and intensity of these inspections. Facilities that have been previously found in violation of environmental regulations, for instance, are more likely to be subjected to subsequent inspections. More precisely, the EPA distinguishes between two types of violators: Regular[6] and High Priority Violator Status (Environmental Protection Agency, 2014). When a violation is discovered at a facility, either through inspection or self-reporting, it is designated as a "violator." This status leads to increased scrutiny and more frequent inspections, and the facility may accrue additional violations. It returns to compliance only after addressing these issues, which often entails both rectification costs and enhanced regulatory oversight. In cases of severe or persistent non-compliance, facilities are classified as "High Priority Violators." This category involves even more stringent oversight, including more frequent and intensive inspections, higher fines, and strict deadlines to remedy violations. Only after fully resolving these issues can a

[5] Unfortunately, specific statistics detailing the proportion of inspections conducted "for cause" versus "neutral selection" are not readily available in the current literature, reflecting an area that might benefit from further research.

[6] Regular violators are also called "Federally Reportable Violators" (FRV).

facility exit the "High Priority Violator" status (Blundell, 2020). If a violation remains unaddressed, it triggers a sequence of sanctions, beginning with informal measures such as warning letters, phone calls, and notices of violation. Should the issue still persist, it escalates to formal sanctions, including administrative orders or fines, to enforce compliance.

Nonattainment areas are another critical aspect of the CAA framework. When a NAAQS for a specific pollutant is established, states are responsible for recommending to the EPA the classification of various areas, generally counties, in relation to these standards. Areas are designated as either in attainment, nonattainment, or nonclassifiable (effectively attainment). This classification is primarily based on the latest three years of monitoring data, supplemented by atmospheric modeling, emissions inventories, and other tools. In nonattainment areas, where air quality does not meet the NAAQS, facilities and local governments are obligated to develop and implement plans to achieve compliance. The development and implementation of these plans bring about heightened scrutiny from regulatory bodies, ensuring that the necessary steps are taken to address and rectify air quality issues in these regions (Esworthy, 2015).

Finally, the EPA asserts its commitment to incorporating considerations of environmental justice into its inspection targeting process by considering the vulnerability of populations near polluting facilities (Environmental Protection Agency, 2002). Section II further discusses the link between environmental justice and monitoring. Regulator actions also appear to be influenced by factors unrelated to direct benefit-cost analysis. For example, CAA inspection probabilities have been linked to the voting scores and committee memberships of congressional representatives. States with higher levels of corruption tend to have more relaxed environmental oversight (Grooms, 2015). Furthermore, inspection and enforcement probabilities have been shown to be closely tied to community characteristics like political activism, income, education, voter turnout, and environmental group membership, particularly influencing state-level interventions (Earnhart, 2004; Kim et al., 2019).

This section documented the multifaceted nature of the EPA's inspection processes under the CAA. It becomes evident that while there are stringent guidelines dictating certain inspections, the EPA retains significant discretion in determining the frequency and focus of its regulatory oversight. This flexibility is not only pivotal in the agency's approach to environmental regulation but also raises important questions about the effectiveness and equity of its enforcement strategies, especially in relation to environmental justice.

II. Environmental Justice in the US

The concept of environmental justice emerged in the late 20th century, driven by the realization that environmental burdens were often unequally borne by marginalized and low-income communities. The movement gained prominence in the United States with key events like the 1982 protest against a hazardous waste landfill in Warren County, North Carolina, a predominantly

African-American community. See Mcgurty (2000) for a detailed analysis of the emergence of the environmental justice movement.

Today, the academic discourse on environmental justice identifies two key dimensions: distributive and procedural (Rawls, 1991; Banzhaf et al., 2019).[7] Specifically, distributive justice focuses on investigating the existence of disparities in exposure to environmental degradation. Procedural justice examines the development and implementation of equitable processes to ensure justice or address its violation.

An extensive stream of literature focuses on distributional justice. Disparities in environmental quality across socio-demographic groups have, for example, been documented in the context of water quality levels (Andarge et al., 2024), or hazardous waste sides (Been, 1994; Gamper-Rabindran and Timmins, 2011). In the context of air pollution, Colmer et al. (2020) identify stark disparities in exposure to fine particulate matter across U.S. census tracts by race. Despite notable reductions in concentrations between 1981 and 2016 across the population, the subpopulations initially most exposed to $PM_{2.5}$ continued to be the most exposed groups in 2016. Mikati et al. (2018), Tessum et al. (2021), and Jbaily et al. (2022) further underline these findings, highlighting the persistence of a racial air pollution gap.

The existing literature on procedural justice has so far primarily focused on evaluating the role of policy interventions in reducing racial disparities in air pollution exposure. The empirical evidence is mixed. First, the literature points to a positive role played by specific environmental policies in reducing racial disparities in air pollution exposure. Hernandez-Cortes and Meng (2023) show that following the implementation of the cap-and-trade program in California, racial disparities in exposure to $PM_{2.5}$, PM_{10}, and NO_x decreased 6–10% annually over 2012–2017. Currie et al. (2023) find that areas with larger African American populations experienced more significant declines in $PM_{2.5}$ over 2000-2015, attributing over 60% of the racial convergence in pollution exposure to the CAA. While both studies effectively highlight the impact of policy changes in mitigating racial disparities, they do not sufficiently explore the procedural mechanisms within these programs that lead to the observed outcomes.

Second, the literature investigates disparities in monitoring and enforcement of environmental policies across the U.S., contingent on regional income levels. Early, Lavelle and Coyle (1992) compare environmental lawsuit outcomes of White and minority groups between 1985 and 1992. Their findings revealed a notable disparity: when it comes to initiating comprehensive cleanup efforts at contaminated sites, those located in minority areas lag 4 percent behind those in White

[7] A third dimension is recognitional justice, which seeks to identify the specific subpopulations disproportionately impacted by these environmental inequities. Research on recognitional justice primarily emerges from the fields of linguistics and law, highlighting how disparities among subpopulations are addressed in legal frameworks. Notably, studies like Blue et al. (2021) and Grant et al. (2022) explore the incorporation of equity considerations within legal texts, focusing on areas such as U.S. urban forest management plans and environmental impact assessments, respectively. These studies reveal a notable omission of recognitional justice themes in most documents, highlighting a lack of emphasis on acknowledging and addressing the needs of marginalized communities within these legal frameworks.

areas (9.9 years compared to 10.4 years). Furthermore, there is a striking 506 percent difference in fines levied under the Resource Conservation and Recovery Act, with minority sites facing significantly lower penalties (average fine of $335,566 in White areas, compared to $55,318 in predominantly minority areas).

Gray and Shadbegian (2005) offers a more nuanced view on discrimination, focusing on enforcement actions at 409 U.S. pulp and paper mills between 1985 and 1994. They argue that the primary discrepancies in enforcement are more closely associated with income levels rather than racial differences. Complementing this perspective, Shadbegian and Gray (2012) in their study of Los Angeles, Boston, Columbus, and Houston uncover evidence of regulatory enforcement disparities near socioeconomically disadvantaged groups within U.S. manufacturing plants. Their research suggests a complex interplay between regulatory enforcement and community demographics, highlighting the significance of both plant characteristics and political factors in understanding these dynamics.

Konisky (2009) presents strong evidence of reduced state regulatory enforcement in poorer counties. The research examining enforcement actions within the CAA from 1985 to 2000 demonstrates a 2 to 5 percent reduction in actions for each percentage point increase in a county's poverty level. This pattern persists for both median household income and poverty levels, highlighting notable class-based disparities in environmental law enforcement. Later, Konisky and Reenock (2018) utilize a comprehensive dataset, including the EPA's Risk-Screening Environmental Indicators model, to assess how state regulatory agencies enforce laws in areas with varying levels of environmental risk and demographic profiles. The study finds that while state agencies focus more on high-risk areas, they tend to be less punitive in Hispanic communities, independent of the risk levels. The existing literature reveals a common limitation: the majority of studies are constrained by their geographical scope or temporal horizon. This restricts the generalizability of findings and the ability to draw comprehensive conclusions about the effectiveness and equity of environmental policy enforcement over time and across different locations.

To explain the disparities observed in regulatory enforcement, the literature identifies two possible explanations: (i) weak political mobilization within low-income and minority communities (Hamilton, 1995; Boone and Modarres, 1999), or (ii) the presence of intentional discrimination (Reskin, 2012).

In summary, the current literature points to a reduction in racial disparities in air pollution exposure over the recent decades, coinciding with the implementation of key environmental policies in the U.S., such as the CAA and the Californian cap-and-trade program. However, disparities in policy enforcement persist, with economically disadvantaged areas experiencing less rigorous implementation. This evidence prompts inquiries into the true efficacy of the CAA in ensuring environmental justice and its direct contribution to the observed reduction in racial disparities. Our paper addresses this gap by examining the EPA's regulatory practices, specifically air pollution inspections, to assess their role in promoting environmental justice.

III. Empirical Approach

A. Data Set Generation

Matching geographic coordinates, we merge six publicly available datasets to construct a balanced county-year panel that encompasses air quality, climate, socio-demographic and economic factors, as well as environmental monitoring activities by the EPA. The final dataset spans 3,014 counties across the contiguous U.S. over the 2000-2018 horizon.[8] To the best of our knowledge, this compiled dataset constitutes the most extensive aggregation of information within an environmental auditing context to date.

The core of our data comes from the EPA's Integrated Compliance Information System for Air (ICIS-AIR), which replaced the Air Facility System in 2014 as the primary database for EPA-regulated air emissions facilities (Environmental Protection Agency, 2013). This dataset provides exhaustive information on the compliance status and history of stationary air pollution sources, including power plants and factories. It also includes details on historic inspection dates, outcomes, and subsequent compliance costs. A total of 251,829 facilities are covered in our dataset.

We rely on two sources of fine particulate matter ($PM_{2.5}$) concentration data, including both remote-sensed data from Hammer et al. (2020) and ground-level monitor data from the EPA's Air Quality System (AQS) (Environmental Protection Agency, 2024). Additionally, we incorporate key climate data, such as wind speed and temperature, sourced from NASA's MODIS satellite program (Huffman et al., 2019; Wan et al., 2021).

We gathered detailed county-level demographic and racial composition data by merging information from the UN (WorldPop, 2020) with annual census data (U.S. Census Bureau, 2018). Income data is sourced from the IRS (Internal Revenue Service, 2024) and adjusted using the Consumer Price Index (CPI) (Bureau of Labor Statistics, 2024) to account for inflation over time. To explore potential mechanisms behind environmental audit patterns, our dataset is enhanced with political donation data from the Database on Ideology, Money in Politics, and Elections (DIME) (Bonica, 2023), alongside protest activity metrics from the Global Database of Events, Language, and Tone (GDELT) (Leetaru and Schrodt, 2013).

B. Estimation Strategy

Over the last decades, the United States has experienced a continuous and notable trend toward increased racial and ethnic diversity (see Panel A in Figure 1). This process has been driven

[8] Appendix A provides an overview of the variable defintions. Additionally, Appendix B offers a detailed description of the data sources and the data set generation process. County-level summary statistics are presented in Table A-3.

by multiple, overlapping influences. First and foremost, a consistent influx of immigrants from regions with large non-White populations outside of the U.S. has played a significant role in altering the demographic landscape (Perez and Hirschman, 2009). Additionally, higher birth rates among non-White communities, coupled with advancements in healthcare and increased access to education, have led to natural population growth within these groups. The prevalence of interracial marriages and relationships has also contributed to this diversity, with individuals of mixed racial backgrounds adding to the numbers of the non-White population (Lee and Bean, 2004). Additionally, changes in the way individuals identify racially, with more people embracing their non-White heritage, have influenced this demographic shift (Stokes-Brown, 2009; Liebler et al., 2017). Lastly, the younger demographic profile of non-White populations, compared to their White counterparts, has contributed to their overall population increase over the past two decades (Johnson and Lichter, 2016). Collectively, these factors underscore the complex dynamics driving the demographic evolution of the United States towards greater racial and ethnic diversity.

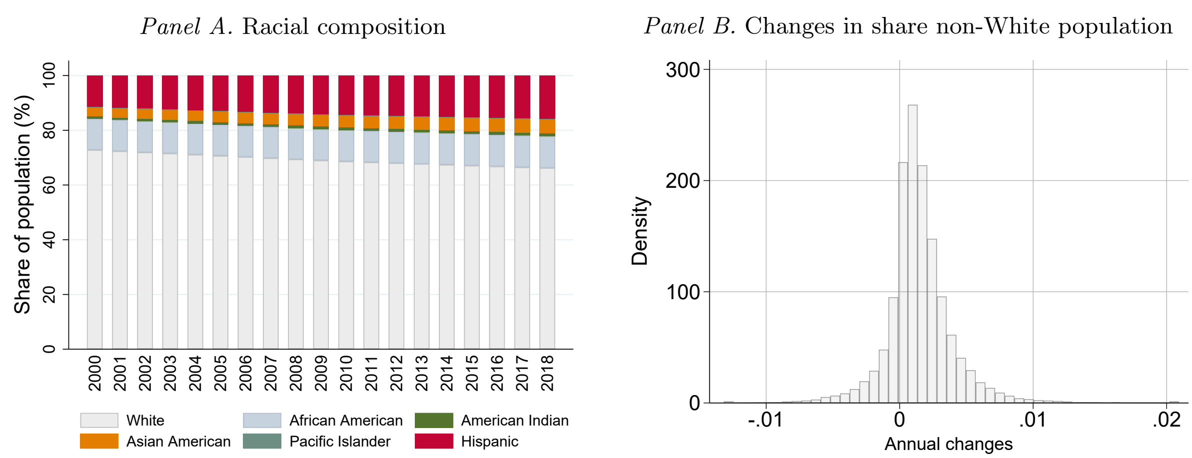

Figure 1 – U.S. Racial composition and county-level annual changes in the share of the non-White population, 2000 - 2018.

Notes: This figure presents the racial composition of the U.S. population over the 2000-2018 horizon, relying on national-level information from the U.S. census (Panel A). Panel B illustrates the distribution of annual county-level changes in the share of the non-White population over 2000-2018, restricted to the 3,014 counties in our sample.

Panel B in Figure 1 portrays a right-skewed distribution of annual county-level changes in the proportion of the non-White population spanning the years 2000 to 2018. Consistent with the trends observed in Panel A, which indicates a steady rise in the proportion of the non-White population, the annual changes at the county level depicted in Panel B exhibit relatively modest magnitudes, predominantly below the threshold of 1%. We leverage this variation in the racial composition of U.S. counties over time in our empirical identification strategy. Namely, we employ a difference-in-differences (DiD) estimation, where the event type we examine is a first jump upward in the annual share of the non-White population in a county. As counties experience changes in their racial composition at different points in time (see Figure 3), we explore this variation with a staggered DiD approach as outlined by Sun and Abraham (2021).

The staggered DiD methodology involves comparing changes in counties that have experienced a jump with changes in counties that have not yet experienced it or never do so over the study period. Recent advancements in DiD research highlight issues encountered when relying on OLS estimations to aggregate heterogeneous treatment effects (Borusyak et al., 2024; Rambachan and Roth, 2023). To address such concerns, Sun and Abraham (2021) apply differential weights to achieve a balanced representation of treated groups in the analysis, thereby addressing potential disparities between treated and control units and enhancing the estimator's accuracy.[9] Our baseline specification can be formulated as:

$$Y_{it} = \Sigma_{k=-18}^{-2}\beta_k \times J_{ik} + \Sigma_{k=0}^{18}\beta_k \times J_{ik} + X_{it}'\Gamma + \gamma_i + \theta_t + \epsilon_{it}, \tag{1}$$

where Y_{it} is the outcome variable of interest in county i and year t. Our focus lies on EPA's environmental auditing activities and, thus, relies on the share of inspected plans as our primary outcome variable. J_{ik} is a dummy indicator equal to 1 for the cohort of counties that experience a jump within k periods relative to the event year. X_{it}' is a vector of time and county-varying covariates, such as income, population, and population-weighted $PM_{2.5}$ concentrations. γ_i and θ_i are county and calendar year fixed effects, respectively. ϵ_{it} denotes the error term clustered at the county level.

In our baseline specification, we define a jump as an increase of 0.5 percentage points or more in the share of the non-White population of a county over consecutive years. We also examine thresholds ranging from 0.05 to 1 percentage point to test the robustness of our findings across varying levels of demographic change. This approach allows us to explore whether the intensity of the demographic shift correlates with the magnitude of the observed effects on environmental monitoring activities.

Figure 2 illustrates the distribution of yearly racial demographic changes, showcasing the median and 95% confidence interval (Panel A). Counties that experienced a jump of at least 0.5 percentage points in a specific year are denoted in red, while those without a jump are depicted in blue. The distributions exhibit consistent patterns across time. Panel B illustrates the number of counties experiencing the jump over time. Approximately one-third of all counties undergo such a change during our estimation horizon. Between 2001 and 2018, the number of counties

[9]The weights, denoted as ω_{it}, are derived from logistic regression models that estimate propensity scores for control units. In our setting, for a given county i in year t, the weight ω_{it} for each control unit is derived through the estimation of the probability of experiencing a jump, conditional on the observed covariates up to that point in time. These probabilities (propensity scores) are calculated via a logistic regression model: $P(T_{it} = 1|X_{it}) = \frac{e^{(X_{it}\beta)}}{1+e^{(X_{it}\beta)}}$ where T_{it} indicates whether county i experienced a jump by year t, and X_{it} represents the vector of pre-jump covariates for county i in year t, with β being the vector of coefficients to be estimated. The weights ω_{it} are then inversely proportional to the propensity score for the control units, thereby up-weighting the counties less likely to experience and creating a balanced representation of the group where jumps occur.

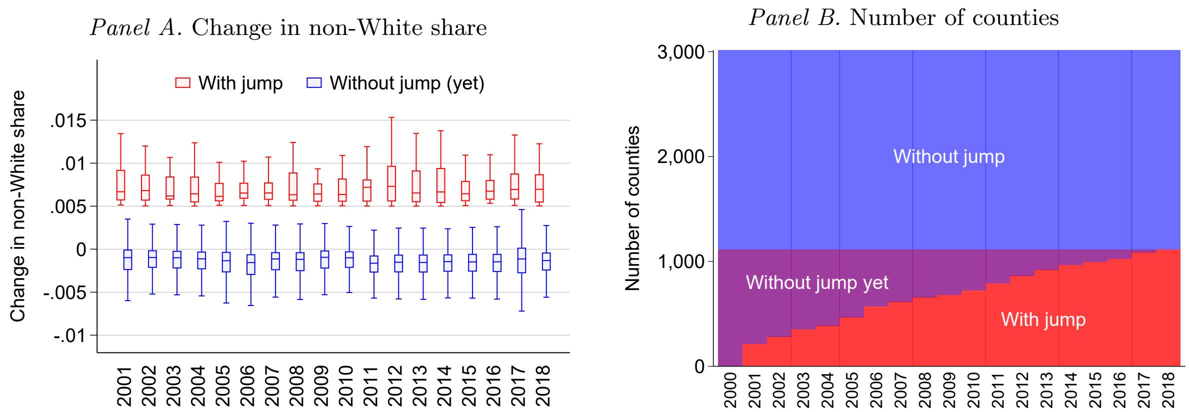

Figure 2 – Changes in the share of the non-White population and number of counties with a jump over time.

Notes: This figure plots the annual county-level change in the share of the non-White population (Panel A) and the number of counties that experience a jump of at least 0.05 percentage points in the share of the non-White population over 2000 - 2018. The data pertains to the 3,014 counties included in our sample.

experiencing a jump gradually increases from 214 to 1,113, with no single year exhibiting a disproportionately high number of jumps. This consistent pattern indicates that the observed demographic changes are not clustered in specific periods, alleviating concerns that particular years could unduly influence the results.

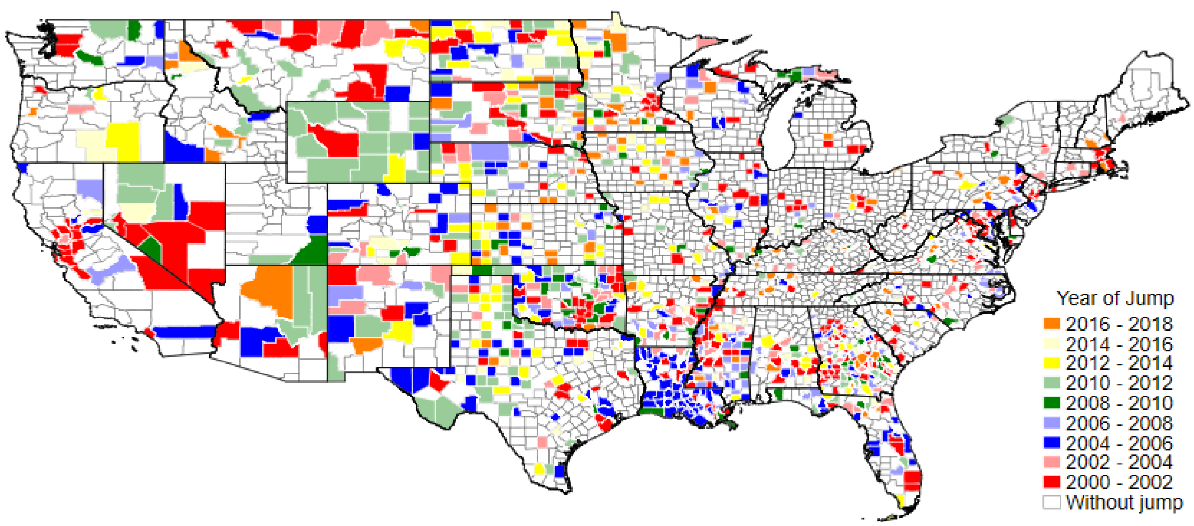

Figure 3 – Spatial distribution of counties with and without jumps in the share of the non-White population across time.

Notes: This figure illustrates the spatial distribution of all U.S. counties with and without jumps in our sample. Counties that have experienced a jump (i.e., an increase of at least 0.5 percentage points in the share of the non-White population) during 2000-2018 are marked in color. Counties that have never experienced a jump over our study period are colored white.

Panel A. share of the non-White population

Panel B. Population size

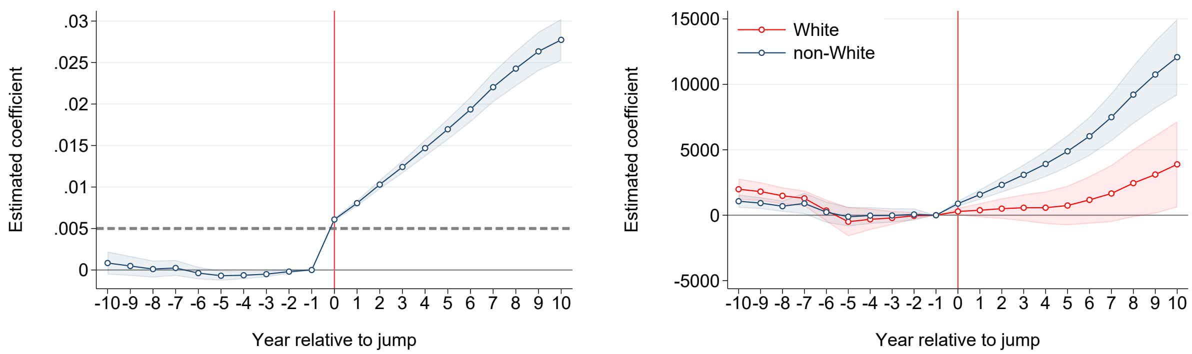

Figure 4 – Changes in racial composition and population size following a jump in the share of the non-White population.

Notes: This figure displays the estimated coefficients of the model in Equation (1), where the dependent variable is the share of the non-White population (Panel A) or the size of the White or non-White population (Panel B). The jump is defined as an increase by 0.5 percentage points or more in the annual share of the non-White population of a county. All models include county and year fixed effects. Standard errors are clustered at the county level. The vertical red line delineates the pre- and post-jump periods. See Table A-1 for variable definitions.

In Figure 4, we scrutinize the assumption of parallel trends that underpins our identification strategy. Panel A illustrates a flat trend in the share of the non-White population prior to the jump. The consistent proximity of the estimated coefficients to zero in the pre-jump period indicates that any subsequent deviations from this baseline can be credibly attributed to the jump. Moreover, after experiencing a positive jump in the share of the non-White population, counties exhibit a sustained increase in this demographic group, albeit at a reduced rate. This observation underscores the notion of an absorbing treatment, where counties remain permanently affected by the demographic shift and do not revert to pre-jump levels of non-White population. Figure A-3 in the Appendix shows that the jump in the share of the non-White population is driven almost exclusively by African Americans.

Panel B in Figure 4 assesses changes in population size following a jump in the share of the non-White population, disaggregated by White and non-White populations. The event study figure shows that the parallel trends assumption holds for both the White and non-White populations prior to the jump. Furthermore, in the period following the jump, the population size exhibits an ascending trajectory driven by the non-White demographic segment, contrasting with the relatively stable trend observed within the White population throughout the entirety of the decade. This is noteworthy, as any changes detected will be linked to an increase in the size of the non-White population (and its share in the total population) without being confounded by changes in the size of the White population.

Next, we investigate the Stable Unit Treatment Value Assumption (SUTVA). SUTVA requires that the treatment received by one unit does not affect the outcomes of other units. In other words, there should be no spillover effects or interference between units, and each unit's treatment assignment should be independent of the treatments assigned to other units. In our study, adherence to the SUTVA assumption hinges on the independence of changes in the share of the non-White population across different counties. This assumption is compromised if shifts in the racial composition of one county are influenced by migration patterns from neighboring counties, leading to a scenario where an increase in non-White population in one county coincides with a decrease in another. To probe the impact of such potential inter-county migration, particularly within proximate areas, we examine how the share of the non-White population in a given county responds when any of its direct neighboring counties undergoes a positive shift. As depicted in Figure 3, counties that undergo demographic shifts are geographically scattered across the contiguous United States and occur over various time periods. This dispersion suggests that these demographic jumps are not concentrated regionally or temporally but tend to occur sporadically and heterogeneously throughout the country. To investigate the issue further, we perform a placebo test to estimate the changes following a jump in the share of the non-White population in a neighboring county. As depicted in Figure 5, the DiD estimates provide evidence that jumps in the share of the non-White population in one county do not exert a discernible influence on neighboring counties. Finally, in Section IV, we explore the potential presence of spillover effects on our primary outcome variable. Our analysis reveals no evidence of such effects, thereby affirming the robustness of the SUTVA in our analysis.

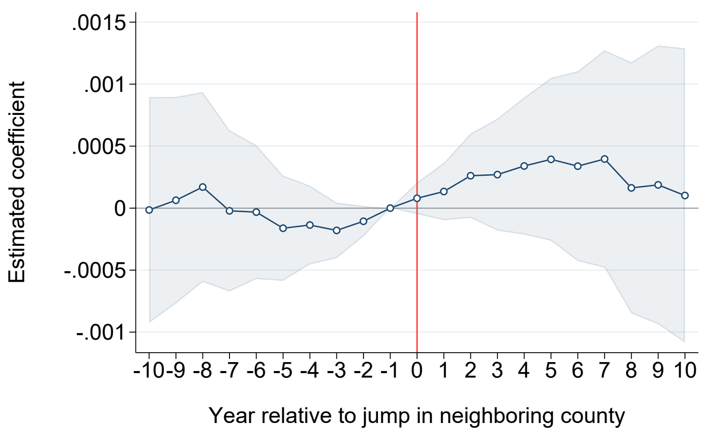

Figure 5 – Changes in the share of the non-White population following jumps in neighboring counties.

Notes: This figure displays the estimated coefficients of the model in Equation (1). The dependent variable is the annual share of the non-White population in counties neighboring those that experience a jump. The jump in a neighboring county is defined as a 0.5 percentage point increase in the share of the non-White population. The model includes county and year fixed effects, and standard errors are clustered at the county-level. The vertical red line delineates the pre- and post-jump periods. See Table A-1 for variable definitions.

IV. Results

To investigate the relationship between racial demographic changes and EPA monitoring activities, we focus on the annual share of inspected plants in a county. This measure directly reflects the extent of environmental monitoring conducted by regulatory agencies like the EPA. Changes in this share following demographic shifts can illuminate potential disparities in environmental justice. Additionally, it enables comparisons across counties and time periods, facilitating a comprehensive assessment of monitoring practices.

Figure 6 displays the estimated coefficients for the DiD model in Equation (1), where the event time is defined as the first occurrence of a positive jump by 0.5 percentage points or more in the share of the non-White population of a county. We find that inspection rates exhibit parallel trends in the decade preceding the demographic shift, and no anticipation of the jump, as all coefficients for the pre-jump period are not statistically different from zero. In contrast, in the years subsequent to the demographic shift, there is a notable decrease in the proportion of inspected plants in counties that underwent the shift. Noteworthy, Figure 6 illustrates that the decline in the share of inspected plants is sudden and aligns closely with the timing of the racial demographic jump, persisting throughout the entirety of the first decade following the shift.

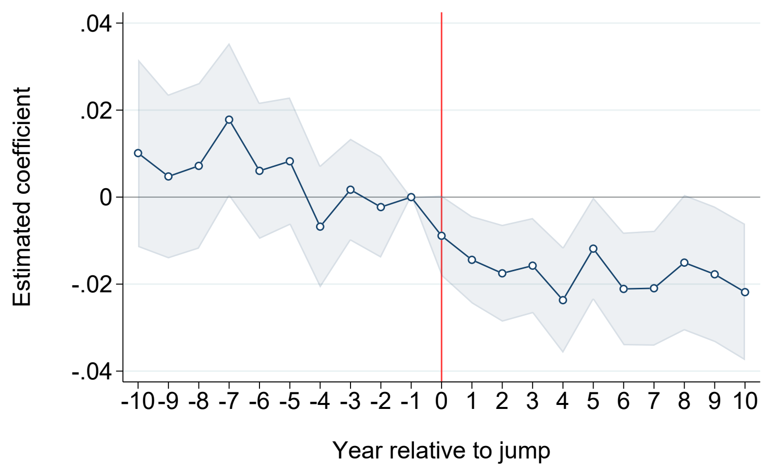

Figure 6 – Changes in the share of inspected plants following a jump in the share of the non-White population.

Notes: This figure displays the estimated coefficients of the model in Equation (1). The dependent variable is the annual county-level share of inspected plants. The jump is defined as the first increase by 0.5 percentage points or more in the share of the non-White population in a county in two consecutive calendar years. The model controls for gross income (CPI adjusted, in log), population size (log), $PM_{2.5}$ concentrations (population-weighted), and includes county and year fixed effects. The standard errors are clustered at the county level. The confidence interval depicted in light gray corresponds to the 95% level. The vertical red line delineates the pre- and post-jump periods. See Table A-1 for variable definitions.

To further investigate the observed patterns, we verify potential heterogeneity across counties with and without ground-level monitors. Table 1 presents the results of estimating Equation (1), where, post-estimation, we group the event time dummies into pre- and post-jump periods, reflecting the average effect over periods of five years before and five years after the jump, respectively.[10] We find further evidence supporting the presence of parallel trends in the share of inspected plants prior to the racial demographic jump, irrespective of whether counties have ground-level $PM_{2.5}$ monitors or not. In contrast, in the 5-year period following the jump, the share of inspected plants significantly decreases in counties that experience a racial shift relative to those that do not. The effect size amounts to a decrease of 1.6 percentage points (p-value < 0.001) in the full sample (column 1). This corresponds to an 8.9% percent decrease in the share of inspected plants relative to the period prior to the jump. An effect of similar magnitude and significance is observed when considering separately counties without and with $PM_{2.5}$ monitors (columns 3 and 5). There, the estimated effect sizes are of -1.6 percentage points (p-value$= 0.002$) and -2 percentage points (p-value$= 0.018$), amounting to an 8.8% and 10.8% decrease in the share of inspected plants, respectively. Note also that the coefficients of the pre-jump and post-jump periods are statistically different from each other across all model specifications, indicating a regime shift between the two periods.

Spillovers. To further validate our research design and assess the adherence to the SUTVA condition, we investigate potential spillover effects from counties that experience a jump onto neighboring counties. With this aim, we include an additional control variable in the DiD models to account for whether any neighboring county experienced a jump in a given year and, thereby, measure potential contamination of the control group.[11] The results of this estimation are presented in columns 2, 4, and 6 of Table 1. We find that the pre- and post-jump coefficients are unaffected when accounting for jumps in neighboring counties. Additionally, the coefficient associated with neighboring jumps is nearly zero and lacks statistical significance, indicating the absence of spillover effects.

A. Robustness.

Threshold for treatment definition. In our baseline specification, a level of 0.5 percentage points increase in the share of the non-White population is used to define the racial demographic jump. We now vary the definition of the jump, considering various thresholds for the increase in the share of the non-White population. Figure 7 provides the estimation results allowing cutoffs to range between 0.05 and 1 percentage points, in 0.05 steps. Independent of the jump level, the parallel trends assumption is satisfied for the pre-jump period. Moreover, in the post-jump period, the share of inspected plants decreases significantly in counties that experience racial changes, a pattern that is consistent across all threshold definitions at and above 0.2 percentage points. Additionally, the results suggest that jumps of higher intensity are followed by more pronounced reductions in inspection shares.

[10] As our dataset spans 2000 - 2018, all our models include 18 event time years before the jump and 18 after the jump. However, when discussing the results, our analysis puts emphasis on the average effects observed over the 5-year horizon before the jump (event time years -6 to -2) and the 5-year horizon after the jump (event time years for 0 to 4).

[11] We define neighboring counties as those that share a geographic border.

Table 1 – Changes in environmental auditing following a jump in the share of non-White population.

	Dependent variable: Share of inspected plants					
	All counties		Without monitors		With monitors	
	(1)	(2)	(3)	(4)	(5)	(6)
Pre-jump	0.001	0.001	-0.000	-0.000	0.007	0.008
	(0.005)	(0.005)	(0.006)	(0.006)	(0.012)	(0.012)
	[0.798]	[0.802]	[0.969]	[0.946]	[0.539]	[0.504]
Post-jump	-0.016***	-0.016***	-0.016***	-0.016***	-0.020**	-0.021**
	(0.004)	(0.004)	(0.005)	(0.005)	(0.008)	(0.008)
	[0.000]	[0.000]	[0.002]	[0.002]	[0.018]	[0.013]
Neighbor jump		-0.000		-0.003		0.005
		(0.002)		(0.002)		(0.003)
		[0.878]		[0.186]		[0.114]
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	57,256	57,256	40,993	40,993	16,263	16,263
Adj. R^2	0.609	0.609	0.598	0.598	0.636	0.637
Diff. Post - Pre	-0.017***	-0.017***	-0.016***	-0.015***	-0.027**	-0.029**
p-value diff.	[0.000]	[0.000]	[0.002]	[0.002]	[0.018]	[0.013]
Pre-jump mean	0.179	0.179	0.181	0.181	0.186	0.186
Relative effect size	-0.089	-0.089	-0.088	-0.088	-0.108	-0.113

Notes: This table presents estimates of Equation (1) from the main text. The dependent variable is the annual county-level share of inspected plants. All models include county and year fixed effects, as well as controls for gross income (CPI adjusted, in log), population size (in log), and remote sensed population-weighted $PM_{2.5}$ concentrations. Additionally, models in columns 2, 4, and 6 include a dummy variable capturing whether any neighboring county incurred a jump in their share of the non-White population in a given year. The pre-jump coefficient refers to the estimated difference in outcome levels between the treatment and control counties pertaining to the average over the event years -6 to -2 relative to the event year -1. The post-jump coefficient refers to the estimated difference in outcome levels between the treatment and control counties pertaining to the average over the event years 0 to 4 relative to the event year -1. The pre-jump mean refers to the average value of the dependent variable in event year -1 across counties experiencing a jump in event year 0. The relative effect size is computed as the ratio between the post-jump coefficient and the pre-jump mean. Standard errors are clustered at the county level and are displayed in rounded parentheses. P-values are presented within square brackets. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1. See Table A-1 for variable definitions.

The findings underscore several key points. Firstly, our baseline specification demonstrates robustness, mitigating concerns about spurious correlations driving the observed effects. Secondly, the correlation analysis reveals a significant relationship between the magnitude of demographic shifts and the extent of decrease in inspected plants, further affirming the strength of this association. Specifically, a linear regression indicates that for every 1 percentage point increase in the share of the non-White population, the share of inspected plants decreases by 0.036 percentage points (p-value < 0.001). Lastly, these results emphasize the necessity of accounting for the scale of demographic changes when assessing the procedural environmental justice of existing monitoring programs.

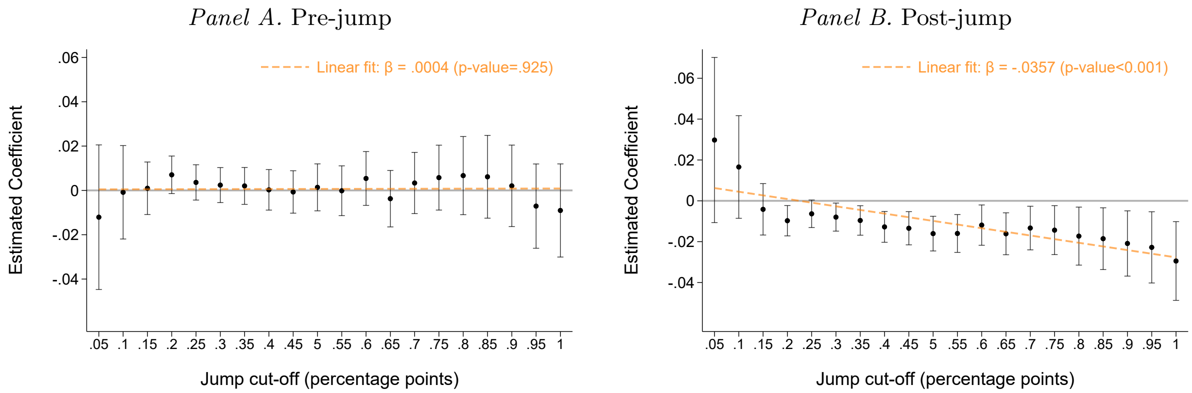

Figure 7 – Changes in the share of inspected plants to a jump in the share of the non-White population for different cutoff levels in defining the racial composition jump.

Notes: This figure presents estimates of Equation (1) from the main text. The dependent variable is the share of inspected plants in a county in a year. Panels A and B present the estimated coefficients for the pre- and post-jump period, respectively. The x-axis captures the cutoff for defining the racial demographic jump in steps of 0.05 percentage points. The estimated coefficients correspond to the average effect in the five-year pre-jump period (grouping event years -6 to -2) and to the average effect in the five-year post-jump period (grouping event years 0 to 4). The orange line depicts a linear fit of the coefficients against the cutoff levels. All models control for gross income (CPI adjusted, in log), population size (in log), $PM_{2.5}$ concentrations (population-weighted), and include county and year fixed effects. The standard errors are clustered at the county level. The confidence intervals correspond to the 95 level. See Table A-1 for variable definitions.

Excluding counties that never experience a jump. The staggered DiD analysis used in our baseline specification relies on comparing outcomes in counties that experience a jump with those in counties that have not yet experienced such a change or have never experienced one throughout our study period. As a robustness test, we now conduct the DiD estimation excluding counties that have never experienced a demographic jump from the analysis. Relying only on a control group that consists of not-yet-treated counties aims to increase comparability between treated and control units and reduce concerns related to the presence of confounding factors. The estimation results are presented in Appendix Figure A-4. While the effects appear slightly less pronounced, we find robustness to the effects observed in our main specification, both in terms of direction and significance. Specifically, we observe an effect size of -0.13 percentage points (p-value=0.004) for the five-year period after the jump.

Multiple jumps. Our identification strategy thus far defined the treatment as the first time that a county incurs a jump in the share of the non-White population. However, it is possible that the racial demographic changes occur repeatedly within the same county, *i.e.* that a county has more than just one jump. Further concerns may arise regarding the possibility that counties may have experienced jumps prior to 2000, the starting year of our dataset. To address these issues, we allow the treatment definition to switch on and off and estimate dynamic treatment effects following the methodology proposed in De Chaisemartin and d'Haultfoeuille (2020). Appendix Figure A-5 displays the estimated coefficients, proving the robustness of our main results to this alternative treatment definition.

Increases in the share of the White population. We further investigate whether changes in the share of inspected plants also occur when counties experience an increase in the share of the *white* population. This control scenario serves as a test to determine if the effects observed so far are specifically associated with increases in the non-White population or merely reflect a general response to demographic shifts. For this analysis, we define a jump as an increase by 0.5 percentage points or more in the share of the white population of a county. Appendix Figure A-6 displays the estimated coefficients. We find that an increase in the share of the White population is not followed by changes in the share of inspected plants in a county. The contrast in inspection responses to increases in the share of white versus non-White population shows that our main findings are specific to increases in the non-White population.

V. Mechanisms

In this section, we investigate potential mechanisms that may elucidate the changes in monitoring activities observed in the period subsequent to shifts in racial demographics. We delve into two primary dimensions: environmental factors and political activism, and civil discourse.

A. Environmental Factors

A jump in the racial composition of a county might coincide with changes in environmental factors, potentially influencing the frequency and intensity of EPA's monitoring activity. In particular, counties that undergo a jump in the share of the non-White population could experience an improvement in air quality. Consequently, this could lead to a diminished necessity for environmental monitoring, manifesting as a reduction in the share of inspected plants.

To investigate this hypothesis, we employ a staggered DiD model, utilizing annual $PM_{2.5}$ concentrations as the outcome measure while incorporating county and year-fixed effects. Additionally, we include controls for income levels, population size, and climate variables such as temperature, precipitation, and wind speed. Table 2 displays the estimated coefficients, wherein we consider three measures of $PM_{2.5}$ concentrations: spatial averages of satellite measurements, population-weighted averages of satellite measurements, and ground-level monitor measurements (columns 1-3). Across all measures, the parallel trends assumption is satisfied for the pre-jump period. Moreover, we find no evidence of changes in $PM_{2.5}$ concentrations following the racial demographic shifts.

We complement the analysis by examining potential changes in the number of federally reportable violators (FRV) and high priority violators (HPV) as designated by the EPA (columns 4 and 5 in Table 2). Consistent with the absence of changes in $PM_{2.5}$ concentrations, our findings indicate no evidence of alterations in the number of violators following a jump in the share of the non-White population.

Furthermore, we investigate changes in the nonattainment designation of counties, as indicated by two measures. First, we utilize the official nonattainment designation received by counties, as assigned by the EPA, based on $PM_{2.5}$ concentration readings from ground-level monitors. Second, given that only 856 out of 3,014 counties in our sample have $PM_{2.5}$ monitors and thus are subject to a potential official nonattainment designation, we calculate an "implied" measure of nonattainment for all counties in our sample based on a comparison of satellite $PM_{2.5}$ readings with official standards.[12] The DiD estimates for the two measures of nonattainment are displayed in columns 6 and 7 of Table 2. The parallel assumption of pre-trends is satisfied for both measures. Moreover, we find that, among counties with $PM_{2.5}$ monitors, the likelihood of being officially assigned in nonattainment increases on average by 2.1 percentage points (p-value=0.035) in the post-jump period. These effects are observed despite the fact that $PM_{2.5}$ monitor readings do not change (see again column 3). Finally, when considering the implied measure of nonattainment, we find no evidence that $PM_{2.5}$ concentrations are more likely to surpass official standards following jumps in the share of the non-White population.

In summary, our analysis rejects the hypothesis that the observed reduction in the share of inspected plants following a positive jump in the share of the non-White population can be explained by improvements in air quality and a reduced need for monitoring activities by the EPA. Furthermore, despite the absence of discernible changes in $PM_{2.5}$ concentrations on the county level or the number of violators, our findings indicate that counties with monitors are more prone to receiving a nonattainment designation by the EPA if they have experienced a demographic shift in the non-White population. This is noteworthy, as the nonattainment designation should prompt the EPA to engage in more intense monitoring activities rather than less.

[12] Appendix Figure A-2 provides a map of the contiguous U.S., featuring details regarding average county-level $PM_{2.5}$ concentrations and monitor placement.

Table 2 – Changes in $PM_{2.5}$ concentrations, compliance, and income following a jump in the share of non-White population.

	Dependent variable							
	$PM_{2.5}$ concentrations			Number violators		Nonattainment		Income
	Satellite	Pop. weighted	Monitor	FRV	HPV	Official	Implied	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pre-jump	-0.036	-0.038	0.003	0.008	-0.075*	-0.000	0.002	0.166
	(0.027)	(0.027)	(0.083)	(0.070)	(0.042)	(0.016)	(0.002)	(0.106)
	[0.185]	[0.160]	[0.969]	[0.908]	[0.076]	[0.997]	[0.348]	[0.117]
Post-jump	0.002	0.013	-0.032	-0.068	0.059	0.021**	-0.005	-0.174
	(0.025)	(0.025)	(0.073)	(0.055)	(0.050)	(0.010)	(0.003)	(0.117)
	[0.938]	[0.592]	[0.657]	[0.219]	[0.238]	[0.035]	[0.137]	[0.135]
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	57,237	57,237	16,263	57,237	57,237	16,263	57,237	57,262
Adj. R^2	0.890	0.880	0.801	0.557	0.766	0.421	0.207	0.866
Diff. Post - Pre	0.038	0.052	-0.035	-0.076	0.134	0.021**	-0.006	-0.340
p-value diff.	[0.938]	[0.592]	[0.657]	[0.219]	[0.238]	[0.035]	[0.137]	[0.135]
Pre-jump mean	7.802	8.222	9.617	0.492	0.747	0.011	0.006	3.261
Relative effect size	< 0.001	0.002	-0.003	-0.138	0.440	1.909	-0.833	-0.053

Notes: This table presents estimates of Equation (1) from the main text. Each column corresponds to a different outcome variable. $PM_{2.5}$ concentrations are measured in $\mu g/m^3$ and income in million USD. All models include county and year fixed effects. Models (1)-(7) include controls for gross income (CPI adjusted, in log), population size (in log), average annual precipitation, average annual temperature, and average annual wind speed. Model (8) controls for population size (in log). The Pre-jump coefficient refers to the estimated difference in outcome levels between the treatment and control counties pertaining to the average over the event years -6 to -2 relative to the event year -1. The Post-jump coefficient refers to the estimated difference in outcome levels between the treatment and control counties pertaining to the average over the event years 0 to 4 relative to the event year -1. The pre-jump mean refers to the average value of the dependent variable in event year -1 across counties experiencing a jump in event year 0. The relative effect size is computed as the ratio between the post-jump coefficient and the pre-jump mean. Standard errors are clustered at the county level and are displayed in rounded parentheses. P-values are presented within square brackets. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1. See Table A-1 for variable definitions.

B. Political Activism and Civil Discourse

The EPA conducts inspections at facilities under the primary mandate of safeguarding air quality levels in line with the CAA. Besides such considerations, the EPA has the right to account for the vulnerability of populations near polluting facilities in its inspection targeting process in line with environmental justice principles (Environmental Protection Agency, 2002). Indeed, the existing literature on procedural environmental justice brings evidence that the intensity of EPA's monitoring activities can be influenced by community characteristics (Earnhart, 2004; Kim et al., 2019). However, the evidence points to reduced monitoring and enforcement activities in regions with vulnerable populations.

In this section, we investigate whether a shift in the racial demographic of counties is associated with changes in key community characteristics, such as income levels and political activism, which might explain the observed drop in EPA's monitoring activity of polluting plants.

B.1 Income

Past studies have shown that monitoring and enforcement of environmental policies across the U.S. hinge on regional income levels (Konisky, 2009; Konisky and Reenock, 2018), whereby poorer areas are subject to reduced regulatory enforcement. Such patterns could be explained by weak political mobilization within low-income communities (Hamilton, 1995; Boone and Modarres, 1999).

To account for such considerations, we test whether the racial demographic shifts that are observed in U.S. counties have been accompanied by changes in income levels. Using total gross annual income as the dependent variable, we estimate the DiD model in Equation (1), controlling for the population size and including county and year fixed effects. The estimates are displayed in column 8 of Table 2. Importantly, we find that the parallel trends assumption holds prior to the occurrence of the jump. Moreover, in the post-jump period, we find no evidence of differential changes in income levels among counties that experienced the racial jump and those that did not.

B.2 Political Stronghold

As an initial step to elucidate the potential influence of political activism on the decline in EPA's inspection activity subsequent to racial demographic shifts, we examine heterogeneity by political stronghold. Namely, by political stronghold, we refer to U.S. states where a particular political party has a dominant influence over electoral outcomes and governance. To this aim, we distinguish between Democratic, Republican, and swing states and estimate the DiD model with the share of inspected plants as the dependent variable for each stronghold subsample. Figure 8 presents the estimated coefficients, demonstrating that a drop in the share of inspected plants following the jump in the share of the non-White population is driven by Republican stronghold states. Here, in the first five years following the jump, the share of inspected plants is reduced on average by 1.9 percentage points (p-value< 0.001). The drop coincides with the timing of the racial shift and remains persistent over the first decade after the jump. In contrast, we find no evidence that the share of inspected plants is affected by the racial demographic jump in Democratic stronghold states (effect size of -0.0018, p-value=0.894).[13] The findings support the hypothesis that environmental activism is more pronounced in Democratic stronghold states, thereby mitigating adjustments in environmental monitoring activities in reaction to racial demographic shifts.

[13] For swing states, the post-jump coefficient is -0.021 with p-value= 0.024; see Appendix Figure A-7.

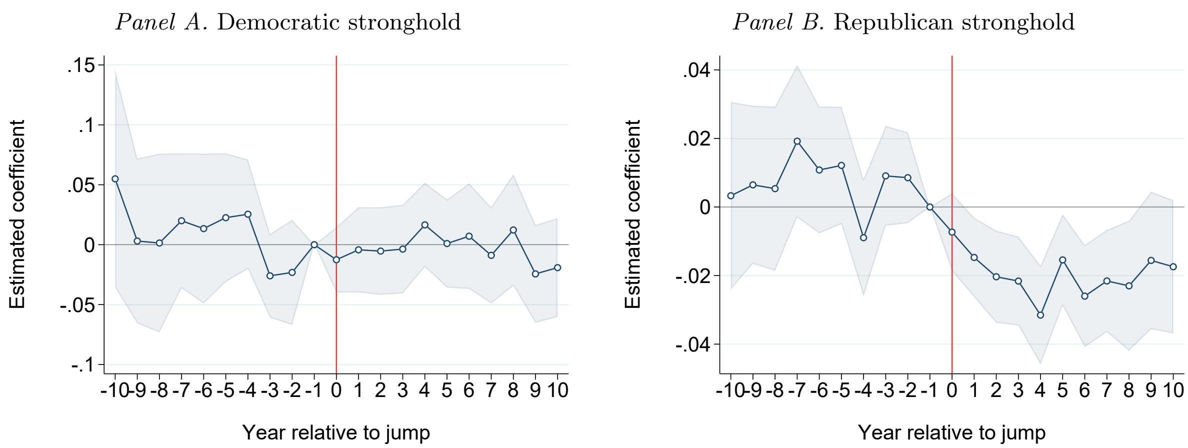

Figure 8 – Changes in the share of inspected plants to a jump in the share of the non-White population.

Notes: This figure displays the estimated coefficients of the model in Equation (1). The dependent variable is the annual share of inspected plants in a county, distinguishing between stronghold Democratic states (Panel A) and stronghold Republican states (Panel B). The list of states by stronghold classification is given in Appendix Table A-4. The jump is defined as the first increase by 0.5 percentage points or more in the share of the non-White population in a county in two consecutive years. The models control for gross income (CPI-adjusted, in log), population size (in log), and $PM_{2.5}$ concentrations (remote sensed population-weighted), and include county and year fixed effects. The standard errors are clustered at the county level. The confidence interval depicted in light gray corresponds to the 95% level. The vertical red line delineates the pre- and post-jump periods. See Table A-1 for variable definitions.

B.3 Political Donations

Next, we explore political donations as a critical avenue for political participation. Our investigation centers on two facets, whereby we study differential changes in the total amount of donations as well as in the number of unique donors following a jump in the share of the non-White population of counties.

The DiD estimates are presented in Panels A and B of Figure 9, where models include controls for income levels, population size, $PM_{2.5}$ concentrations, and county and year-by-state fixed effects.[14] We find that the total volume of donations momentarily dips following the demographic change. In the year of the racial shift, donation amounts fall on average by about 0.69 million USD (p-value=0.023), representing a 31% decrease compared to the pre-jump period (Figure 9, Panel A). However, in the following years, donation amounts quickly rebound to pre-jump levels, indicating no long-term alterations. See column 1 in Panel A, Table 3 for estimated average effects over multiple years. In stark contrast, the number of individual donors shows an abrupt and enduring decrease in the post-jump period: about 246 fewer donors contribute on average annually (p-value$<$ 0.001) during the first 5 years following the jump. The effect

[14] As data for political donations is only available biannually, the DiD event time is defined based on an increase by 0.5 percentage points or more in the annual share on non-White population in any of the two years since the last available political donations observation.

corresponds to a notable 35% decrease relative to the pre-jump period (column 1 Panel B in Table 3). The decline in the number of unique donors, despite stable donation amounts, holds significance as it suggests a consolidation of financial support within a smaller pool of contributors. This concentration may indicate a shift in the landscape of political advocacy, with fewer individuals actively engaging in supporting environmental causes.

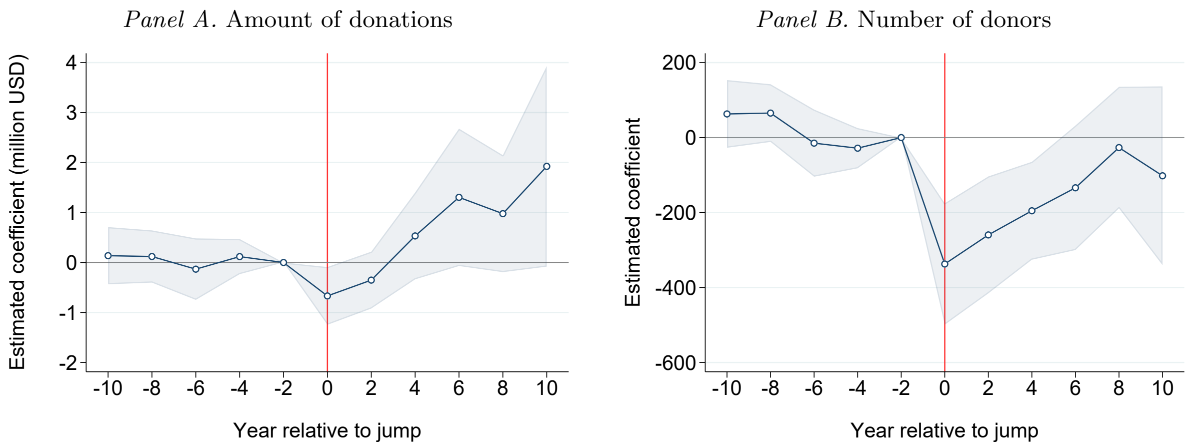

Figure 9 – Changes in political donations following a jump in the share of the non-White population.

Notes: This figure displays the estimated coefficients of the model in Equation (1). The dependent variable is the total amount of donations (in million USD) in Panel A, and the number of unique donors in Panel B. Note that political donation data is only available biannually. The jump is defined as the first increase by 0.5 percentage points or more in the share of the non-White population in a county in two consecutive years. The models control for gross income (CPI-adjusted, in log), population size (in log), and $PM_{2.5}$ concentrations (remote sensed population-weighted), and include county and year-by-state fixed effects. The standard errors are clustered at the county level. The confidence interval depicted in light gray corresponds to the 95% level. The vertical red line delineates the pre- and post-jump periods. See Table A-1 for variable definitions.

To further comprehend these findings, we differentiate between political donations made by individuals and those made by companies (columns 2 and 3 in Table 3). We find that the observed reduction in the number of unique donors can be primarily attributed to individuals. The effect size corresponds to 279 fewer donors biannually (p-value<0.001) in the post-jump period, a decrease by 41.5%. In contrast, the number of corporate donors increases by about 15.2 biannually (p-value$=0.012$) in the post-jump period, an increase by 18.6%. The withdrawal of donations by individuals compensated by the increase in corporate donations appears as a potential explanation for the reduction in the proportion of inspected plants following the racial demographic shift. This phenomenon could occur as individuals redirect their financial support away from environmental advocacy causes, possibly due to shifts in personal priorities or perceptions, while corporations, motivated by strategic interests or regulatory concerns, increase their contributions to influence environmental policy outcomes.

Lastly, we categorize donations based on the political alignment of donors (columns 4 and 5 in Table 3). Despite a brief decrease immediately after the jump, donation amounts remain unchanged on average across the political spectrum during the post-jump period.[15] However, the number of unique donors exhibits a distinct pattern of response to the demographic shift. Among left-leaning donors, there are, on average, about 305 fewer donors (p-value$<$ 0.001) during the post-jump period, representing a stark decrease of 89.8% compared to the pre-jump period. Left-leaning donors may make fewer donations following an increase in the share of the non-White population for several reasons. First, they may perceive a shift in political priorities, allocating their resources towards other pressing social or political issues that emerge with demographic changes (Miller and Krosnick, 2004). Additionally, they may feel less urgency for political activism if they believe that the increased representation of non-White populations will inherently lead to greater attention to social and environmental justice issues through other channels (Barber, 2016). Lastly, changes in the political landscape may lead left-leaning donors to feel less effective or motivated in their support, resulting in a reduction in donations (Bronars and Lott, 1997).

Among right-leaning donors, we observe a contrasting trend. On average, 41 additional donors contribute biannually (p-value$=$ 0.005) during the post-jump period, marking a 10% rise. Taken together, these results could shed light on why the proportion of inspected plants decreases following the demographic shift towards a higher share of the non-White population. The reduction in the number of unique donors, particularly among left-leaning donors, may signal a decrease in advocacy and pressure for stringent environmental regulations and monitoring activities. Conversely, the increase in donations from right-leaning donors suggests a potential shift towards reduced environmental oversight.

[15]See Appendix D for event study plots.

Table 3 – Changes in political donations following a jump in the share of non-White population.

	Donations by donor type				
	All	Company	Individual	Left-leaning	Right-leaning
	(1)	(2)	(3)	(4)	(5)
Panel A: Amount of donations					
Pre-jump	-0.007	-0.009	0.001	0.057	-0.064
	(0.191)	(0.117)	(0.122)	(0.087)	(0.127)
	[0.969]	[0.940]	[0.994]	[0.515]	[0.614]
Post-jump	-0.163	0.096	-0.259	-0.149	-0.014
	(0.302)	(0.189)	(0.169)	(0.165)	(0.181)
	[0.589]	[0.612]	[0.126]	[0.366]	[0.937]
Observations	30,124	30,124	30,124	30,124	30,124
Adj. R^2	0.839	0.842	0.739	0.838	0.722
Diff. Post - Pre	-0.156	0.105	-0.260	-0.205	0.050
p-value diff.	0.589	0.612	0.126	0.366	0.937
Pre-jump mean	2.219	1.283	0.936	1.037	1.181
Relative effect size	-0.073	0.075	-0.277	-0.144	-0.012
Panel B: Number of donors					
Pre-jump	-21.626	3.048	-24.679	-8.166	-13.460
	(33.735)	(4.105)	(32.538)	(22.079)	(16.261)
	[0.521]	[0.458]	[0.448]	[0.711]	[0.408]
Post-jump	-264.142***	15.213**	-279.335***	-305.515***	41.373***
	(70.157)	(6.049)	(71.905)	(72.103)	(14.842)
	[0.000]	[0.012]	[0.000]	[0.000]	[0.005]
Observations	30,124	30,124	30,124	30,124	30,124
Adj. R^2	0.904	0.906	0.883	0.854	0.928
Diff. Post - Pre	-242.515***	12.165**	-254.656***	-297.349***	54.833***
p-value diff.	0.000	0.012	0.000	0.000	0.005
Pre-jump mean	754.20	81.807	672.441	340.072	414.127
Relative effect size	-0.350	0.186	-0.415	-0.898	0.100

Notes: This table presents estimates of Equation (1) from the main text. The dependent variable is the total annual county-level amount of donations (Panel A) and the annual county-level number of donors (Panel B). All models include county and year-by-state fixed effects, as well as controls for gross income (CPI adjusted, in log), population size (in log), and remote sensed population-weighted $PM_{2.5}$ concentrations. Models in columns 2 and 3 distinguish between donations by companies and donations by individuals. Models in columns 4 and 5 distinguish between left- and right-leaning donors. The Pre-jump coefficient refers to the estimated difference in outcome levels between the treatment and control counties pertaining to the average over the event years -6 to -4 relative to the event year -2. The Post-jump coefficient refers to the estimated difference in outcome levels between the treatment and control counties pertaining to the average over the event years 0 to 4 relative to the event year -2. The pre-jump mean refers to the average value of the dependent variable in event year -2 across counties experiencing a jump in event year 0. The relative effect size is computed as the ratio between the post-jump coefficient and the pre-jump mean. Standard errors are clustered at the county level and are displayed in rounded parentheses. P-values are presented within square brackets. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1. See Table A-1 for variable definitions.

B.4 Public Protests

To further investigate potential shifts in individual political activism following racial demographic changes, we examine the occurrence of public protests.[16] Theoretically, an increase in the non-White population could result in changes in public protest occurrence in either direction.

[16]By public protests, we refer to all civilian demonstrations and other collective actions carried out as protests.

On one hand, a racial demographic shift might elevate protest frequency due to heightened social and political awareness among minority groups, as well as evolving perceptions of social justice and equality. On the other hand, it could lead to fewer public protests as minority representation in political institutions rises, fostering greater cooperation and dialogue among different racial and ethnic groups. Additionally, demographic shifts may alter the composition of activist groups or coalitions, potentially resulting in changes to protest strategies or priorities. Finally, shifts in social dynamics and power structures accompanying demographic changes may influence the perceived efficacy or appropriateness of protest as a means of addressing grievances, leading to a decrease in mobilization efforts.[17] Overall, changes in protest frequency could affect EPA's monitoring activities: more protests might raise awareness of environmental justice, prompting increased monitoring, while fewer protests could lead to reduced attention and monitoring by the EPA.

To explore this mechanism, we analyze data on annual county-level protests. Due to data availability constraints, we restrict our analysis to the period between 2007 and 2018, encompassing nevertheless the majority of our study period. We analyze two outcome variables, including the likelihood of a public protest occurring and the annual number of protests. The DiD estimates for both outcomes are presented in Figure 10. While the likelihood of protesting remains unaffected, we find a noticeable decline in the average annual number of protests over the five-year period following the demographic shift, accounting on average for about 15 fewer protests yearly (p-value= 0.001) in counties with a racial demographic jump. This amounts to a reduction by about 27% compared to the pre-jump year. Approximately five years after the demographic change, the frequency of protests gradually returns to the levels observed prior to the shift. This pattern suggests a temporary adjustment period in public response and activism following significant demographic changes.

In the appendix, we present further analysis regarding public protests; see Section 3. First, our analysis indicates that the intensity of protests – in terms of violence or aggressive behavior – remains unaffected by the racial demographic shift.[18] Furthermore, we investigate the portrayal of these protests by the media, focusing on both the number of newspaper articles written and the tone of news coverage. Consistent with the reduction in the number of protests, we observe a decrease in the total number of newspaper articles covering protests. In the five-year period following the jump, about 428 fewer articles (p-value=0.002) are written annually in counties

[17] Van Zomeren et al. (2008) emphasized the centrality of perceived efficacy in motivating individuals to participate in protests. Changes in the demographic composition could affect collective perceptions of efficacy within a community. Furthermore, Bursztyn et al. (2021) underline that the individual social network plays a key role. Moreover, Benson and Rochon (2004) highlight the importance of interpersonal trust in fostering protest participation. Demographic shifts might impact the levels of trust within communities, thereby affecting collective action likelihood. Additionally, van Stekelenburg and Klandermans (2013) argue that instrumentality, identity, and ideology are critical motivators for protest activity. A demographic shift could potentially dilute or fragment these motivating factors, particularly ideological alignment, reducing the overall propensity to engage in protests.

[18] The GDELT dataset provides information on the intensity of public protests as measured according to the Goldstein Scale. See Table A-1 for more details on variable definitions.

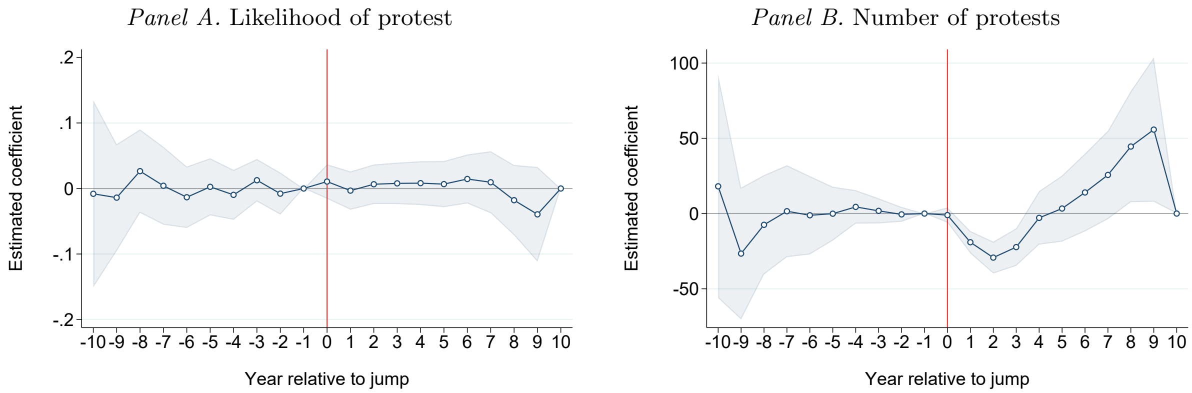

Figure 10 – Changes in the likelihood and number of protests following a jump in the share of the non-White population.

Notes: This figure displays the estimated coefficients of the model in Equation (1). The dependent variable is the likelihood of at least one annual protest in a county (Panel A) and the annual number of protests in a county (Panel B). The jump is defined as the first increase by 0.5 percentage points or more in the share of the non-White population in a county in two consecutive years. The model includes county and year-by-state fixed effects, and controls for gross income (CPI-adjusted, in log), population size (in log), and $PM_{2.5}$ concentrations (remote sensed population-weighted). The standard errors are clustered at the county level. The confidence interval depicted in light gray corresponds to the 95% level. The vertical red line delineates the pre- and post-Jump periods. See Table A-1 for variable definitions.

that experienced the jump. However, we find no evidence of changes in the number of newspaper articles written per protest. Finally, our analysis reveals a shift towards a more sympathetic tone by the media towards the protesters following the demographic jump.

In summary, we find that while income levels are unaffected following a racial demographic shift, changes in political activism factors align with such shifts. This appears reflected in both political donations and public protests. Specifically, the total amount of donations experiences a temporary reduction, while the number of donations sees a long-term sizable decrease. These effects are primarily driven by individuals and left-leaning donors. In contrast, the number of corporate donations and those by right-leaning donors sees an increase. In terms of civil discourse, we observe a sharp decline in the number of public protests and their corresponding news coverage. The general decline in political activism by entities typically advocating for more stringent environmental protection emerges as a potential mechanism to elucidate the decreased monitoring activity of the EPA.

VI. Conclusion

This paper examines the extent to which the U.S. Environmental Protection Agency (EPA) fulfills its mandate to advance environmental justice through monitoring and enforcement efforts mandated by the Clean Air Act. We leverage existing variation in the racial composition of U.S. counties over time to study adjustments in environmental auditing following increases in the share of the non-White population. Our study uses a comprehensive dataset including auditing information from 251,829 plants across the contiguous United States.

Our analysis reveals a significant and sustained reduction in the proportion of inspected plants within a county subsequent to an uptick in its non-White population share. Specifically, following a racial shift of 0.5 percentage points, the share of inspected plants decreases by approximately 8.9% compared to the year preceding the shift. This effect remains consistent across varying degrees of demographic changes, with stronger shifts yielding larger impacts. Notably, these effects are specific to increases in the non-White population share and are not observed when the share of the white population increases.

We take several steps to identify potential explanatory mechanisms. Importantly, we find no discernible shifts in air quality or the compliance of polluting facilities with official standards subsequent to the racial demographic shift. Moreover, income levels remain unaffected by such demographic changes. The primary mechanism we identify revolves around a significant reduction in political activism, as evidenced by both political donations and public protests. First, following an increase in the share of the non-White population, the number of political donors decreases sharply by 35%, an effect primarily observed among left-leaning individuals. In contrast, the number of right-wing donors experiences an increase by about 10%. Despite an initial decline in donation volumes, these levels remain relatively stable on average over the five-year period following the demographic shift, indicating a consolidation of financial support among a narrower set of contributors. Secondly, we note a significant decrease in the number of protests, constituting a reduction of approximately 27% compared to the year preceding the racial demographic shift. Collectively, these findings suggest that the observed decline in political activism, particularly among entities typically advocating for more stringent environmental protection, may underpin the decrease in EPA monitoring activity.

Overall, our findings highlight the complex interplay between demographic shifts, political activism, and environmental monitoring activities, underscoring the need for multifaceted policy approaches to address environmental justice challenges effectively. In light of these findings, several policy implications emerge. Firstly, there is a clear imperative for environmental justice policies that ensure equitable monitoring and enforcement activities across communities, irrespective of demographic composition. Secondly, the observed reduction in political activism following demographic shifts underscores the importance of policies aimed at promoting inclusive political participation and representation, particularly among marginalized groups. Thirdly, policymakers should prioritize transparency and accountability in political donations to mitigate the influence of concentrated financial interests on environmental policies. Lastly, the decline in the number of protests emphasizes the significance of public awareness and engagement in environmental justice issues, warranting investment in initiatives to educate and mobilize communities for effective advocacy.

We notice several limitations in our analysis that open avenues for future research. Our study primarily examines the overall annual share of inspected plants. Future research could delve deeper into identifying specific plant characteristics associated with more pronounced reductions. Exploring potential heterogeneity could provide a better understanding of the underlying reasons for the overall reduction and help assess its intentionality. Secondly, exploring the underlying mechanisms behind the observed decline in political activism post-demographic shifts warrants further attention. Thirdly, our analysis primarily focuses on the continental United States, and future studies could explore whether similar patterns emerge in other regions or countries with diverse demographic compositions. Addressing these limitations could enhance our understanding of the dynamics between demographic shifts, political activism, and environmental justice, thereby informing more targeted policy interventions in the future.

References

Andarge, T., Ji, Y., Keeler, B. L., Keiser, D. A., and McKenzie, C. (2024). Environmental Justice and the Clean Water Act: Implications for Economic Analyses of Clean Water Regulations. *Environmental and Energy Policy and the Economy*, 5:70–126.

Baker, A. C., Larcker, D. F., and Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, 144(2):370–395.

Banzhaf, S., Ma, L., and Timmins, C. (2019). Environmental justice: The economics of race, place, and pollution. *Journal of Economic Perspectives*, 33(1):185–208.

Barber, M. (2016). Donation Motivations: Testing Theories of Access and Ideology. *Political Research Quarterly*, 69(1):148–159.

Been, V. (1994). Locally undesirable land uses in minority neighborhoods: Disproportionate siting or market dynamics? *Yale Law Journal*, pages 1383–1422.

Benson, M. and Rochon, T. R. (2004). Interpersonal Trust and the Magnitude of Protest. *Comparative Political Studies*, 37:435–457.

Blue, G., Bronson, K., and Lajoie-O'Malley, A. (2021). Beyond distribution and participation: A scoping review to advance a comprehensive environmental justice framework for impact assessment. *Environmental Impact Assessment Review*, 90:106607.

Blundell, W. (2020). When threats become credible: A natural experiment of environmental enforcement from Florida. *Journal of Environmental Economics and Management*, 101:102288.

Blundell, W., Gowrisankaran, G., and Langer, A. (2020). Escalation of scrutiny: The gains from dynamic enforcement of environmental regulations. *American Economic Review*, 110(8):2558–85.

Bobo, L. and Gilliam, F. D. (1990). Race, Sociopolitical Participation, and Black Empowerment. *American Political Science Review*, 84(2):377–393.

Bonica, A. (2023). Database on ideology, money in politics, and elections: Public version 3.1. https://data.stanford.edu/dime.

Boone, C. G. and Modarres, A. (1999). Creating a Toxic Neighborhood in Los Angeles County: A Historical Examination of Environmental Inequity. *Urban Affairs Review*, 35(2):163–187.

Borusyak, K., Jaravel, X., and Spiess, J. (2024). Revisiting Event-Study Designs: Robust and Efficient Estimation. *The Review of Economic Studies*, page 1–33.

Bronars, S. and Lott, Jr., J. (1997). Do Campaign Donations Alter How a Politician Votes? Or, Do Donors Support Candidates Who Value the Same Things That They Do? *The Journal of Law and Economics*, 40(2):317–350.

Bureau of Labor Statistics (2024). Consumer price index data. Bureau of Labor Statistics. Retrieved from the BLS website: https://www.bls.gov/cpi/data.htm.

Bursztyn, L., Cantoni, D., Yang, D. Y., Yuchtman, N., and Zhang, Y. J. (2021). Persistent Political Engagement: Social Interactions and the Dynamics of Protest Movements. *American Economic Review: Insights*, 3(2):233–250.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230.

Charnley, S. and Engelbert, B. (2005). Evaluating public participation in environmental decision-making: EPA's superfund community involvement program. *Journal of Environmental Management*, 77(3):165–182.

Colmer, J., Hardman, I., Shimshack, J., and Voorheis, J. (2020). Disparities in PM $_{2.5}$ air pollution in the United States. *Science*, 369(6503):575–578.

Currie, J., Voorheis, J., and Walker, R. (2023). What Caused Racial Disparities in Particulate Exposure to Fall? New Evidence from the Clean Air Act and Satellite-Based Measures of Air Quality. *American Economic Review*, 113(1):71–97.

De Chaisemartin, C. and d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–96.

Deryugina, T. (2017). The fiscal cost of hurricanes: Disaster aid versus social insurance. *American Economic Journal: Economic Policy*, 9(3):168–198.

Earnhart, D. (2004). Regulatory factors shaping environmental performance at publicly-owned treatment plants. *Journal of Environmental Economics and Management*, 48(1):655–681.

Environmental Protection Agency (2002). Response to the commission's interrogatory question 43. https://www.epa.gov/.

Environmental Protection Agency (2011). Air facility system (afs) business rules compendium. https://www.epa.gov/sites/default/files/2013-10/documents/afsbusinessrulescompendium.pdf. Accessed: 2024-01-20.

Environmental Protection Agency (2013). Facility Registry Service (FRS).

Environmental Protection Agency (2014). Guidance on stationary sources under the clean air act. Environmental Protection Agency. Retrieved from https://www.epa.gov/sites/default/files/2013-10/documents/caastationary-guidance.pdf.

Environmental Protection Agency (2016). Clean air act stationary source compliance monitoring strategy. https://www.epa.gov/sites/default/files/2013-09/documents/cmspolicy.pdf. Accessed: 2024-01-20.

Environmental Protection Agency (2023). Clean air act (caa) compliance monitoring. https://www.epa.gov/compliance/clean-air-act-caa-compliance-monitoring#cms. Accessed: 2024-01-20.

Environmental Protection Agency (2024). Airdata download files. Accessed: 2024-01-23.

Esworthy, R. (2015). 2013 National Ambient Air Quality Standard (NAAQS) for Fine Particulate Matter (PM2.5): Designating Nonattainment Areas. Congressional Research Service Report No. R43953.

Gamper-Rabindran, S. and Timmins, C. (2011). Hazardous Waste Cleanup, Neighborhood Gentrification, and Environmental Justice: Evidence from Restricted Access Census Block Data. *American Economic Review*, 101(3):620–624.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277.

Grainger, C. and Schreiber, A. (2019). Discrimination in ambient air pollution monitoring? In *AEA Papers and Proceedings*, volume 109, pages 277–282.

Grant, A., Millward, A. A., Edge, S., Roman, L. A., and Teelucksingh, C. (2022). Where is environmental justice? A review of US urban forest management plans. *Urban Forestry & Urban Greening*, 77:127737.

Gray, W. B. and Shadbegian, R. J. (2005). When and why do plants comply? Paper mills in the 1980s. *Law & Policy*, 27(2):238–261.

Grooms, K. K. (2015). Enforcing the clean water act: The effect of state-level corruption on compliance. *Journal of Environmental Economics and Management*, 73:50–78.

Hamilton, J. T. (1995). Testing for Environmental Racism: Prejudice, Profits, Political Power? *Journal of Policy Analysis and Management*, 14(1):107.

Hammer, M. S., van Donkelaar, A., Li, C., Lyapustin, A., Sayer, A. M., Hsu, N. C., Levy, R. C., Garay, M. J., Kalashnikova, O. V., Kahn, R. A., Brauer, M., Apte, J. S., Henze, D. K., Zhang, L., Zhang, Q., Ford, B., Pierce, J. R., and Martin, R. V. (2020). Global Estimates and Long-Term Trends of Fine Particulate Matter Concentrations (1998–2018). *Environmental Science & Technology*, 54(13):7879–7890.

Harford, J. D. (1987). Self-reporting of pollution and the firm's behavior under imperfectly enforceable regulations. *Journal of Environmental Economics and Management*, 14(3):293–303.

Hernandez-Cortes, D. and Meng, K. C. (2023). Do environmental markets cause environmental injustice? Evidence from California's carbon market. *Journal of Public Economics*, 217:104786.

Holbrook, A., Sterrett, D., Johnson, T., and Krysan, M. (2016). Racial Disparities in Political Participation Across Issues: The Role of Issue-Specific Motivators. *Political Behavior*, 38(1):1–32.

Hu, S., Fruin, S., Kozawa, K., Mara, S., Paulson, S. E., and Winer, A. M. (2009). A wide area of air pollutant impact downwind of a freeway during pre-sunrise hours. *Atmospheric Environment*, 43(16):2541–2549.

Huffman, G., Stocker, E., Bolvin, D., Nelkin, E., and Tan, J. (2019). Gpm imerg final precipitation l3 1 day 0.1 degree x 0.1 degree v06. Goddard Earth Sciences Data and Information Services Center (GES DISC). Accessed: 2024-01-23.

Internal Revenue Service (2024). Soi tax stats - county data. Internal Revenue Service. Retrieved from the IRS website: https://www.irs.gov/statistics/soi-tax-stats-county-data.

Jbaily, A., Zhou, X., Liu, J., Lee, T.-H., Kamareddine, L., Verguet, S., and Dominici, F. (2022). Air pollution exposure disparities across US population and income groups. *Nature*, 601(7892):228–233.

Johnson, K. M. and Lichter, D. T. (2016). Diverging Demography: Hispanic and Non-Hispanic Contributions to U.S. Population Redistribution and Diversity. *Population Research and Policy Review*, 35(5):705–725.

Kim, I., Wan, H., Wang, B., and Yang, T. (2019). Institutional Investors and Corporate Environmental, Social, and Governance Policies: Evidence from Toxics Release Data. *Management Science*, 65(10):4901–4926.

Konisky, D. M. (2009). Inequities in enforcement? Environmental justice and government performance. *Journal of Policy Analysis and Management*, 28(1):102–121.

Konisky, D. M. and Reenock, C. (2018). Regulatory Enforcement, Riskscapes, and Environmental Justice. *Policy Studies Journal*, 46(1):7–36.

Konisky, D. M., Reenock, C., and Conley, S. (2021). Environmental injustice in Clean Water Act enforcement: racial and income disparities in inspection time. *Environmental Research Letters*, 16(8):084020.

Lavelle, M. and Coyle, M. (1992). Unequal protection: the racial divide in environmental law. *National Law Journal*, 15(3):S1–S12.

Lee, J. and Bean, F. D. (2004). America's changing color lines: Immigration, race/ethnicity, and multiracial identification. *Annual Review of Sociology*, 30:221–242.

Leetaru, K. and Schrodt, P. (2013). Gdelt: Global data on events, language, and tone, 1979-2012. In *International Studies Association Annual Conference*, San Diego, CA.

Liebler, C. A., Porter, S. R., Fernandez, L. E., Noon, J. M., and Ennis, S. R. (2017). America's churning races: Race and ethnicity response changes between census 2000 and the 2010 census. *Demography*, 54(1):259–284.

Mcgurty, E. (2000). Warren County, NC, and the Emergence of the Environmental Justice Movement: Unlikely Coalitions and Shared Meanings in Local Collective Action. *Society & Natural Resources*, 13:373–387.

Mikati, I., Benson, A. F., Luben, T. J., Sacks, J. D., and Richmond-Bryant, J. (2018). Disparities in Distribution of Particulate Matter Emission Sources by Race and Poverty Status. *American Journal of Public Health*, 108(4):480–485.

Miller, J. M. and Krosnick, J. (2004). Threat as a Motivator of Political Activism: A Field Experiment. *Political Psychology*, 25:507–523.

Oestreich, A. M. (2015). Firms' emissions and self-reporting under competitive audit mechanisms. *Environmental and Resource Economics*, 62(4):949–978.

Perez, A. D. and Hirschman, C. (2009). The changing racial and ethnic composition of the us population: Emerging american identities. *Population and Development Review*, 35(1):1–51.

Rambachan, A. and Roth, J. (2023). A More Credible Approach to Parallel Trends. *The Review of Economic Studies*, 90(5):2555–2591.

Rawls, J. (1991). Justice as Fairness: Political Not Metaphysical. In Corlett, J. A., editor, *Equality and Liberty*, pages 145–173. Palgrave Macmillan UK, London.

Reskin, B. (2012). The Race Discrimination System. *Annual Review of Sociology*, 38(1):17–35.

Shadbegian, R. J. and Gray, W. B. (2012). Spatial patterns in regulatory enforcement. *The Political Economy of Environmental Justice*, 225. Publisher: Stanford University Press.

Shimshack, J. P. (2014). The economics of environmental monitoring and enforcement. *Annual Review of Resource Economics*, 6(1):339–360.

Stokes-Brown, A. K. (2009). The Hidden Politics of Identity: Racial Self-Identification and Latino Political Engagement. *Politics & Policy*, 37(6):1281–1305.

Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199.

Tessum, C. W., Paolella, D. A., Chambliss, S. E., Apte, J. S., Hill, J. D., and Marshall, J. D. (2021). PM $_{2.5}$ polluters disproportionately and systemically affect people of color in the United States. *Science Advances*, 7(18):eabf4491.

U.S. Census Bureau (2018). United States Census 2018. U.S. Census Bureau. Retrieved from the U.S. Census Bureau website.

van Stekelenburg, J. and Klandermans, B. (2013). The social psychology of protest. *Current Sociology*, 61(5-6):886–905.

Van Zomeren, M., Postmes, T., and Spears, R. (2008). Toward an integrative social identity model of collective action: A quantitative research synthesis of three socio-psychological perspectives. *Psychological Bulletin*, 134(4):504.

Wan, Z., Hook, S., and Hulley, G. (2021). MODIS/Terra Land Surface Temperature/Emissivity Monthly L3 Global 0.05Deg CMG V061.

WorldPop (2020). Global 100m Population total adjusted to match the corresponding UNPD estimate. Type: dataset.

Zou, E. Y. (2021). Unwatched pollution: The effect of intermittent monitoring on air quality. *American Economic Review*, 111(7):2101–2126.

Appendix

A. Variable Definitions

Table A-1 – Variable definitions.

Panel A: Auditing variables	
Inspection share	The proportion of environmentally relevant plants within a county that undergoes EPA inspections. Environmentally relevant plants are given through the EPA's Facility Registry System (FRS).
Official nonattainment	Designation by the EPA for counties failing to meet the National Ambient Air Quality Standards (NAAQS) for $PM_{2.5}$, applicable only where air quality is directly monitored.
Implied nonattainment	Self-derived for areas without direct air quality monitoring, using population-weighted $PM_{2.5}$ levels against thresholds set by U.S. legislation to identify non-compliance with NAAQS for $PM_{2.5}$.
Number of violators	Represents the total number of facilities in a county identified as violators, with a possible further distinction between Federally Reportable Violators (FRV) and High Priority Violators (HPV). FRVs refer to facilities with violations of environmental regulations that must be reported to federal authorities, covering a wide range of compliance issues. HPVs are those facilities identified with more serious violations that pose significant environmental or public health risks, warranting immediate regulatory attention.
Panel B: Demographic variables	
Income	Represents the Adjusted Gross Income (AGI) as reported to the IRS, further adjusted for inflation using the Consumer Price Index (CPI) to ensure the value reflects real income levels over time.
Jump	Defined in our main specification as an increase of 0.5 percentage points in the non-White population share between two consecutive years.
Neighbor jump	Defined as an increase of 0.5 percentage points or more in the share of the non-White population in a neighboring county within consecutive years. Neighboring is established if the counties share a common border point, as captured by the condition $(\mathrm{Int}(A) \cap \mathrm{Int}(B) \neq \emptyset) \wedge (A \cap B \neq \emptyset)$.
Population size	Total number of residents in a county.
White & non-White share	The "White share" refers to the percentage of the population classified as "White" according to the 1997 OMB standards adopted by the U.S. Census Bureau, i.e., individuals having origins in any of the original peoples of Europe, the Middle East, or North Africa. Conversely, the "non-White share" includes the percentage of the population not classified under the White category, encompassing all other recognized racial groups or combinations thereof as per self-identification.
Panel C: Air pollution variables	
Monitor $PM_{2.5}$	This variable captures the average of all $PM_{2.5}$ concentration measurements recorded by at least one EPA-certified ground-level monitor in a county. The value is calculated only for those counties where such monitoring stations are present.
Population-weighted $PM_{2.5}$	This variable represents the average concentration of fine particulate matter (PM2.5) in the air, estimated from satellite data sources and ground-based observations (Hammer et al., 2020). These $PM_{2.5}$ concentrations are weighted according to the distribution of the population across a 1x1 km grid.

(continued)

(Table A-1 continued)

Panel D: Political variables

Intensity of protests	Utilizes the Goldstein scale to measure the severity of protests based on their actions' potential impact. This scale assigns numerical values to different types of protest activities, reflecting their intensity in terms of promoting peace or conflict. The variable captures the cumulative intensity score of all protests within a county, providing a quantified representation of the overall level of protest activity and its potential implications for social stability or unrest.
Nr of protests	Represents the count of protests within a specific county, derived from GDELT data that includes all U.S.-based protests with geographical precision at the county level.
Political donations	Utilizes data from the Database on Ideology, Money in Politics, and Elections (DIME) to measure the number and total sum of financial contributions made by individuals and organizations to political campaigns. This includes analyzing Common Space Scores (CFscores) to assess the ideological leanings of donors. A donor is classified as "right" if the CF-score ¿ 0, and "left" if the CF-score ¡ 0.
Stronghold	Indicates whether a state is recognized as a Republican stronghold, Democratic stronghold, or a swing state. This classification is based on state-level analysis of historical voting patterns.
Tone of news coverage	Calculated by GDELT, this variable measures the sentiment of news coverage on protests, using a scale from -100 (extremely negative) to +100 (extremely positive), although most values lie between -10 and +10. The tone score is derived from the balance of positive and negative words within the text, normalized by the total word count. A score near zero may indicate either low emotional content or a balance of positive and negative sentiments.

B. Data and Summary Statistics

1. Data Set Generation

Table A-2 – Data sources with time and spatial resolution.

Variable	Source	Orig. Res.	Available Years	Used Res.	Used Years
Climate Data	Huffman et al. (2019); Wan et al. (2021)*	0.1x0.1°	2000 - 2024	County	2000 - 2018
Enforcement	Environmental Protection Agency (2013)	Long-Lat	1974 - 2018	County	2000 - 2018
Ethnic Comp.	U.S. Census Bureau (2018)*	County	2000 - 2023	County	2000 - 2018
Income	Bureau of Labor Statistics (2024); Internal Revenue Service (2024)*	County	1990 - 2023	County	2000 - 2018
$PM_{2.5}$	Hammer et al. (2020)	0.01x0.01°	1998 - 2020	County	2000 - 2018
Pol. Donations	Bonica (2023)	Addresses (lat-lon)	1998 - 2023	County	2000 - 2018
Population	WorldPop (2020)*	100x100m	2000 - 2020	County	2000 - 2018
Protests	Leetaru and Schrodt (2013)	Long-Lat	1998 - 2024	County	2000 - 2018

Note: The table summarizes the datasets employed in this analysis, detailing the original sources, spatial resolutions, and temporal spans. The variables include enforcement measures, air quality indices, sociopolitical variables, demographic statistics, and climate data, each sourced from reputable databases and publications pertinent to the study's focus. Data coverage extends from as early as 1974, with the period of interest for this study being 2000 to 2018 to match the enforcement data availability and the key timeline of the environmental audits examined. Spatial resolutions were standardized to the county level to maintain analytical consistency across the diverse datasets.

In our study, we initially utilize data from the Environmental Protection Agency's Integrated Compliance Information System for Air (ICIS-AIR) (Environmental Protection Agency, 2013). This comprehensive database compiles information on the compliance status of stationary sources of air pollution, including but not limited to electric power plants, steel mills, manufacturing facilities, and educational institutions. Moreover, ICIS-AIR provides detailed records on historical inspection dates and their outcomes, which may range from compliance to designation as federally reported or high-priority violators.

Furthermore, ICIS-AIR offers insights into the historical violation statuses of plants, categorizing them as compliant, regular violators, or high-priority violators. It also documents the financial repercussions for the facilities in question, encompassing both the penalties levied and the expenditures undertaken to achieve compliance post-violation.

The ICIS-AIR database integrates into the broader framework of the Environmental Protection Agency's (EPA) Environfacts and the Integrated Data for Enforcement Analysis (IDEA) systems, accessible via the Enforcement and Compliance History Online (ECHO) platform. The IDEA system, inaugurated in 1990 and meticulously maintained by the EPA, aggregates compliance and enforcement data across various tracking systems on a monthly basis.

A pivotal component of our data integration process involves the Facility Registry Service (FRS), which provides a unique identifier for each facility. This identifier is essential for merging datasets accurately. The resultant comprehensive dataset not only specifies the exact geographic coordinates of each facility but also elaborates on the plant's operational sector. It incorporates detailed classifications based on the North American Industry Classification System (NAICS) and the Standard Industrial Classification (SIC) system, ensuring a thorough analysis of the industry dynamics and the specific environmental impact of each plant.

By integrating these datasets, we compiled a comprehensive list of environmentally significant facilities—those subject to any of the EPA's air regulations or programs. This list includes detailed information on the type of industry each plant belongs to, along with their addresses and precise geographical locations. Leveraging the merged datasets, we subsequently aggregated the plant-level data into an annual county-level panel. This panel encompasses data on environmental inspections and compliance activities from the year 2000 through 2018.

Subsequently, the dataset was enriched by merging it with county-level racial demographics from the US Census. We utilized the absolute figures to compute the proportions of major ethnic groups within each county for every year. This enriched dataset was further augmented with county-level income statistics sourced from the Internal Revenue Service (IRS), which were then adjusted for inflation using the Consumer Price Index (CPI) data obtained from the Bureau of Labor Statistics.

In the fourth step of our dataset generation process, we enhance the county-level annual panel by incorporating data on average yearly concentrations of fine particulate matter ($PM_{2.5}$). Our approach utilizes two primary sources of air pollution data: remote-sensed and ground monitor pollution data managed by the Environmental Protection Agency (EPA) (Environmental Protection Agency, 2024).

Initially, we obtain remote-sensed data from Hammer et al. (2020), which provides estimates of monthly ground-level PM2.5 with a high geographical resolution of 0.01x0.01°. This is achieved by combining satellite aerosol observations from NASA's MODIS, MISR, and SeaWIFS instruments.[19] Additionally, we employ UN-adjusted county-level population size data from WorldPop (2020), offering insights into US population density at a 100x100m scale based on census and satellite imagery. Using this information, we calculate population-weighted PM2.5 estimates.

Secondly, we source ground-level monitor data from the Air Quality System (AQS) database, overseen by the EPA, which includes $PM_{2.5}$ readings from 1,989 outdoor ground monitors throughout the United States. Both datasets are aggregated to the yearly county level to align with our panel data on environmental inspections.

Furthermore, we enrich the panel with key climate data, including wind speed, precipitation, and temperature, derived from NASA's MODIS satellite program. For each observation, daily measures from all grid points within a specific county are averaged to derive county-day and, subsequently, county-year metrics.

To delve deeper into the potential mechanisms influencing environmental audit patterns, our analysis incorporates additional layers of data. Specifically, we augment our dataset with political donation information sourced from the Database on Ideology, Money in Politics, and Elections (DIME) (Bonica, 2023). This database provides comprehensive records of political contributions, offering insights into the financial flows from individuals and organizations to political candidates and causes.

Additionally, our dataset is enriched with metrics of protest activity obtained from the Global Database of Events, Language, and Tone (GDELT) (Leetaru and Schrodt, 2013). GDELT tracks global events, including protests, in near-real-time, compiling data on the location, scale, and nature of protest activities.

The final panel consists of yearly observations for a total of 3,014 US counties from 2000 - 2018.

[19] The dataset from Hammer et al. (2020) features a geographical resolution of 0.01x0.01° at a monthly temporal frequency. We aggregate this data to a yearly county-level basis.

2. Summary Statistics

Table A-3 – County-level summary statistics.

	All	No jump			Jump			No jump - Jump	
		W/ monitor	W/o monitor	P-val. diff.	W/ monitor	W/o monitor	P-val. diff.	P-val. diff. w/ monitors	P-val. diff. w/o monitors
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$PM_{2.5}$									
Ground monitors	9.79	9.86	-	-	9.70	-	-	0.29	-
Remote sensed	8.54	8.96	8.58	0.00	9.04	7.99	0.00	0.60	0.00
Above WHO standard	0.94	0.97	0.97	0.61	0.91	0.88	0.09	0.00	0.00
EPA activity									
Share inspected plants	0.20	0.23	0.20	0.00	0.18	0.17	0.43	0.00	0.00
N inspected plants	0.19	0.40	0.11	0.00	0.48	0.09	0.00	0.07	0.01
N onsite inspections	0.24	0.55	0.13	0.00	0.55	0.09	0.00	0.98	0.00
N offsite inspections	0.15	0.24	0.08	0.00	0.42	0.08	0.00	0.00	0.67
Non-attainment	0.51	1.44	-	-	1.47	-	-	0.90	-
Demographic									
N plants	83.45	184.69	38.59	0.00	201.96	44.43	0.00	0.66	0.13
Share white pop.	0.86	0.87	0.92	0.00	0.77	0.79	0.06	0.00	0.00
Population	0.10	0.23	0.04	0.00	0.34	0.03	0.00	0.01	0.00
Income	2.59	5.93	0.75	0.00	9.75	0.62	0.00	0.00	0.05
Climate									
Precipitation	2.96	2.92	3.08	0.00	2.91	2.79	0.13	0.89	0.00
Wind speed	3.50	3.32	3.51	0.00	3.47	3.63	0.00	0.00	0.00
Temperature	56.08	54.15	55.26	0.01	56.63	58.56	0.00	0.00	0.00
Pol. donations									
Amount of donations	36.36	100.09	4.27	0.00	148.16	3.46	0.00	0.21	0.11
Nr of unique donors	12.10	30.51	3.36	0.00	42.98	2.25	0.00	0.02	0.00
Protests									
Protest likelihood	0.54	0.67	0.51	0.00	0.68	0.46	0.00	0.28	0.00
Nr of protests	1.35	3.81	0.43	0.00	3.76	0.29	0.00	0.97	0.00
Protest intensity	-5.25	-5.27	-5.24	0.04	-5.25	-5.26	0.76	0.43	0.13
Tone of news coverage	-0.72	0.20	-1.05	0.00	0.30	-1.18	0.00	0.25	0.07
Nr of articles	15.86	48.55	3.84	0.00	45.22	2.60	0.00	0.86	0.00
Nr of articles by protest	6.85	7.07	6.66	0.03	6.95	6.98	0.93	0.63	0.07
Observations	3,014	537	1,364	1,901	319	794	1,113	856	2,158

Notes: This table presents summary statistics of the main variables of interest at the county-level, averaged over 2000 - 2018. Column (1) presents summary stats for all 3,014 counties. The additional columns differentiate between counties that had a sudden increase in the Nonwhite population share (defined as a 0.5 percentage point increase between two years) and those that did not, as well as between counties with and without monitors. We report p-values of t-tests in columns (4), (7), (8), and (9) to examine differences in means between the mentioned categories. Column (4) shows the difference in means between counties with a "jump" in the presence of at least one PM2.5 monitor compared to those without. Column (7) represents the difference in means between counties *without* a "jump" for areas with and without at least one PM2.5 monitor. Additionally, column (8) displays the difference in means between "jump" counties and "no-jump" counties with monitors. Finally, column (9) indicates the difference in means between "jump" and "no-jump" counties without monitors. $PM_{2.5}$ is measured in $\mu g m^{-3}$. *Above WHO* refers to the share of counties for whom the average $PM_{2.5}$ concentrations is above the WHO recommended level of 5 $\mu g/m^3$. The number of inspected plants, as well as the number of on- and offsite inspections is given in thousands; population is given in million people, income in million USD, precipitation in mm/m², wind speed in m/s, and temperature in degrees Fahrenheit. The amount of donations is given in million USD, and the number of unique donors is in thousands.

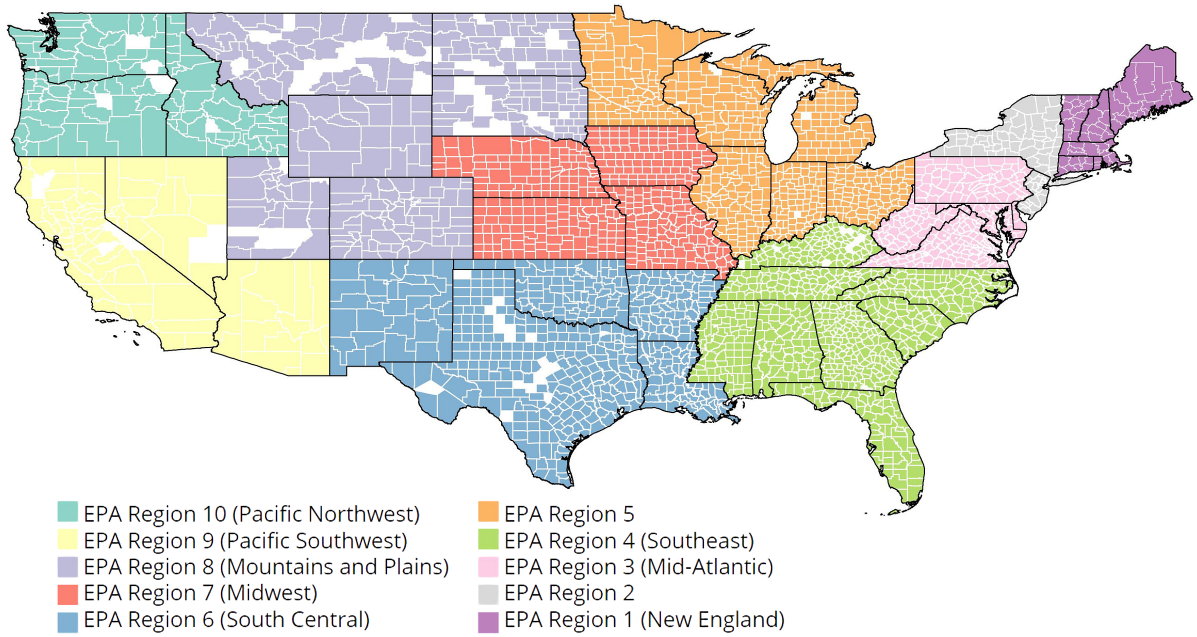

FIGURE A-1 – THE EPA'S REGIONAL AND GEOGRAPHIC OFFICES.

Notes: This figure displays the division of the contiguous United States into the ten regional and geographic offices of the EPA. Divisions are always aligned to state borders and often encompass a geographical region characterized by similar climate features.

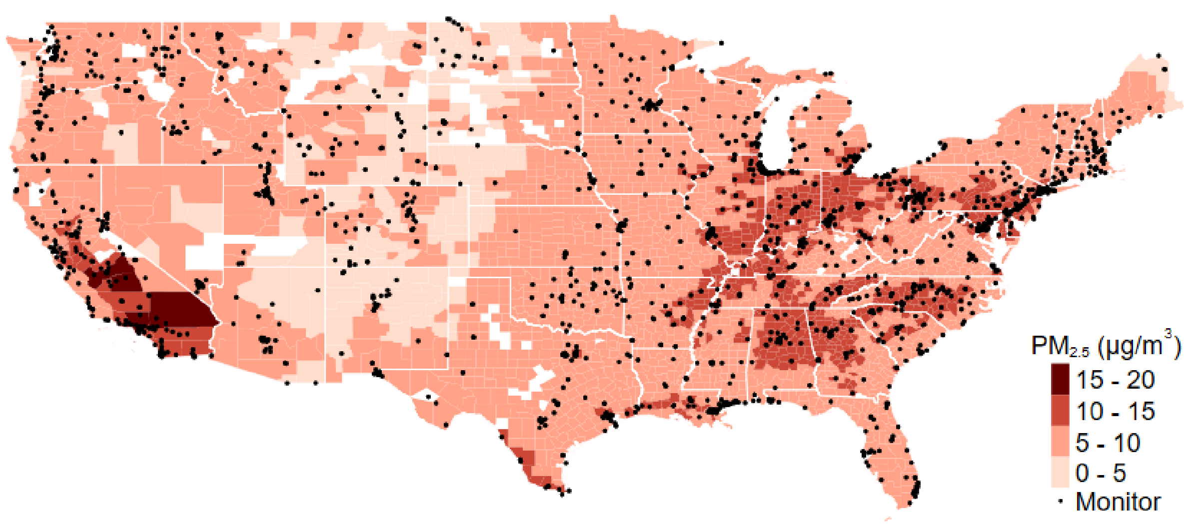

FIGURE A-2 – AVERAGE $PM_{2.5}$ CONCENTRATIONS AND GROUND-LEVEL MONITOR PLACEMENT.

Notes: This figure maps the average population-weighted $PM_{2.5}$ concentration in all 3,014 US counties in our sample period from 2000 to 2018. A darker red color indicates higher average $PM_{2.5}$ concentrations. Ground-level $PM_{2.5}$ monitors that were at some point active over this sample period, are indicated by black dots.

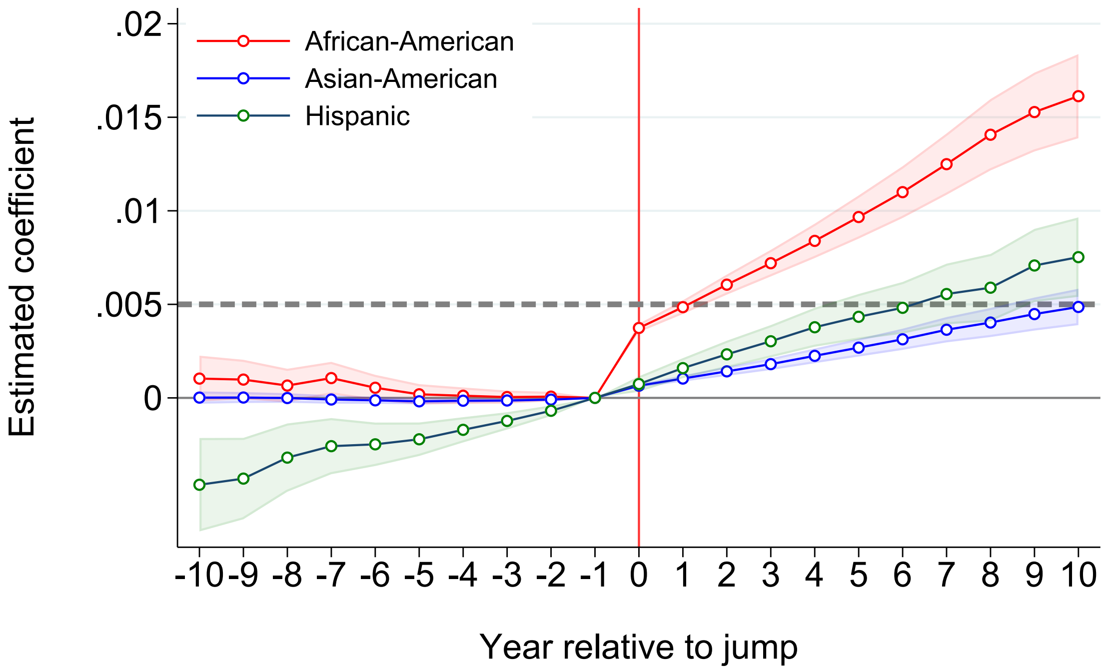

Figure A-3 – Changes in racial composition following a jump in the share of the non-White population.

Notes: This figure displays the estimated coefficients of the model in Equation (1), where the dependent variable is the share of African American, Asian American, and Hispanic population. The jump is defined as an increase by 0.5 percentage points or more in the annual share of the overall non-White population of a county. All models include county and year fixed effects. Standard errors are clustered at the county level. The vertical red line delineates the pre- and post-jump periods. See Table A-1 for variable definitions.

C. Robustness

1. Only not-yet-treated as Control Group

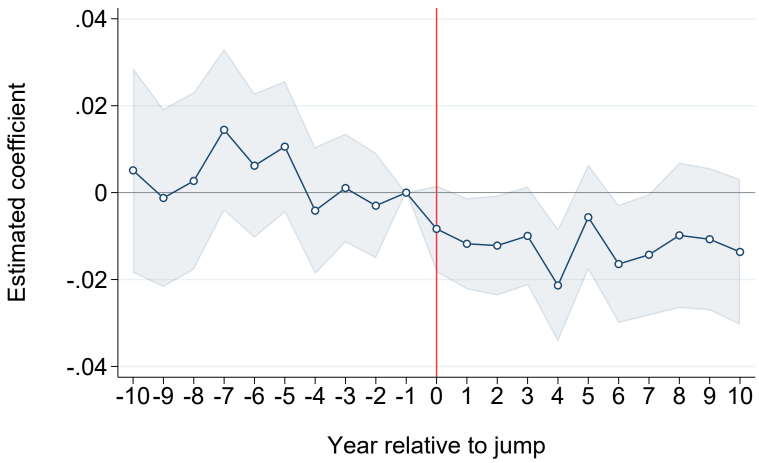

Figure A-4 – Changes in the share of inspected plants following a jump in the share of the non-White population, excluding counties that never experience a jump.

Notes: The dependent variable is the share of inspected plants in a county in a year. All models control for $PM_{2.5}$ concentrations (population-weighted), gross income (CPI adjusted, in log), population size (log), and include county and year-fixed effects. The standard errors are clustered at the county level. The confidence interval depicted in light blue corresponds to the 95 level. The vertical red line delineates the pre- and post-jump periods.

2. Multiple Jumps: Event Study with In- and Out-Switching

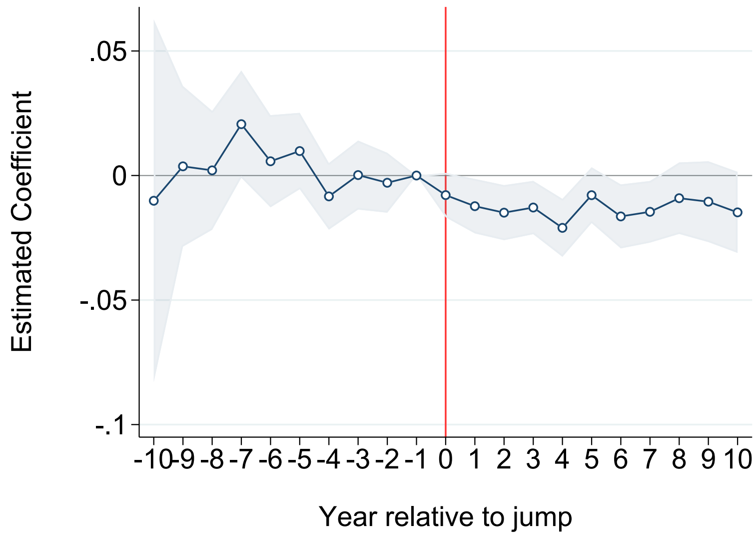

Figure A-5 – Changes in the share of inspected plants following a jump in the share of non-White population.

Notes: The figure above shows the results of estimating equation (1). The dependent variable is the annual share of inspected plants in a county. The jump is defined as a 0.5 or more percentage point increase in the share of the non-white population over consecutive years. Here, counties are allowed to switch back from treated to not-treated, as described in De Chaisemartin and d'Haultfoeuille (2020). The model controls for gross income (CPI adjusted, in log), population size (in log), and $PM_{2.5}$ concentrations (population-weighted), including county and year fixed effects. Standard errors are clustered at the county level. The confidence interval depicted in light blue corresponds to the 95 level. The red line separates the pre- and post-jump periods.

3. Jump in the share of the White Population

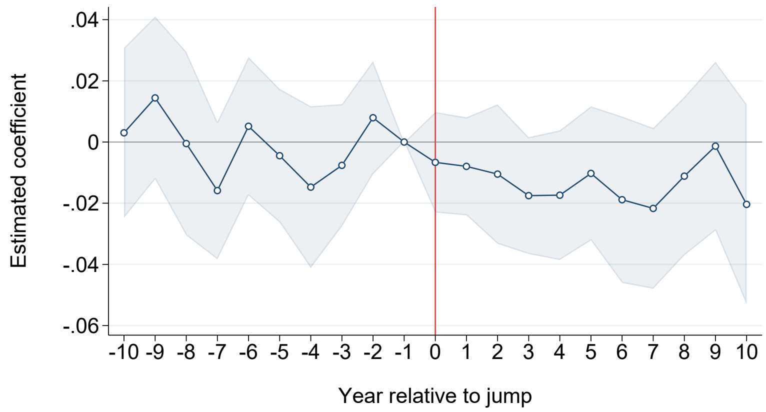

Figure A-6 – Estimated effects of a jump in the share of Whites on the share of inspected plants in a county.

Notes: This figure displays the estimated coefficients of the model in Equation (1). The dependent variable is the annual share of inspected plants in a county. The jump is defined as a 0.5 percentage point or more increase in the share of the **White** population. The model controls for $PM_{2.5}$ concentrations (population-weighted), gross income (CPI adjusted, in log), and population size (log) and includes county and year fixed effects. The standard errors are clustered at the county levels. The confidence interval depicted in light blue corresponds to the 95% level.

D. Political Activism and Civil Discourse

1. Political stronghold

Table A-4 – List of states by political stronghold.

Democratic	Connecticut, Maine, Massachusetts, Maryland, Rhode Island, Vermont, New Jersey, New York, Illinois, Michigan, Minnesota, California, Hawaii, Oregon, Washington.
Republican	West Virginia, Alabama, Georgia, Kentucky, Mississippi, South Carolina, Tennessee, Arkansas, Louisiana, Oklahoma, Texas, Kansas, Missouri, Nebraska, Montana, North Dakota, South Dakota, Utah, Wyoming, Arizona, Idaho.
Swing states	New Hampshire, Delaware, District of Columbia, Pennsylvania, Virginia, Florida, North Carolina, Indiana, Ohio, Wisconsin, New Mexico, Iowa, Colorado, Nevada.

Notes: Only states of the contiguous U.S. are considered in our analysis.

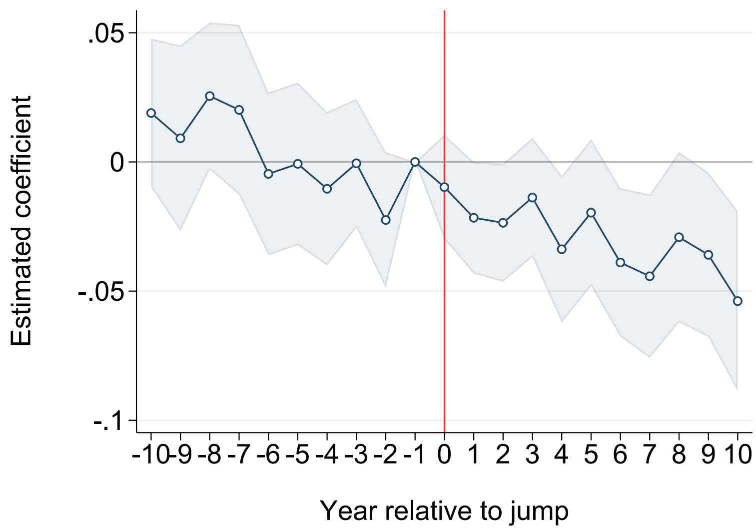

Figure A-7 – Changes in the share of inspected plants to a jump in the share of the non-White population, U.S. swing states only.

Notes: The dependent variable is the annual share of inspected plants in a county, if it is located in a Swing State. The list of states by stronghold classification is given in Appendix Table A-4. The jump is defined as the first increase by 0.5 percentage points or more in the share of the non-White population in a county in two consecutive years. The models control for gross income (CPI-adjusted, in log), population size (in log), and $PM_{2.5}$ concentrations (remote sensed population-weighted), and include county and year fixed effects. The standard errors are clustered at the county level. The confidence interval depicted in light blue corresponds to the 95% level. The vertical red line delineates the pre- and post-jump periods. See Table A-1 for variable definitions.

2. Political donations

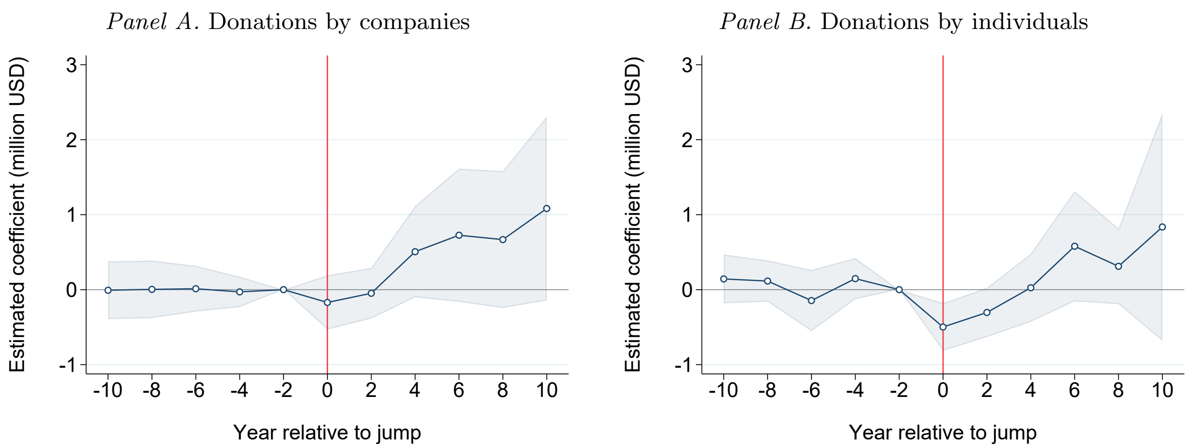

Figure A-8 – Estimated effects of a jump in the share of the non-Whites on the amount of political donations, by donor type.

Notes: This figure displays the estimated coefficients of the model in Equation (1). The dependent variable is the amount of political donations. Panel (A) depicts the estimates for donations by individuals and panel (B) for donations by companies. The jump is defined as a 0.5 percentage point increase in the share of the non-White population between two consecutive calendar years. Donation data is solely available biannually. The model controls for $PM_{2.5}$ concentrations, income (CPI adjusted, in log), and population size (log) and includes county and year-fixed effects. The standard errors are clustered at the county levels. The confidence interval depicted in light blue corresponds to the 95% level.

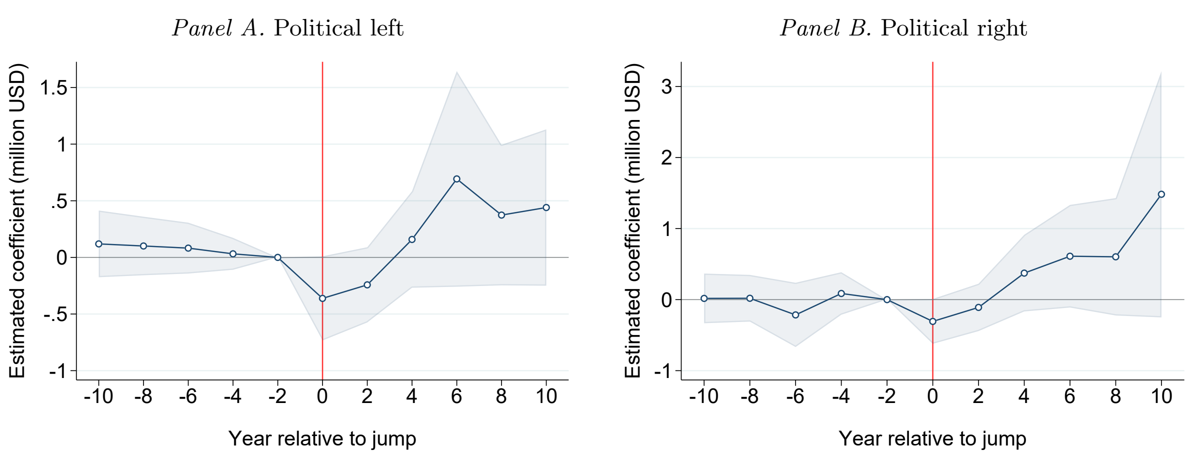

Figure A-9 – Changes in the Amounts of Political Donations Following a Jump in the share of the non-White Population, by Political Affiliation of Donor.

Notes: This figure displays the estimated coefficients of the model in Equation (1). The dependent variable is the annual amount of political donations (in million USD). Panel (A) depicts the estimates for the donors supporting the political left and panel (B) for donors supporting the political right. The jump is defined as a 0.5 percentage point increase in the share of the non-White population between two consecutive calendar years. Donation data is solely available biannually. The model controls for $PM_{2.5}$ concentrations, income (CPI adjusted, in log), and population size (log) and includes county and year-fixed effects. The standard errors are clustered at the county levels. The confidence interval depicted in light gray corresponds to the 95% level.

Figure A-10 – Changes in the number of donors following a jump in the share of the non-White population, by political affiliation of donor.

Notes: This figure displays the estimated coefficients of the model in Equation (1). The dependent variable is the unique number of donors. Panel (A) depicts the estimates for the donors supporting the political left, and panel (B) for donors supporting the political right. The jump is defined as a 0.5 percentage point increase in the share of the non-White population between two consecutive calendar years. Donation data is solely available biannually. The model controls for $PM_{2.5}$ concentrations, income (CPI adjusted, in log), and population size (log) and includes county and year-fixed effects. The standard errors are clustered at the county levels. The confidence interval depicted in light blue corresponds to the 95% level.

3. Intensity and News Coverage of Public Protests

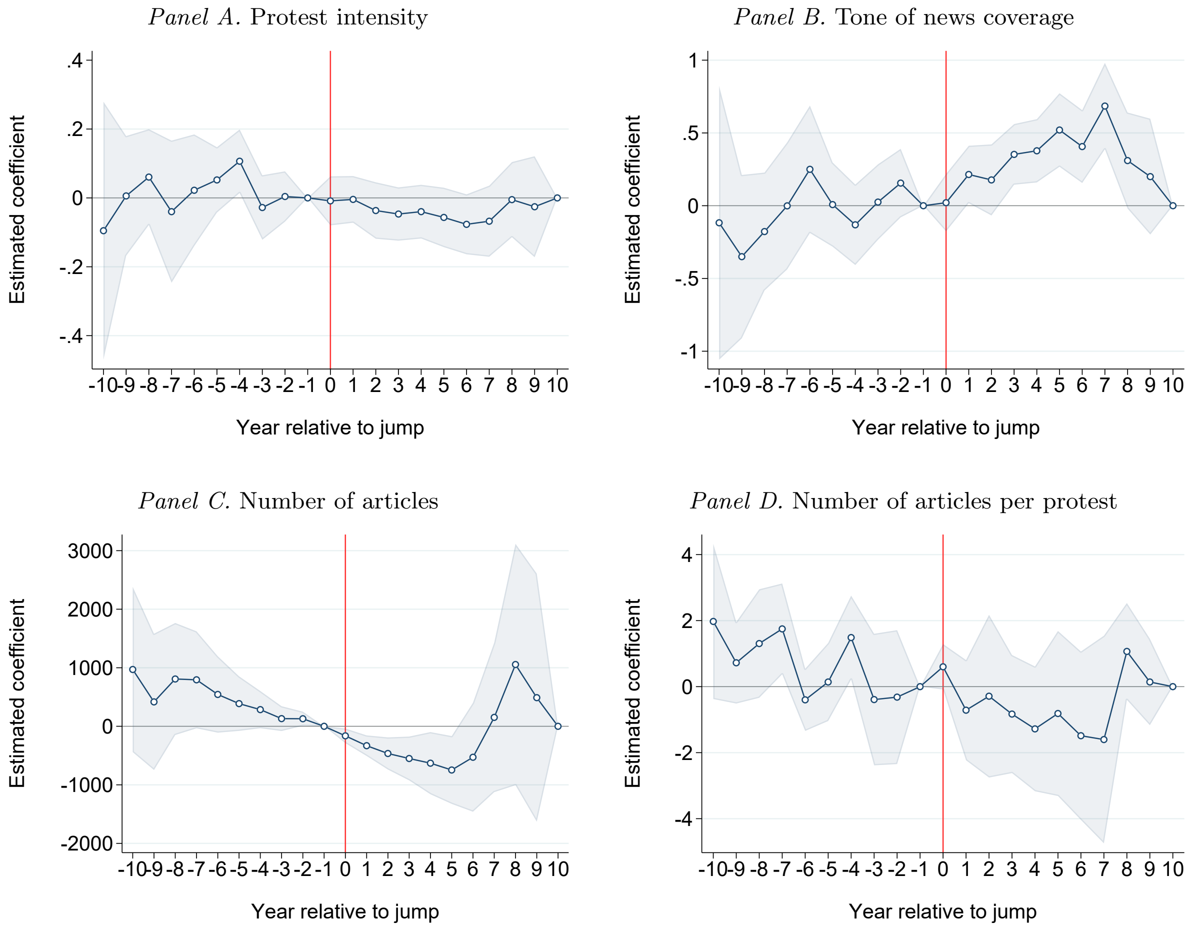

Figure A-11 – Changes in the Intensity of Protests and News Coverage Following a Jump in the share of the non-White Population.

Notes: This figure displays the estimated coefficients of the model in Equation (1). The dependent variable in Panel A is the intensity of protests, which depends on levels of violence and aggression. In Panel B, the dependent variable is the average tone of news coverage of the protests. Higher values indicate more benevolent coverage, while lower values indicate critical coverage. The jump is defined as a 0.5 percentage point increase in the share of the non-White population between two calendar years. The model controls for $PM_{2.5}$ concentrations, income (CPI adjusted, in logs), and population size (in logs) and includes county and year-fixed effects. The standard errors are clustered at the county levels. The confidence interval depicted in light blue corresponds to the 95% level.