Racial Demographics and Environmental Auditing in the USA

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Abstract

One mandate of the US Environmental Protection Agency is to use its legal authority to promote and ensure environmental justice. This paper investigates to what extent this has been the case in the recent past. Our analysis draws on a comprehensive dataset that links auditing information from all environmentally relevant plants across the USA over 2000 - 2018 to county-level demographic and ethnic yearly information. We study whether changes in the racial composition of US counties are followed by adjustments in the volume of air quality inspections to polluting plants. Using a staggered difference-in-differences design, we find robust evidence that the share of inspected plants within a county decreases following an increase in the share of the Nonwhite population. This coincides with higher air pollution levels and an increased rate of nonattainment designations.

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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 US over the last decades. Blundell et al. (2020), for instance, estimate that the CAA incurred a cost of 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. With the growing academic interest in environmental

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justice, a recent stream of literature additionally investigates the impact of the CAA on discrepancies in pollution exposure between various strata of society, leading to mixed results. Most recently, Currie et al. (2023) show evidence consistent with the fact that the CAA contributed to an ongoing racial convergence in ambient air pollution exposure between African-American and White communities in the US. They argue 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. However, Colmer et al. (2020) argue that despite progress in reducing absolute gaps, relative differences in exposure prevail.

This paper provides new insights into the impact of the CAA on air pollution and its role in mitigating environmental inequalities. More precisely, we disentangle what role a county's racial composition plays in the application and volume of inspections and nonattainment designations. We find that the EPA inspects a lower share of environmentally important plants in counties that experience a positive jump in the share of non-white population. At the same time, Nonwhite counties are more often in nonattainment, surpass federal pollution thresholds, and have higher particulate matter concentration than their white counterparts.

Furthermore, we are able to show that the share of inspected plants follows demographic changes. Making use of changes in counties' racial composition between two periods, we estimate a staggered difference-in-differences model with dynamic treatment effects as laid out in Sun and Abraham (2020).[1] Our results indicate that an increase in the share of the Nonwhite population leads to a significantly lower share of inspected plants in the periods after the population change. This change in inspection behavior persists in counties without ground monitors, while counties with monitors return to former inspection levels after two periods. Changes in pollution levels cannot explain the change in inspection behavior.

Using a spatial Durbin model to account for geographic dependencies of pollution, we underline that these differences matter, as the overall design of environmental scrutiny effectively reduces particulate matter ($PM_{2.5}$) concentrations. Assigning the "nonattainment" status to a county, for instance, lowers $PM_{2.5}$ levels by 2.5 percentage points in the upcoming year. Similarly, increasing the share of inspected plants by ten percentage points leads to 0.05% lower $PM_{2.5}$ levels. However, we also highlight the importance of geographical spillovers, which appear to reduce these estimated effect sizes. Additionally,

[1] Allowing for groups to switch to and from treated to not treated, as discussed in De Chaisemartin and d'Haultfoeuille (2020), leads to similar outcomes.

we notice that the effect size depends on whether $PM_{2.5}$ is measured by ground monitors or satellites, with the latter displaying a lower estimated impact.

This paper adds to the literature in four ways. First, to our knowledge, we construct the most comprehensive dataset on environmental scrutiny and air pollution exposure currently in existence. Using auditing information from 251,829 plants across the contiguous USA and combining this data with ground monitor and high resolution remotely sensed air pollution information (Hammer et al., 2020), we compile a county-year panel dataset spanning from 2000 - 2018. By doing so, we overcome severe data limitations that previous studies have faced. Hanna and Oliva (2010), for example, used a panel of only 17,200 firms combined with self-reported pollution data to estimate the impact of inspections. Liu and Yang (2020), on the other hand, relied on a total of 8,755 major manufacturing facilities in the US to estimate the role of the high-priority violator status on a plant's emissions.

Second, our paper makes an important contribution to the environmental justice literature. Previous studies, using only regions where ground level monitors exist, show that the regulations introduced within the CAA scope led to a convergence in racial air pollution exposure (Currie et al., 2023). Our analysis expands to consider also counties without ground-level monitors and finds robust evidence that the share of inspected plants decreases following an increase in the share of Nonwhite population within a county. These results appear consistent with a discrimination in the extent of safeguarding the environment against regions where the share of minorities is on the rise.

Our findings cary important implications for regulatory policies aimed at improving air quality and reducing racial disparities in environmental protection. First and most importantly, our study sheds light on the issue of racial discrimination in the implementation of the Clean Air Act, calling for a revision of the environmental auditing mechanism. Policymakers should ensure that the auditing mechanism is impartial and equitable to avoid discriminatory practices in the enforcement of environmental regulations. Second, our study highlights the importance of using satellite measurements to determine inspection probabilities. As more than two-thirds of US counties have no ground-level monitors, a racially just environmental auditing system should aim to be inclusive with its pollution measurements.

I. The Environmental Regulatory Framework in the US

The US EPA is a federal agency guided by environmental legislation applied at the national level. However, a large part of the regulatory enforcement process is conducted by regional and a total of ten state-level EPAs.[2] Regional EPAs conduct inspections, issue sanctions, and assist states with major violation cases. Regions and states can take different approaches to implementing enforcement programs. Hence, the interpretation of federal policy and preferences for enforcement can differ across regions.

When states or localities have primary authority, they are still required to regularly provide key activity data to EPA regional and federal offices. EPA offices regularly review state operations. EPA actions most often occur when and where more local enforcement is perceived as insufficient or when and where potential environmental impacts from specific violations are unusually large.

Self-Reporting: Self-reported pollution data are the primary source of compliance monitoring information. In most cases, facilities self-report pollution snapshots or longer-term pollution summary measures at the pollutant-point source level. Regulator inspections help confirm the accuracy of self-reported data.

Inspections: All plants (compliant or not) can be inspected regularly. The frequency of inspections depends on (i) baseline differences across states and regions in enforcement budgets and priorities, (ii) the size of the plant and (iii) whether a plant is located in a NAAQS non-attainment area.[3] Evaluations can vary in scope and scale across facilities, industries, statutes, states, and time. Low-intensity inspections may involve visual inspections of emissions and abatement equipment. Medium-intensity inspections may involve reviews of facility operations, maintenance, sampling, and reporting procedures. High-intensity inspections may typically involve extensive sampling by the regulator.

Inspections are conducted at specific facilities "for cause" or, more commonly, for administrative reasons based on "neutral selection." For-cause inspections are based on compliance history, citizen complaints, anonymous employee complaints, or facility characteristics correlated with frequent violations or significant damages. Neutral selection inspections are based on time since the last inspection and regulator cost factors, such as geographic proximity to other facilities scheduled to be inspected. Monitoring guidelines set inspection frequency targets for facilities, but these targets are generally not legally binding. Thus, neither for cause nor neutral selection are purely random inspections but are based on observable criteria. The agency also uses environmental justice as a targeting consideration, looking at the vulnerability of populations near plants. Finally,

[2] In the US, there are ten regional EPA assigned to specific geographic regions, see https://www.epa.gov/aboutepa/regional-and-geographic-offices.

[3] Non-attainment areas were required to have plans to return to attainment, which could lead to increased levels of scrutiny for plants in these areas.

facilities are usually notified by authorities in advance of impending inspections, so on-site inspections are often not a surprise to facilities.

Selection of Plants: Based on previous empirical work, environmental regulators take into consideration the benefits and costs of enforcement activities. A plant with higher emissions and damages can be expected to have a higher inspection probability as well as higher penalty magnitudes. Regarding administrative costs, states with higher-paid employees conduct lower-intensity inspections on average. Facilities recently inspected are less likely to be immediately inspected again. Regarding compliance costs, the EPA and states direct fewer monitoring and enforcement actions toward facilities that are important local employers or that have especially high probabilities of the shutdown.

Facilities' compliance history is usually an important determinant of monitoring and enforcement activity (Kleit et al. (1998); Oljaca et al. (1998); Eckert and Eckert (2010)) with the expectation that past violators are more likely to violate again.

Regulator actions that have no basis in direct benefit and cost comparisons are also readily observed. CAA inspection probabilities are related to congressional representatives' voting scores and committee memberships (Helland (1998a); Innes and Mitra (2011)). Highly corrupt states pursue more lax environmental oversight (Grooms (2015)). Inspection probabilities and enforcement probabilities are closely related to community characteristics such as political activism, income, education, voter turnout, and environmental group membership and appear to be especially influential for state-level interventions (Earnhart (2004a,b); Helland (1998b)).

Regular Violator Status: If a violation is discovered either through an inspection or a self-report, the plant will enter "violator" status. As a violator, there are additional inspections. Plants can accumulate multiple violations within the violator status and only return to compliance once those violations have been resolved. The cost to the plant of being a violator, therefore, comes not only from the investment cost required to resolve outstanding violations but also from an increased level of regulatory oversight.

High Priority Violator Status: If particularly damaging or repeated violations occur – a plant becomes a "High Priority Violator". This can occur through substantial testing or chronic violations. After a plant becomes HPV, it begins intense oversight that includes more frequent inspections, higher fines, and explicit deadlines to resolve any outstanding violations. A plant can only exit HPV status after resolving all outstanding violations, regardless of whether those violations would independently elevate the plant to HPV status.

Fines: When a violation is detected, the plant can be informally sanctioned through warning letters, telephone calls, and notices of violation. These actions are most frequently carried out by the lowest-level authority. The next stage is formal sanctions, which are usually administrative orders or fines.

II. Data

A. Data Set Generation

Matching geographic coordinates, we merge six publicly available datasets to construct a county-year panel that encompasses air quality, climate, ethnic and demographic composition, as well as environmental scrutiny information for 251,829 facilities located in 3,014 counties spanning the contiguous US. To the best of our knowledge, this compiled dataset constitutes the most extensive aggregation of information within an environmental scrutiny context to date.

As an initial step, we make use of data sourced from the EPA's Integrated Compliance Information System for Air (ICIS-AIR)[4] which gathers information on the current compliance status of stationary air pollution sources, such as electric power plants, steel mills, factories, and universities. Additionally, ICIS-AIR contains data on historic inspection dates and inspection outcomes, ranging from compliant to federally reported or high-priority violators. The ICIS-AIR database has been made available in 2014 when it replaced the Air Facility System (AFS) as the database of record for EPA-regulated air emissions facilities. As inspections can occur at multiple levels in the American environmental regulatory framework, this data is assembled by the EPA through systematic reporting by state and local air pollution authorities. ICIS-AIR also includes data on a plant's historical violation status (e.g., compliant, regular violator, or high-priority violator) and the costs incurred by the plant - both fines and investments combined - to return to compliance after a violation.

The ICIS-AIR database is part of the EPA's larger Environfacts and IDEA (Integrated Data for Enforcement Analysis) database, which can be accessed by the Enforcement and Compliance History Online (ECHO) website. The IDEA system was first introduced in 1990. It is maintained by the EPA and contains compliance and enforcement data for different tracking systems on a monthly basis. Both datasets have a unique identifier based on which we perform the merge (the Facility Registry Service - FRS)[5]. The merged

[4] https://echo.epa.gov/files/echodownloads/ICIS-AIR_downloads.zip

[5] https://catalog.data.gov/dataset/facility-registry-service-frs

dataset includes then information on the exact geographic location of each plant, as well as details on the plant's operating industry. We then collapse the plant-level into a yearly panel at the county-level, containing information on environmental inspections and compliance spanning from 2000 until 2018.

As a third step, we combine the county-level yearly panel with information about average yearly fine particulate matter ($PM_{2.5}$) concentrations. We rely on two sources for the air pollution data. First, we retrieve remote-sensed data from Hammer et al. (2020).[6] who Second, we download the ground-level monitor data provided by the Air Quality System (AQS) database managed by the EPA, which has $PM_{2.5}$ data from 1,989 outdoor ground monitors across the United States.[7] We aggregate both datasets to the yearly county level to match our inspection panel data. Moreover, we merge to the panel key climate data, such as wind speed, precipitation, and temperature from NASA's MODIS satellite program.

Finally, county-level demographics and ethnic composition data are added to the previously generated panel. Two distinct data sets are used for this scope. First, we use the UN-adjusted county-level population count data provided by WorldPop (2020). This dataset provides information on the US population density on a 100x100m scale, taking census and satellite imagery data into account. Additionally, we use annual census data on county-level racial and ethnic composition, as well as income from the decennial census 100-Count survey, to finalize our dataset. The final panel consists of yearly observations for a total of 3,014 US counties from 2000 - 2018.

B. Stylized Facts

This section provides a short description of the main patterns observed in the data. Our main focus is on the relationship between a county's air pollution concentrations and the changes in its racial composition on the one hand, and the environmental auditing activity led within its boundaries on the other hand.

Figure 1 illustrates the average yearly $PM_{2.5}$ concentrations over 2000 - 2017 of all contiguous US counties where at least one environmentally relevant plant is located. Additionally, the placement of ground-level monitors that measure $PM_{2.5}$ is marked with yellow dots. We make three main observations. First, there appears to be substantial geographic clustering in air pollution across the US, whereby the eastern parts of the US

[6] The dataset available from Hammer et al. (2020) has a geographical resolution of 0.01x0.01° at a monthly temporal frequency. We collapse this dataset at a yearly county-level.

[7] https://aqs.epa.gov/aqsweb/airdata/download_files.html

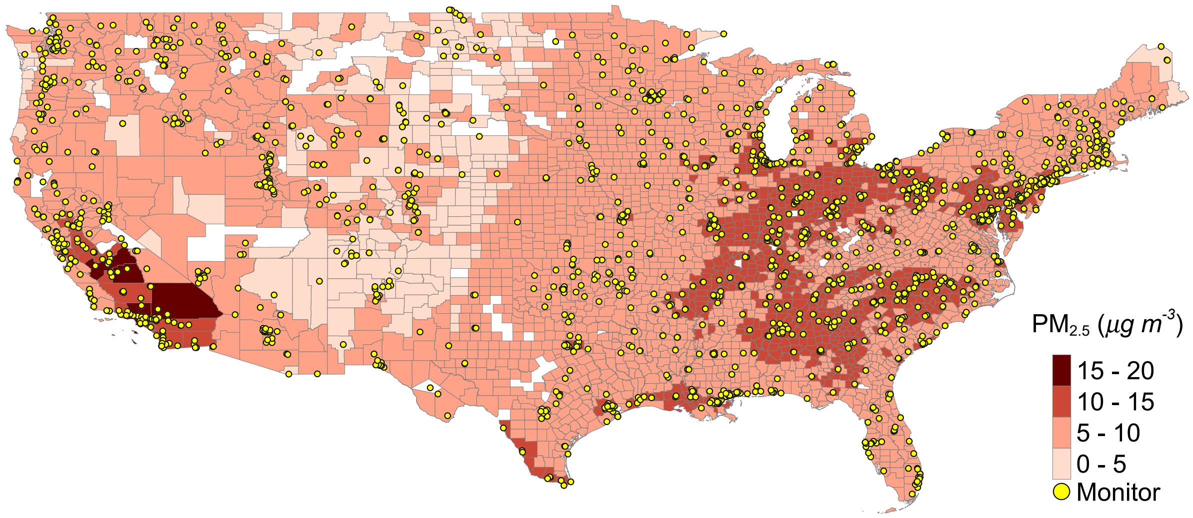


Figure 1 – Average PM$_{2.5}$ concentrations and ground-level monitor placement.

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 yellow dots.

and Southern California experienced on average lowest air quality. Second, the placement of ground-level monitors appears to follow the pollution clustering pattern, being predominantly located in areas that have higher pollution levels. Third, a large share of all US counties have no ground-level monitors, despite average PM$_{2.5}$ concentration levels being above the WHO recommended threshold of $5\mu g/m^3$.

We further explore these qualitative patterns in Table 1, which presents summary statistics of key variables at the county level, averaged over time. Column 1 provides mean values across all counties. We make the following observations with respect to the whole sample statistics. PM$_{2.5}$ concentration levels measured by ground-level monitors are higher than remote-sensed PM$_{2.5}$ concentrations, suggesting that monitors are strategically placed where air pollution is higher. Abound 20% of all plants have been inspected at least once during the time horizon that our data spans. Across counties, the population is predominantly white, with an average share of 86%.

In the remaining columns, Table 1 distinguishes counties along two dimensions. The first dimension groups counties according to the racial demographic changes they have experienced over the time horizon 2000 - 2018. Namely, we differentiate between counties that have experienced a sudden increase in their share of nonwhite population – as defined by a 0.5 or more percentage point increase from one year to the next – and those that did not. We henceforth refer to these two groups of counties as *Jump* and *No jump*,

Table 1 – 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	0.94	0.97	0.97	0.61	0.91	0.88	0.09	0.00	0.00
Scrutiny									
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	22.44	24.27	21.80	0.00	26.16	20.80	0.00	0.00	0.00
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
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 μgm^{-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 thousand USD, precipitation in mm/m², wind speed in m/s, and temperature in degrees Fahrenheit.

respectively. The second dimension divides the sample according to the existence of at least one $PM_{2.5}$ ground-level monitor.

Table 1 further reveals that counties with monitoring stations experience, on average higher levels of air pollution compared to those without such stations. Moreover, among counties without monitors, air quality is significantly better in counties where the non-white population experienced a jump. In contrast, no significant differences are observed in counties with monitors. Interestingly, the share of inspected plants is higher in counties that did not experience a jump in the racial composition than in those where no such jump occurred, and this result holds true in both counties with and without monitors. ?? provides a graphic illustration confirming that these patterns also hold over time.

Panel A. Counties w/ monitors — *Panel B.* Counties w/o monitors

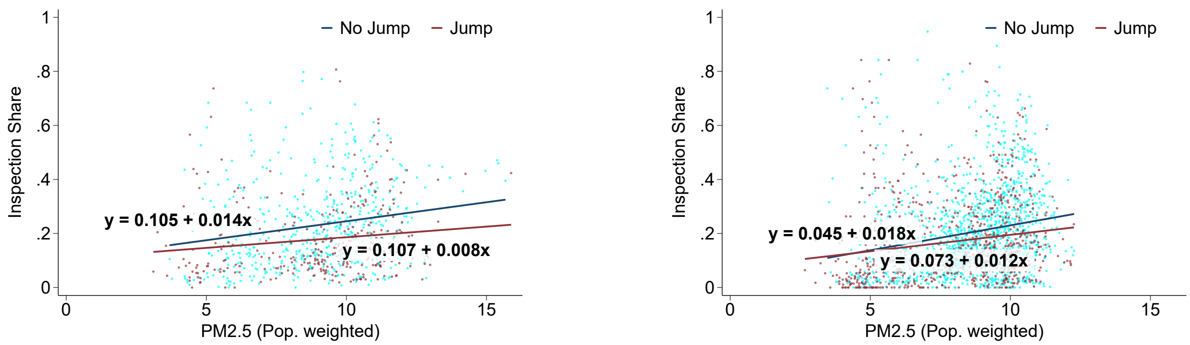


Figure 2 – Share of inspected plants and $PM_{2.5}$ concentrations.

Notes: This figure plots the average share of inspected plants versus the average $PM_{2.5}$ levels of each county over 2000-2018. Panel A exclusively focuses on counties without ground-level $PM_{2.5}$ monitors, while Panel B considers counties with such monitors. Within each panel, the data points are divided into two groups: red points represent counties that experienced a jump in the share of Nonwhite population. In contrast, blue points depict counties without such a jump.

2 further explores the cross-sectional correlation between air pollution concentrations and the share of inspected plants in a county. Panel A exclusively considers counties with ground-level $PM_{2.5}$ monitors, while Panel B is focused on counties without. Furthermore, each panel distinguishes counties with and without a jump in the racial composition. Across all plots, a positive correlation is observed between $PM_{2.5}$ levels and the share of inspected plants. Moreover, in both panels, the correlation is higher for counties that did not experience a racial jump, as indicated by the steepness of the slopes.

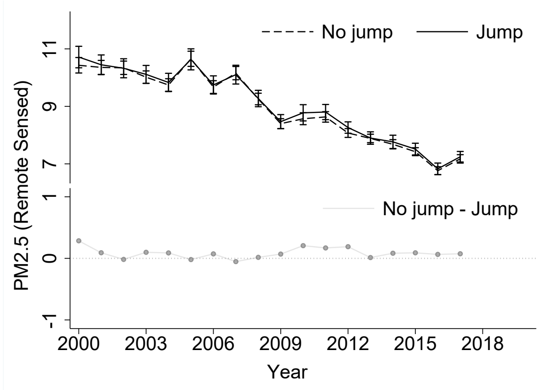
III. Changes in Racial Composition and Environmental Inspections

A. Identification strategy

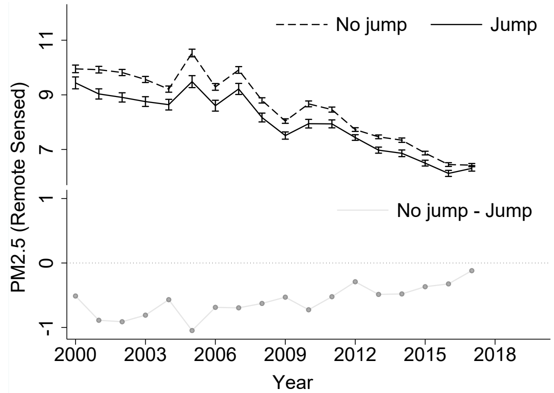
This section further explores the relationship between the racial composition of US counties and the prevalence of environmental auditing. For identification, we exploit within-county variation in the racial composition as well as the share of inspected plants over time. Using a county-level yearly panel, we employ a staggered difference-in-differences approach that compares outcomes in "*treated*" counties to those in "*not-yet treated*" ones. We define the *treatment* as an increase of 0.5 percentage points or more in the share of the nonwhite population of a county within consecutive years.

Figure 4 depicts the distribution of changes in the share of non-white population within a county in the year of treatment (Panel A). Counties that never experience such

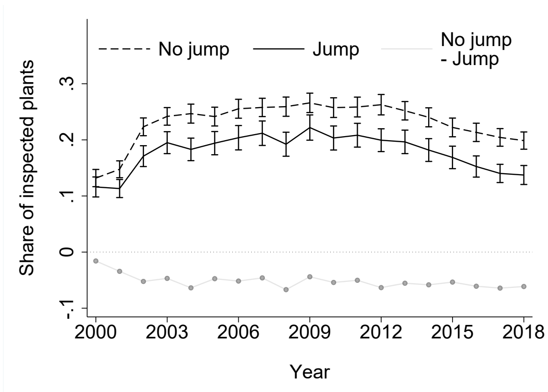
Panel A. PM2.5, counties w/ monitors



Panel B. PM2.5, counties w/o monitors



Panel C. Share inspections, counties w/ monitors



Panel D. Share inspections, counties w/o monitors

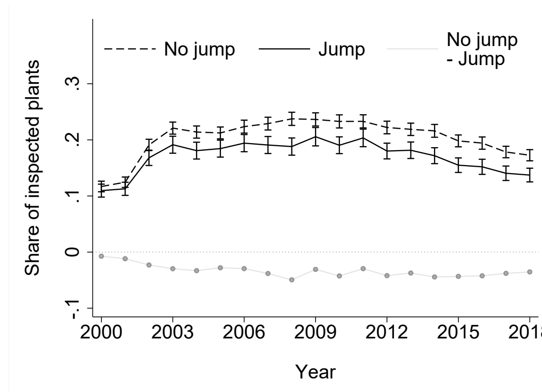


Figure 3 – Average PM2.5 concentrations and share of inspected plants over time.

Notes: The figure above presents how PM2.5 (pop. weighted) and the share of inspected plants develop over time. Panels A and C depict this development for counties with monitors, while panels B and D only consider counties that do not have ground monitors. In each panel, we, additionally, distinguish between counties that experienced a jump in the Nonwhite population and those that do not.

a jump are not depicted in the histogram. The figure shows that, among counties that experienced a jump in the share of non-white population, more than 80% of them had a jump between 0.5 and 1 percentage points. Panel B depicts the time-varying number of counties that experience such a jump. We observe an increase in the number of treated counties over time that progresses smoothly. At the end of the estimation horizon, about one third of all counties have encountered a rise of 0.5 percentage points or more in the proportion of non-white population. Furthermore, Figure A-1 in the Appendix illustrates that counties with jumps are spatially distributed all across the contiguous US.

Panel A. Change in nonwhite share. *Panel B.* Number of counties by treatment.

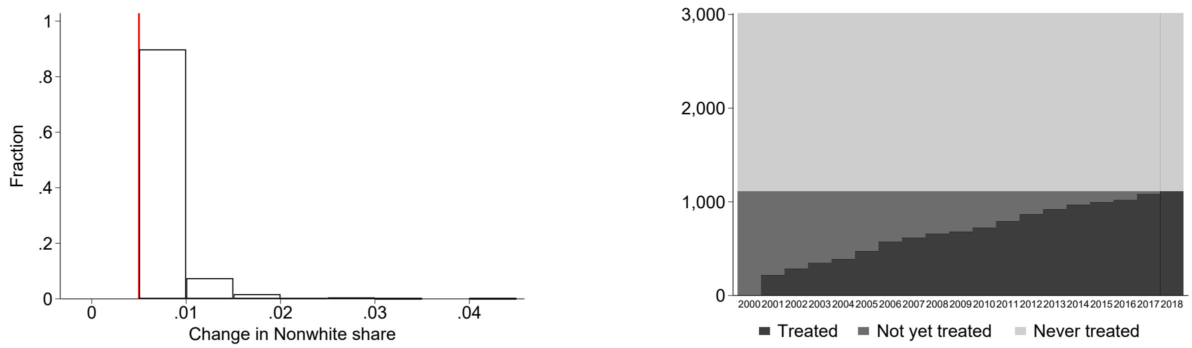


FIGURE 4 – THE DISTRIBUTION OF CHANGES IN THE SHARE OF NONWHITE POPULATION AND NUMBER OF COUNTIES, BY TREATMENT.

Notes: This figure plots the distribution of changes in the share of non-white population in the year of treatment (Panel A) and the number of counties by treatment over time (Panel B). The red line in Panel A marks the 0.5 percentage points threshold used to define the treatment in our main specifications.

Following the approach in Sun and Abraham (2020), we estimate the following differences-in-differences model with dynamic treatment effects:

$$Y_{i,t} = \Sigma_{k=-18}^{-2} \beta_k \times T_{i,k} + \Sigma_{k=0}^{18} \beta_k \times T_{i,k} + X'_{i,t}\Gamma + \gamma_i + \theta_t + \epsilon_{i,t}, \tag{1}$$

where $Y_{i,t}$ is the outcome variable of interest in county i and year t. In our analysis, we first estimate the model for yearly $PM_{2.5}$ concentrations and secondly for a series of environmental scrutiny outcomes, including the share of inspected plants, the number of inspected plants, the number of on- and offsite inspections, as well as the designation of counties in nonattainment. $T_{i,k}$ is a dummy indicator equal to one for the cohort of treated observations within k periods relative to the treatment. $X'_{i,t}$ is a vector of time and county-varying covariates, such as income and population. Models with $PM_{2.5}$ concentrations as outcome variables additionally control for wind speed, temperature, and precipitation. All other models control for population-weighted $PM_{2.5}$ concentrations. γ_i and θ_i are county and calendar year fixed effects, respectively. $\epsilon_{i,t}$ denotes the error term clustered at the county level.

B. Results

Figure 5 displays the estimated coefficients for the model in Equation 1, where the outcome variable is either the share of inspected plants (Panel A) in a county or its average yearly $PM_{2.5}$ concentrations (Panel B). We find that, in the years following the jump in the share of nonwhite population, the share of inspected plants in a county decreases significantly and remains below the pre-jump level for most of the ten-year period that follows. The pattern does not appear to be explained by changes in $PM_{2.5}$ concentrations, which appear to remain at similar levels or even slightly increase post-jump.

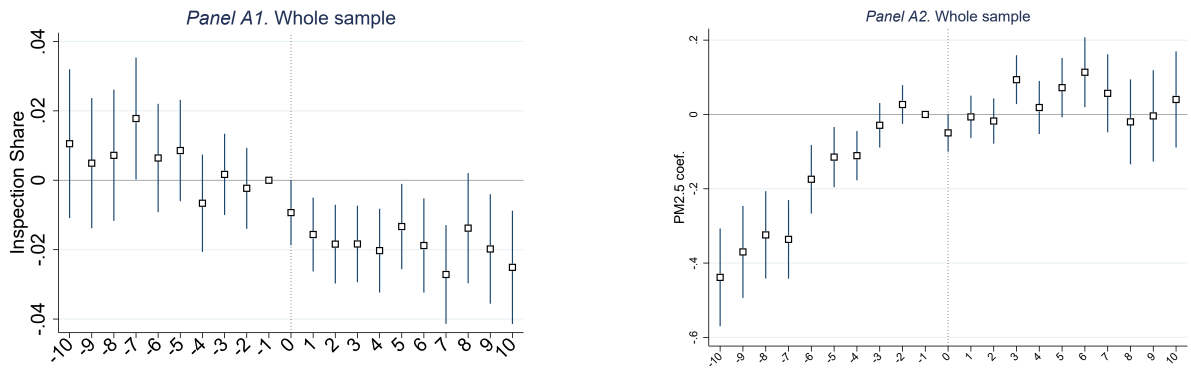


FIGURE 5 – DYNAMIC EFFECTS OF A JUMP IN THE SHARE OF NONWHITE POPULATION ON THE SHARE OF INSPECTED PLANTS.

Notes: This figure displays the estimated coefficients of the model in Equation (1). The treatment is defined as a 0.5 percentage point increase in the share of the non-white population. Panels A and B present the outcomes for the share of inspections and for population-weighted $PM_{2.5}$ concentrations using all counties in our sample.

To further investigate the observed patterns, we extend the analysis to other environmental scrutiny measures, as well as verify potential heterogeneity across counties with and without ground-level monitors. Table 2 presents the results of estimating Equation 1, where, instead of allowing one coefficient for each event time year, we group the event time dummies into four categories.[8] For space considerations, Table 2 displays only the coefficient corresponding to the five-year period before the jump (grouping event years -6 to -2 and denoted *Pre-Jump*) and the coefficient corresponding to the average effect at and five-years after the jump (grouping event years 0 to 5 and denoted *Post-Jump*). Our main focus is on the *Post-Jump* coefficients, estimating the average impact of a jump in the racial composition. Nevertheless, we are interested in documenting also the *Pre-Jump* coefficients in order to ensure the absence of pre-existing trends before the occurrence of the event.

Panel A displays the estimation results for the whole sample of counties. While $PM_{2.5}$ concentrations appear not affected by the change in the racial composition, the share of inspected plants experiences a 1.6 percentage point decrease significant at the 1% level (p-value<0.01). The effect coincides with a significant increase in the number of offsite

[8]We estimate one coefficient for all event time years -18 to -7, one coefficient for -6 to -2, one coefficient for 0 to 5, and one coefficient for 6 to 18.

Table 2 – Volume of environmental scrutiny and share of the non-white population.

	Dependent variable					
	$PM_{2.5}$ (Pop. weighted)	Share inspected plants	N inspected plants	N onsite inspections	N offsite inspections	Nonattainment designation
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Counties						
Pre-Jump	-0.051*	0.002	0.190	0.197	-0.413	
	(0.027)	(0.005)	(0.231)	(0.366)	(0.415)	
Post-Jump	0.009	-0.016***	0.423	0.114	3.020***	
	(0.027)	(0.004)	(0.448)	(0.546)	(0.628)	
Observations	54,224	54,242	54,242	54,242	54,242	
R-Squared	0.89	0.64	0.82	0.79	0.65	
Panel B: Counties without monitors						
Pre-Jump	-0.040	-0.000	0.118	0.213	-0.402	
	(0.032)	(0.006)	(0.170)	(0.158)	(0.263)	
Post-Jump	0.074**	-0.016***	-0.157	-0.574***	1.252***	
	(0.032)	(0.005)	(0.205)	(0.170)	(0.429)	
Observations	38,816	38,834	38,834	38,834	38,834	
R-Squared	0.90	0.63	0.74	0.78	0.56	
Panel C: Counties with monitors						
Pre-Jump	-0.086	0.007	0.592	0.544	-0.561	0.003
	(0.055)	(0.012)	(0.833)	(1.494)	(1.646)	(0.016)
Post-Jump	-0.134**	-0.018**	0.563	-0.416	6.214***	0.029**
	(0.052)	(0.009)	(1.475)	(1.909)	(1.838)	(0.011)
Observations	15,408	15,408	15,408	15,408	15,408	15,408
R-Squared	0.89	0.67	0.80	0.77	0.67	0.47

Notes: This table presents estimates of Equation (1) from the main text. Each column corresponds to a different outcome variable. $PM_{2.5}$ refers to population-weighted fine particulate matter concentrations. All models include county and year-fixed effects, as well as log values of population and income as controls. The model in column (1) additionally controls for wind-speed, temperature, and precipitation. All models in Columns (2)-(6) additionally control for population-weighted $PM_{2.5}$ concentrations. Standard errors are clustered at the county level and presented in parentheses. Significance is denoted as follows: *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.

inspections (p-value<0.01). The pattern appears consistent also when distinguishing between counties without (Panel B) and with (Panel C) monitors. Namely, in the medium term, after the jump in the share of the nonwhite population within a county, the share of inspected plants is significantly reduced, while the number of offsite inspections increases. Interestingly, these effects coincide with an increase in air pollution concentrations in the post-jump period in counties without monitors and a decrease in the number of onsite inspections. In contrast, air pollution concentrations decrease in counties with monitors in the period following the jump, while the probability of receiving nonattainment designation increases by 3 percentage points.

Robustness Tests. We perform various tests to further probe the robustness of these results. First, we vary the definition of the treatment, considering various thresholds for the increase in the share of nonwhite population. Appendix A-4 provides the estimation results when the treatment is defined as an increase in the share of nonwhites by 0.75, and 1 percentage points, respectively. Independent of the treatment definition, the same pattern emerges: following an increase in the share of the nonwhite population, the share of inspected plants decreases. The results suggest that, if anything, higher treatment levels led to more pronounced reductions in inspection shares.

Second, our identification strategy so far defined the treatment as the first time that a county incurs a jump in the share of non-whites. 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. To address this possibility, we allow the treatment definition to switch on and off. We estimate dynamic treatment effects following the methodology proposed in De Chaisemartin and d'Haultfoeuille (2020). Appendix Figure A-5 displays the estimated coefficients and prove the robustness of our main results to this alternative treatment definition.

IV. Impact of Inspections and Nonattainment Designation on $PM_{2.5}$

The analysis so far documents that the share of inspected plants in a county tends to decrease once a county experiences a positive jump in the share of nonwhite population. The result is surprising and does not appear justified by changes in fine particulate matter concentrations in the same counties. We put forward two potential mechanisms that could explain these patterns. On the one hand, recent literature in political science argues that white neighborhoods often see higher lobbying power (Davidson, 2017; Salvo, 2020). Following such pronounced political participation, the EPA might be more inclined to inspect these very regions.[9] A different mechanism that could explain EPA's prioritization of counties with stable racial demographics could be that inspections are more efficient in reducing ambient air pollution in these counties compared to those where the racial composition changes. In other words, the EPA might select which counties to audit more in order to maximize the return on inspections.

To verify the validity of this hypothesis, we first assess the relationship between the intensity of environmental auditing in a county and its $PM_{2.5}$ concentrations. Second, we investigate whether there is heterogeneity in this relationship across predominantly white and more racially mixed counties.

[9] We are currently working on gathering and analysing data to assess whether this mechanism is indeed relevant.

We start with a two-way fixed effects model, where current $PM_{2.5}$ concentrations in a county are regressed on the current and lagged share of inspected plants:

$$\text{PM2.5}_{i,t} = \beta_1 \text{SI}_{i,t} + \beta_2 \text{SI}_{i,t-1} + X'_{i,t}\Gamma + \phi_i + \gamma_t + \varepsilon_{i,t}, \tag{2}$$

where, $\text{PM2.5}_{i,t}$ stands for the level of $PM_{2.5}$ concentrations (either population-wighted remote sensed or measured by the ground monitors, where available) in year t and county i. $\text{SI}_{i,t}$ and $\text{SI}_{i,t-1}$ represent the share of inspected plants in the year t and $t-1$, respectively. Additionally, we include current and lagged nonattainment designations for counties that have at least one monitor. $X'_{i,t}$ is a vector of time-varying control variables, including temperature, precipitation, wind speed, population count, and average income level. ϕ_i and γ_t represent county and year-fixed effects, respectively. The standard errors are clustered at the county level.

To account for the tendency of $PM_{2.5}$ to disperse across space, we also estimate a spatial model, whereby we include a spatial lag of the dependent variable on the right-hand side of the regression equation. Furthermore, we correct for spatial correlation in the error terms. We rely on an inverse spatial weight matrix, where counties further away from the county of interest are asigned a lower weight than those closer to it.[10]

$$\text{PM2.5}_{i,t} = \mu\Psi\text{PM2.5}_{j,t} + \beta_1 \text{SI}_{i,t} + \beta_2 \text{SI}_{i,t-1} + X'_{i,t}\Gamma + \phi_i + \gamma_t + (I - \rho\Psi)^{-1}\varepsilon_{i,t}, \tag{3}$$

where Ψ represents the inverse spatial weights matrix. Table 3 presents the estimation results of Equations (2) and (3).[11] We present whole sample results in columns 1 and 2. In columns 3 and 4, we restrict the sample to counties that are predominantly white, *i.e.*, their average share of the white population across time is of 80% or higher. Columns 5 and 6 show the estimation results for counties where the average share of the white population is below 80%.

Overall, we find that a higher share of inspected plants in the previous year tents of be associated with lower air pollution concentrations in the current year. The effects appear more pronounced in counties without monitors, especially among counties with a predominantly white population. In counties with monitors, counties designated in nonattainment reduce their $PM_{2.5}$ concentrations in the following year, and the impact

[10]We test the robustness of our results to using two other differently defined weight matrices, namely: queen and rook contiguity matrices. Additionally, we estimate the models using a placebo weight matrix, where weights have been randomly generated. Appendix D provides detailed information on the weight matrices and the estimation results.

[11]Detailed on the estimated coefficients of the spatially lagged variables are presented in the appendix.

Table 3 – Environmental scrutiny and fine particulate matter concentrations.

	Dependent variable: PM2.5 concentrations					
	All counties		White counties		Non-white counties	
	Standard (1)	Spatial (2)	Standard (3)	Spatial (4)	Standard (5)	Spatial (6)
Panel A: All counties						
Lag share inspected	-0.059	-0.022	-0.087**	-0.044**	0.020	-0.092**
	(0.041)	(0.016)	(0.044)	(0.018)	(0.082)	(0.040)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,229	51,238	40,247	40,256	10,982	10,982
Panel B: Counties without monitors						
Lag share inspected	-0.088**	-0.020	-0.122**	-0.031*	0.128*	0.025
	(0.043)	(0.016)	(0.048)	(0.018)	(0.076)	(0.038)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,677	36,686	29,333	29,342	7,344	7,344
Panel C1: Counties with monitors						
Lag share inspected	0.051	-0.060	0.031	-0.046	-0.269	-0.307***
	(0.101)	(0.038)	(0.105)	(0.042)	(0.232)	(0.117)
Lag nonattainment	-0.771***	-0.239***	-0.819***	-0.279***	-0.622***	-0.599***
	(0.055)	(0.039)	(0.068)	(0.045)	(0.078)	(0.085)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,552	14,552	10,914	10,914	3,638	3,638
Panel C2: Counties with monitors (Ground monitor $PM_{2.5}$)						
Lag share inspected	-0.094	-0.186***	-0.182	-0.160**	-0.018	-0.242
	(0.151)	(0.067)	(0.162)	(0.075)	(0.316)	(0.168)
Lag nonattainment	-0.872***	-0.492***	-0.994***	-0.525***	-0.566***	-0.664***
	(0.064)	(0.070)	(0.080)	(0.081)	(0.103)	(0.124)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,408	15,408	11,556	11,556	3,852	3,852

Notes: This table presents estimates of Equations (2) and (3) from the main text. Every two columns correspond to a different outcome variable (either ground monitored, remotely sensed, or population-weighted $PM_{2.5}$). We omit reporting the coefficients of the current share of inspected plants and the current nonattainment designation. All models include county and year-fixed effects, as well as time-varying controls for temperature, precipitation, wind speed, the logarithm of population count, and the logarithm of the annual income. The spatial models are estimated using an inverse distance matrix without a distance cut-off. In the standard models, standard errors are clustered at the county level. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

is significant also when distinguishing counties by their racial composition. The results are robust to estimating either the standard or spatial models. The analysis indicates no evidence that the environmental scrutiny activity is more effective in predominantly white counties vis-a-vis the rest.

V. Conclusion

This paper investigates the effectiveness of the Clean Air Act (CAA) in mitigating environmental inequalities and examines the role of dynamics in the racial composition of counties for the application of different scrutiny types. Our study uses a comprehensive dataset on environmental scrutiny and air pollution exposure, which includes auditing information from 251,829 plants across the contiguous USA, combined with ground-level monitor and high-resolution remotely sensed air pollution information.

We find that despite being exposed to higher particulate matter concentrations, counties are inspected less often when the share of the Nonwhite population in a county increases. We are able to show that this discrepancy cannot be explained by differences in the efficiency of environmental audits, or by decreasing pollution levels after a change in the racial composition. We see that the decrease in inspection shares is especially prevalent in counties that do not have any ground-level monitors for $PM_{2.5}$. Considering that these are the very counties that experience continuous growth in pollution levels underlines the severity that this development entails. In counties with pollution monitoring systems, however, we observe only a short decrease in inspection rates and no ongoing increase in pollution levels, giving less reason for worry.

Furthermore, our findings indicate that the nonattainment designation plays a vital part not only in the reduction of $PM_{2.5}$ but also in closing the racial pollution gap. These findings overlap with the key results of Currie et al. (2023). However, we argue that the disproportionate distribution of inspections away from Nonwhite counties hinders an effective closing in the future. Also, we claim that the impact of the EPA's environmental scrutiny might be overestimated when only accounting for ground-level data and disregarding spatial spillover effects of pollution and inspections.

We conclude that policymakers should pursue targeted and efficient regulatory policies based on accurate, all-encompassing measurements while ensuring that the implementation of these policies is impartial and equitable. Specifically, policymakers should be cautious in overregulating areas that are in compliance with air quality standards while under-regulating areas that appear to be in violation. Using satellite measurements to improve the accuracy of targeting pollution sources can be a valuable step in this direction.

Moreover, our study underlines the vital role that ground monitors play in tackling racial air pollution disparities. Not only do our results suggest that possible discriminatory issues might be restrained by the data objectivity of these instruments, but they further allow the continuous observation of pollution levels in an area and facilitate the possibility to take impacting legal action against areas breaching legal pollution levels, in the form of nonattainment designations.

It is important to continue to investigate the root causes of these disparities and to address them through policy and regulatory changes to ensure that all communities have equal access to clean and healthy environments. In future instances of this ongoing study, we want to identify the role of lobbying power in the process of inspection place choices.

References

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.

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.

Davidson, S. (2017). Public affairs practice and lobbying inequality: Reform and regulation of the influence game. *Journal of Public Affairs*, 17(4):e1665.

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

Earnhart, D. (2004a). Panel data analysis of regulatory factors shaping environmental performance. *Review of Economics and Statistics*, 86(1):391–401.

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

Eckert, H. and Eckert, A. (2010). The geographic distribution of environmental inspections. *Journal of regulatory economics*, 37(1):1.

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.

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. Publisher: American Chemical Society.

Hanna, R. N. and Oliva, P. (2010). The impact of inspections on plant-level air emissions. *The BE Journal of Economic Analysis & Policy*, 10(1).

Helland, E. (1998a). The enforcement of pollution control laws: Inspections, violations, and self-reporting. *Review of Economics and Statistics*, 80(1):141–153.

Helland, E. (1998b). Environmental protection in the federalist system: The political economy of npdes inspections. *Economic Inquiry*, 36(2):305–319.

Innes, R. and Mitra, A. (2011). Parties, politics, and regulation: how congressmen affect local epa enforcement of clean air laws. *Work. Pap., Cent. Energy Environ. Econ., Univ. Calif., Berkeley.*

Kelejian, H. H. and Prucha, I. R. (2010). Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances. *Journal of Econometrics*, 157(1):53–67.

Kleit, A. N., Pierce, M. A., and Hill, R. C. (1998). Environmental protection, agency motivations, and rent extraction: the regulation of water pollution in louisiana. *Journal of Regulatory Economics*, 13(2):121–137.

Liu, L. and Yang, Z. (2020). Leveraged enforcement under the EPA's High Priority Violation Policy. *Empirical Economics*, 58(3):1279–1304. Publisher: Springer Nature.

Oljaca, N., Keeler, A. G., and Dorfman, J. (1998). Penalty functions for environmental violations: evidence from water quality enforcement. *Journal of Regulatory Economics*, 14(3):255–264.

Salvo, A. (2020). Local Pollution as a Determinant of Residential Electricity Demand. *Journal of the Association of Environmental and Resource Economists*, 7(5):837–872. Publisher: The University of Chicago Press Chicago, IL.

Sun, L. and Abraham, S. (2020). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*.

Wang, J., Zhang, M., Bai, X., Tan, H., Li, S., Liu, J., Zhang, R., Wolters, M. A., Qin, X., Zhang, M., Lin, H., Li, Y., Li, J., and Chen, L. (2017). Large-scale transport of PM2.5 in the lower troposphere during winter cold surges in China. *Scientific Reports*, 7(1):13238. Number: 1 Publisher: Nature Publishing Group.

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

Appendix

A. Expanded Summary Statistics

Table A-1 – Extended Summary statistics.

	All	White			Non-white			White - Non-white	
		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	9.50	9.57	0.04	10.70	10.68	0.60	0.00	0.00
Remote sensed	7.93	7.45	7.62	0.00	9.49	9.06	0.00	0.00	0.00
Population weighted	8.54	8.59	8.11	0.00	10.18	9.36	0.00	0.00	0.00
Scrutiny									
Nr monitors	0.32	0.99	-	-	1.58	-	0.00	-	
Inspection share	0.20	0.21	0.18	0.00	0.22	0.22	0.09	0.08	0.00
Nr inspected plants	10.17	17.60	5.07	0.00	37.53	5.94	0.00	0.00	0.00
Nr inspections	20.15	35.83	9.69	0.00	72.99	12.49	0.00	0.00	0.00
Nr onsite inspections	12.51	23.11	5.78	0.00	46.60	6.73	0.00	0.00	0.00
Nr offsite inspections	7.65	12.72	3.91	0.00	26.39	5.76	0.00	0.00	0.00
Non-attainment	-	0.07	-	-	0.09	-	-	0.01	-
HPV share	0.02	0.03	0.02	0.00	0.02	0.01	0.00	0.00	0.00
Nr HPV plants	0.85	1.53	0.40	0.00	3.41	0.35	0.00	0.00	0.00
FRV share	0.01	0.02	0.01	0.74	0.01	0.01	0.41	0.40	0.08
Nr FRV plants	0.78	1.65	0.39	0.00	2.27	0.27	0.00	0.00	0.00
Avg fines	0.01	0.02	0.01	0.00	0.01	0.01	0.00	0.03	0.18
Demographic									
Nr plants	83.45	159.94	40.23	0.00	284.69	42.76	0.00	0.00	0.02
Share white pop.	0.86	0.91	0.94	0.00	0.63	0.60	0.00	0.00	0.00
Share afro-american pop.	0.09	0.04	0.03	0.00	0.28	0.34	0.00	0.00	0.00
Share hispanic pop.	0.08	0.10	0.08	0.00	0.09	0.04	0.00	0.00	0.00
Share asian pop.	0.01	0.02	0.01	0.00	0.04	0.01	0.00	0.00	0.08
Population	0.10	0.21	0.03	0.00	0.47	0.03	0.00	0.00	0.00
Income	22.43	25.07	22.09	0.00	24.68	18.78	0.00	0.00	0.00
Climate									
Precipitation	2.96	2.72	2.80	0.08	3.37	3.60	0.00	0.00	0.00
Wind speed	3.50	3.42	3.67	0.00	3.26	3.11	0.00	0.00	0.00
Temperature	56.08	52.65	54.98	0.00	60.97	62.04	0.02	0.00	0.00
Observations	57,266	12,198	32,794	44,992	4,066	8,208	12,274	16,264	41,002

Notes: This table presents county-level summary statistics for different sub-samples spanning from 2000 - 2018. We define "White counties" as counties with more than 80% of the population identifying as white. Non-white is the inverse, respectively. Columns (4), (7), (8), and (9) report p-values of t-test statistics for the difference in means. Column (4) refers to the difference in means between white counties that have at least one PM2.5 monitor versus white counties that have no monitors. Column (7) refers to the difference in means between non-white counties that have at least one PM2.5 monitor versus non-white counties that have no monitors. Further, column (8) presents the difference in means between white counties with monitors versus non-white counties with monitors. Finally, column (9) refers to the difference in means between white counties without monitors against non-white counties without monitors.
PM$_{2.5}$ is measured in μgm^{-3}, population is given in million people, income in thousand USD, precipitation in mm/m², wind speed in m/s, and temperature in °F. Population-weighted PM$_{2.5}$ is not available for 2018 due to missing high-resolution population density data, leading to a total of 54,252 observations for this particular variable.

B. Changes in Racial Demographics

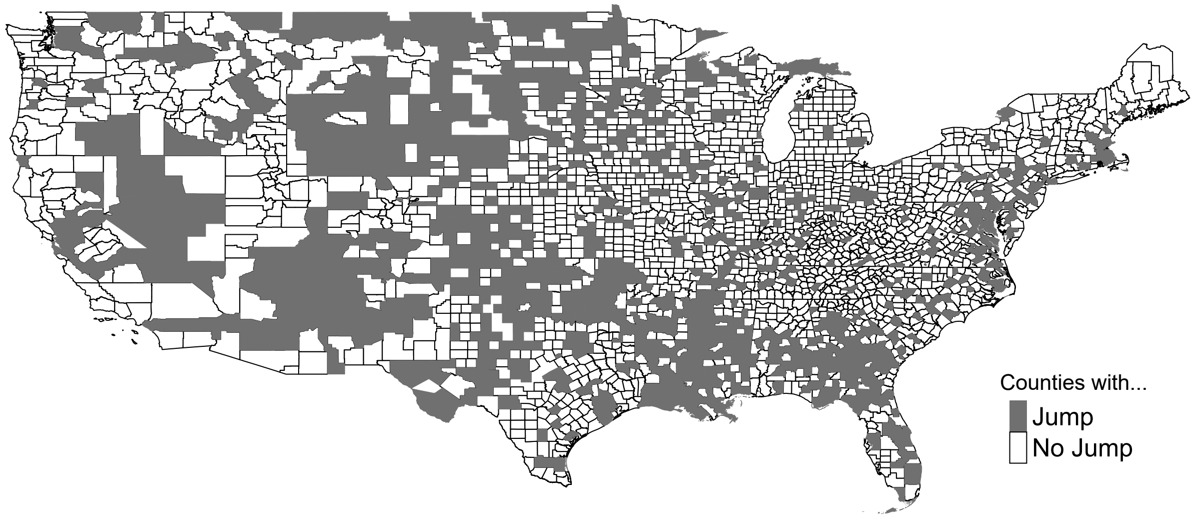


FIGURE A-1 – SPATIAL DISTRIBUTION OF COUNTIES WITH AND WITHOUT JUMPS IN THE SHARE OF NON-WHITE POPULATION.

Notes: This figure illustrates the spatial distribution of all US counties in our sample. Counties that have experienced an increase of at least 0.5 percentage points in the share of non-white population in any year during 2000-2018 are marked with gray. All other counties are colored white.

Panel A. Counties w/ monitors — *Panel B.* Counties w/o monitors

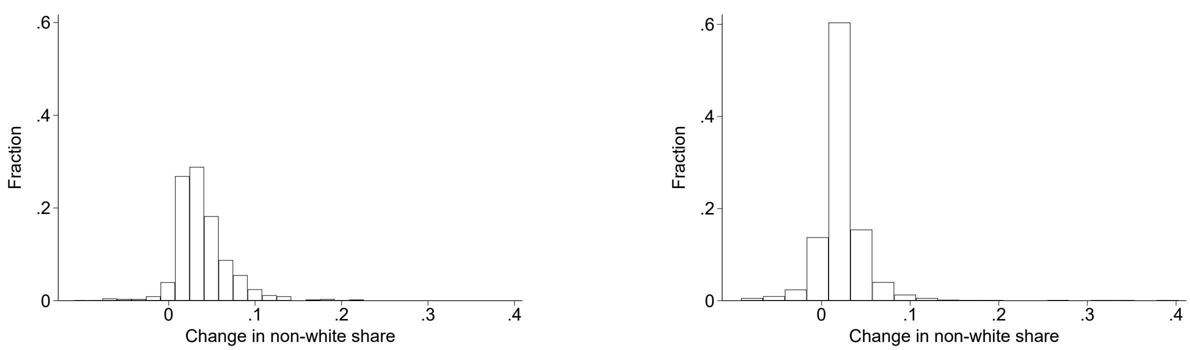


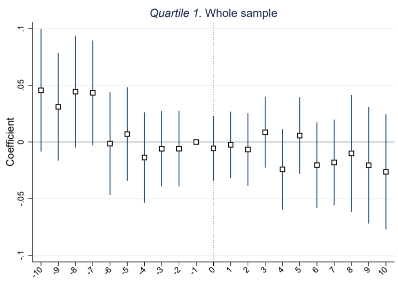
FIGURE A-2 – THE DISTRIBUTION OF CHANGES IN THE SHARE OF NONWHITE POPULATION.

Notes: Panels A and B of the figure display demographic changes over our sample period from 2000 to 2018. More precisely, both histograms indicate the difference in the share of the Nonwhite population between 2000 and 2018. Hence, positive numbers highlight an increase in the Nonwhite population, while negative numbers indicate a decrease.

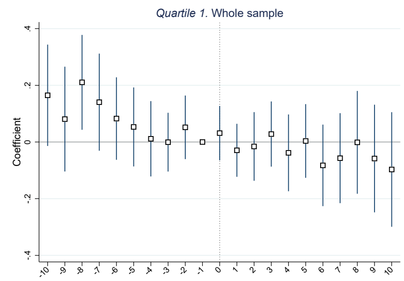
C. Event Study Outcomes

1. Event Study by Quantile

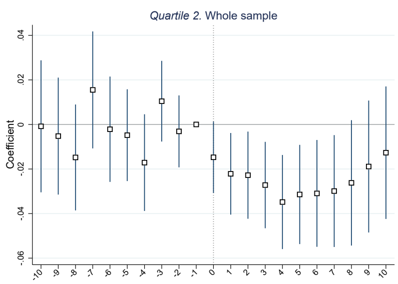
Panel A1. Share Inspections



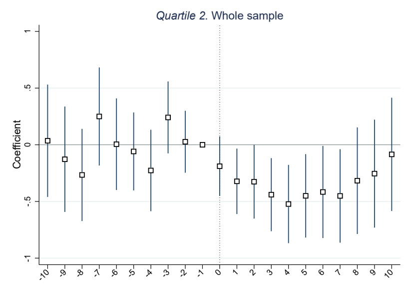
Panel A2. Nr. Inspections



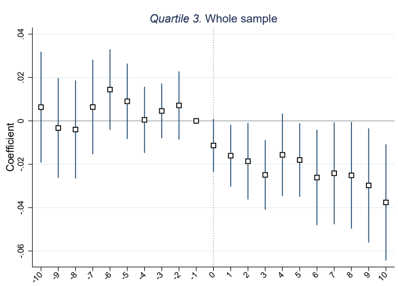
Panel B1. Share Inspections



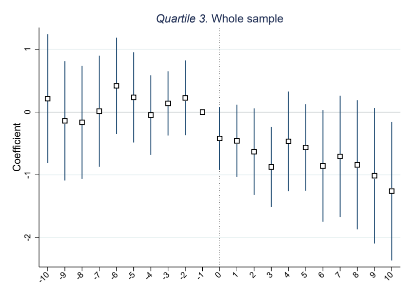
Panel B2. Nr. Inspections



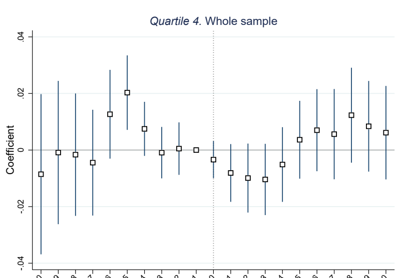
Panel C1. Share Inspections



Panel C2. Nr. Inspections



Panel D1. Share Inspections



Panel D2. Nr. Inspections

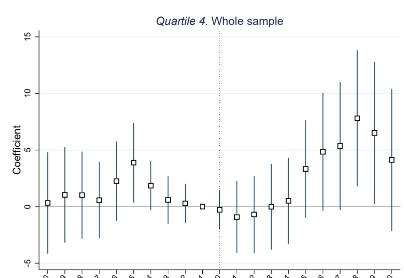
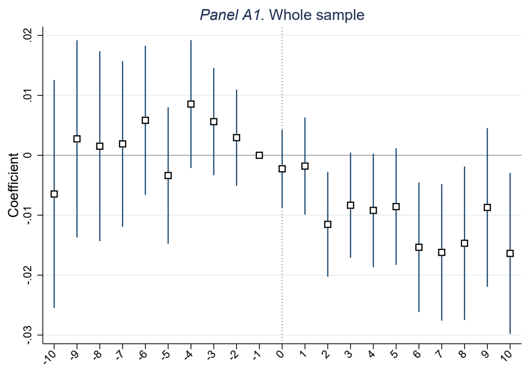


FIGURE A-3 – QUANTILE EVENT STUDY.

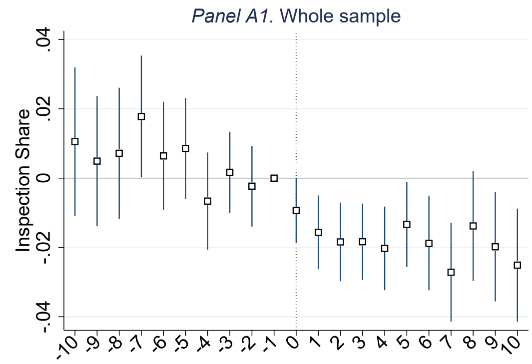
Notes: The figure above displays the outcome of the dynamic event study as described in equation 1 of the main text for the share of inspected plants and the absolute number of inspected plants. Each panel A-D presents the results of the event study for a subsample of the data divided by quantiles for the number of plants in each county. More precisely, Panel A presents the results for counties with 0-25 plants in the county. Panel B for 26-51 plants, panel C for 52-69 plants, and panel D for 70 or more plants.

2. Event Study for Different Treatment Thresholds

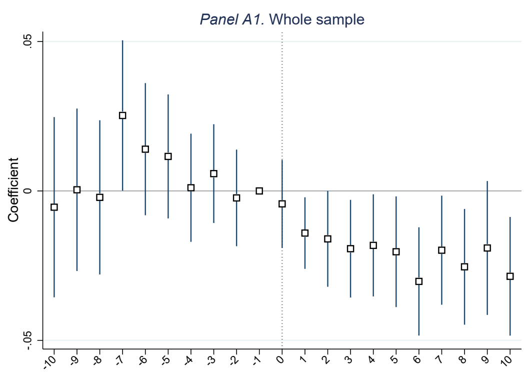
Panel A. 0.25 percentage points treatment



Panel B. 0.5 percentage points treatment



Panel C. 0.75 percentage points treatment



Panel D. 1 percentage point treatment

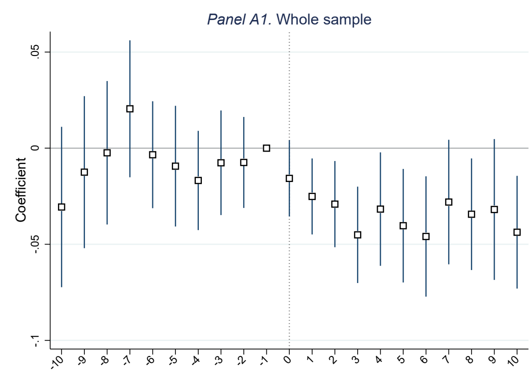


Figure A-4 – Event Study for different Thresholds.

Notes: The figure above shows the results of equation 1 for different subsamples. The treatment is defined as a 0.5 percentage point increase in the share of the non-white population. Panels A1 and A2 present the outcomes for the share of inspections and for remote sensed $PM_{2.5}$ for the whole sample. Panels B1 and B2 for the share of inspections and for remote sensed $PM_{2.5}$ for counties without monitors. Finally panels C1 and C2 show the results for the share of inspections and for remote sensed $PM_{2.5}$ for counties with monitors.

3. Event Study with In- and Out-Switching

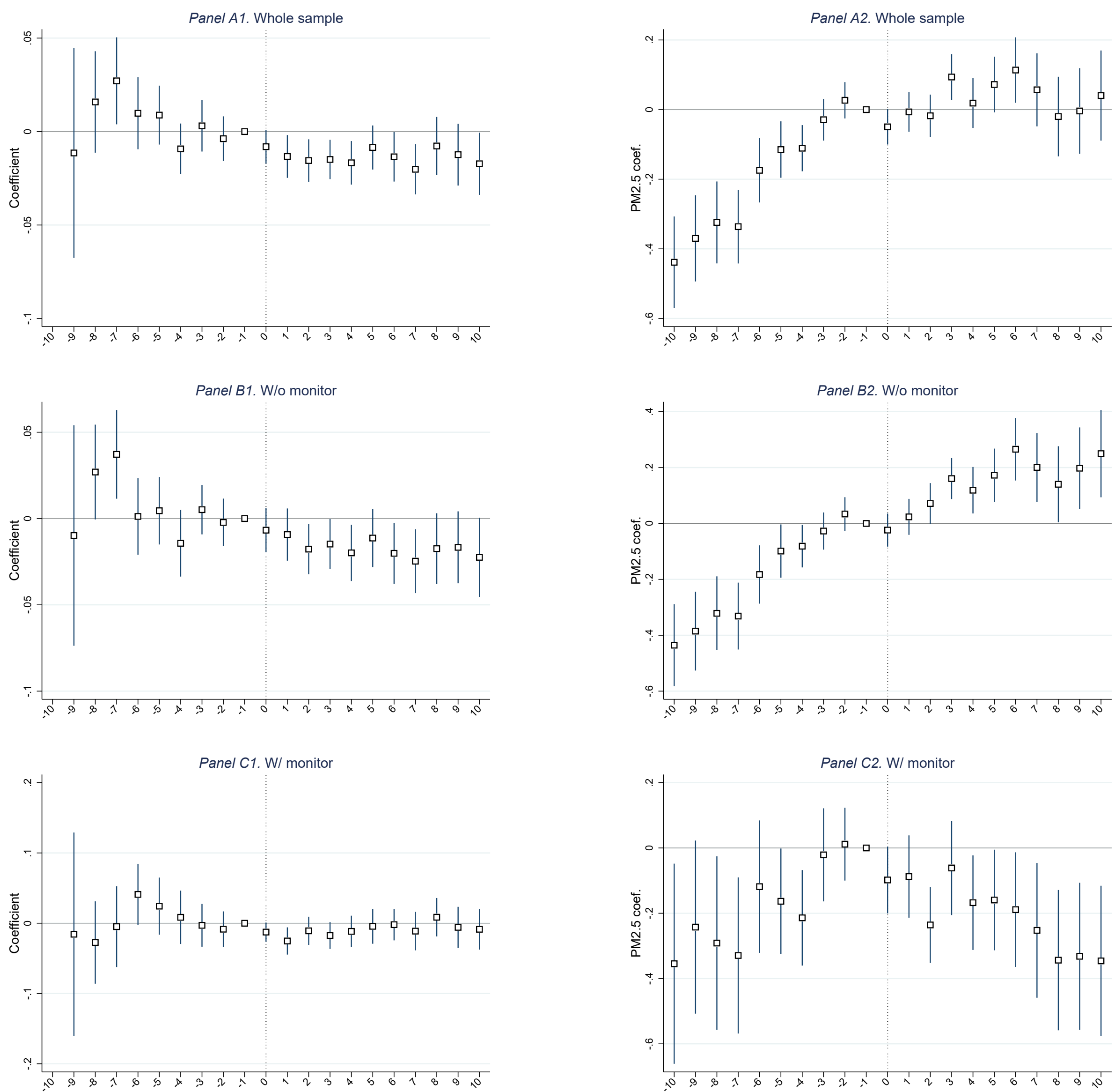


FIGURE A-5 – EVENT STUDY ALLOWING FOR ON AND OFF-SWITCHING.

Notes: The figure above shows the results of equation 1 for different subsamples. The treatment is defined as a 0.5 percentage point increase in the share of the non-white population. Here, counties are allowed tow switch back from treated to not-treated, as described in De Chaisemartin and d'Haultfoeuille (2020). Panels A1 and A2 present the outcomes for the share of inspections and for remote sensed $PM_{2.5}$ for the whole sample. Panels B1 and B2 for the share of inspections and for remote sensed $PM_{2.5}$ for counties without monitors. Finally panels C1 and C2 show the results for the share of inspections and for remote sensed $PM_{2.5}$ for counties with monitors.

4. Event Study for Off- and Onsite Inspections

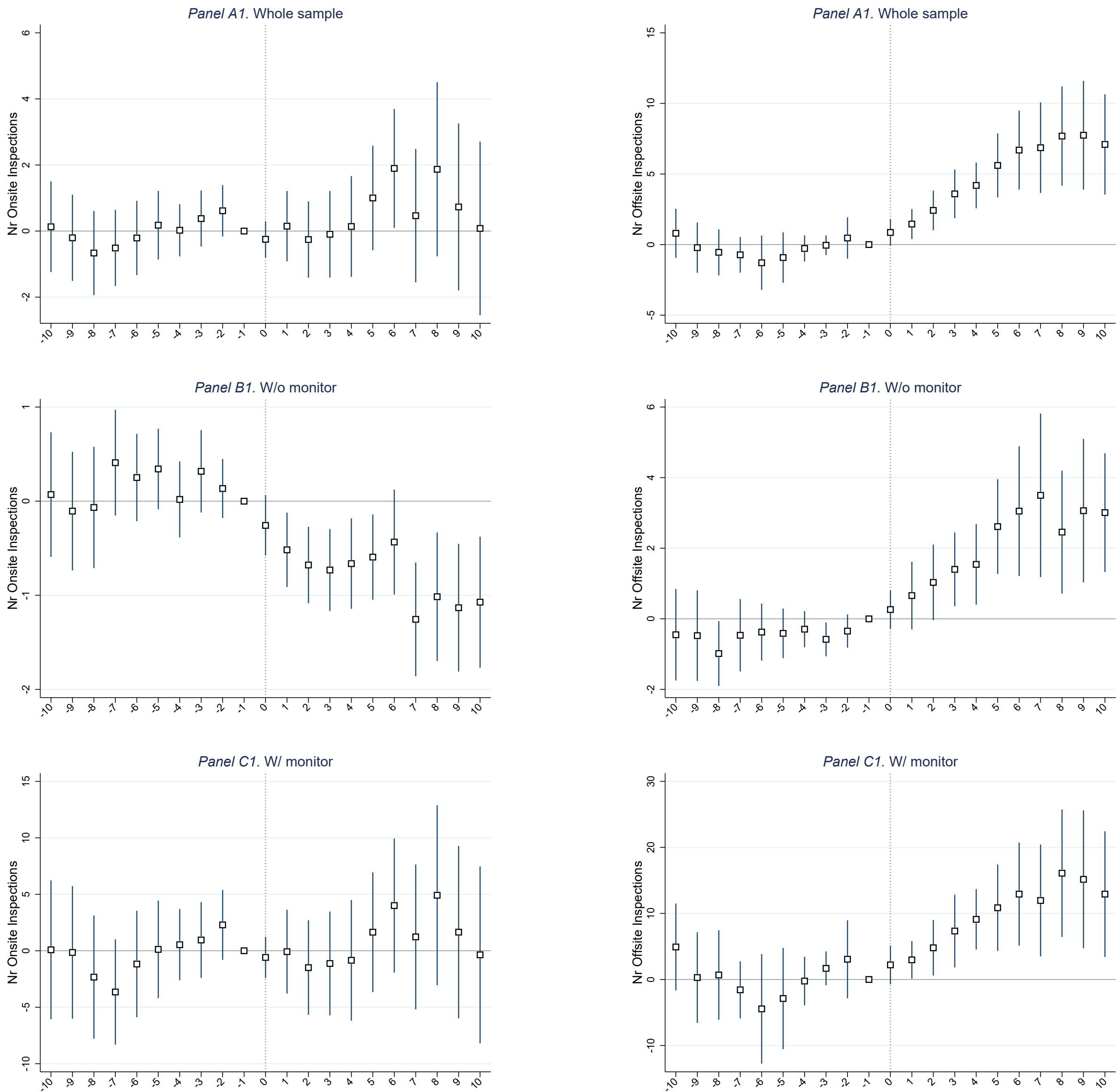


Figure A-6 – Event Study for the Off- and Onsite Inspections.

Notes: The figure above shows the results of equation 1 for different subsamples. The treatment is defined as a 0.5 percentage point increase in the share of the non-white population. Panels A1 and A2 present the outcomes for the number of on- and offsite inspections for the whole sample. Panels B1 and B2 for the number of on- and offsite inspections for counties without monitors. Finally, panels C1 and C2 show the results for the number of on- and offsite inspections for counties with monitors. Note that one plant can have either multiple onsite, or offsite inspections per year, or even a mix of both.

5. OLS Regression Outcomes for Afro-American, Asian, and Hispanics

Table A-2 – Volume of environmental scrutiny and share of ethnic minorities.

	Dependent variable: Environmental scrutiny type				
	Inspection Share	HPV Share	FRV Share	Avg. Investments	Non-Attainment
	(1)	(2)	(3)	(4)	(5)
Panel A: All Counties					
Share afro-american population	-0.047	0.038	-0.016	0.002	
	(0.088)	(0.024)	(0.031)	(0.016)	
Share hispanic population	0.057	-0.088	-0.227***	-0.034	
	(0.098)	(0.061)	(0.058)	(0.028)	
Share asian population	-0.850***	-0.018	0.094	-0.023	
	(0.217)	(0.078)	(0.083)	(0.054)	
Dep. Var. Mean	0.20	0.02	0.01	0.01	
Observations	57,256	57,256	57,256	57,256	
Controls	Yes	Yes	Yes	Yes	
Panel B: Counties without monitors					
Share afro-american population	0.020	0.047	-0.013	-0.005	
	(0.103)	(0.030)	(0.037)	(0.019)	
Share hispanic population	-0.051	-0.199***	-0.329***	-0.106***	
	(0.096)	(0.071)	(0.069)	(0.028)	
Share asian population	-1.023***	0.082	-0.028	0.077	
	(0.331)	(0.111)	(0.102)	(0.054)	
Dep. Var. Mean	0.19	0.02	0.01	0.01	
Observations	45,611	45,611	45,611	45,611	
Controls	Yes	Yes	Yes	Yes	
Panel C: Counties with monitors					
Share afro-american population	-0.275	0.028	-0.135**	-0.003	-0.234
	(0.193)	(0.055)	(0.064)	(0.038)	(0.397)
Share hispanic population	0.244	0.414***	0.206**	0.256***	1.635***
	(0.260)	(0.120)	(0.105)	(0.083)	(0.557)
Share asian population	-0.290	-0.177	-0.069	-0.235**	2.367***
	(0.345)	(0.122)	(0.113)	(0.100)	(0.836)
Dep. Var. Mean	0.22	0.03	0.01	0.02	0.10
Observations	11,594	11,594	11,594	11,594	11,594
Controls	Yes	Yes	Yes	Yes	Yes

Notes: This table presents estimates of Equation **??** from the main text. Each column corresponds to a different outcome variable. All models include county and year fixed effects, $PM_{2.5}$ refers to remote sensed fine particulate matter concentrations. For population and income, log values are included in the estimations. Standard errors are clustered at the county level and presented in parentheses. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

6. Event Study for Afro-American, Asian, and Hispanics

Afro-American Population

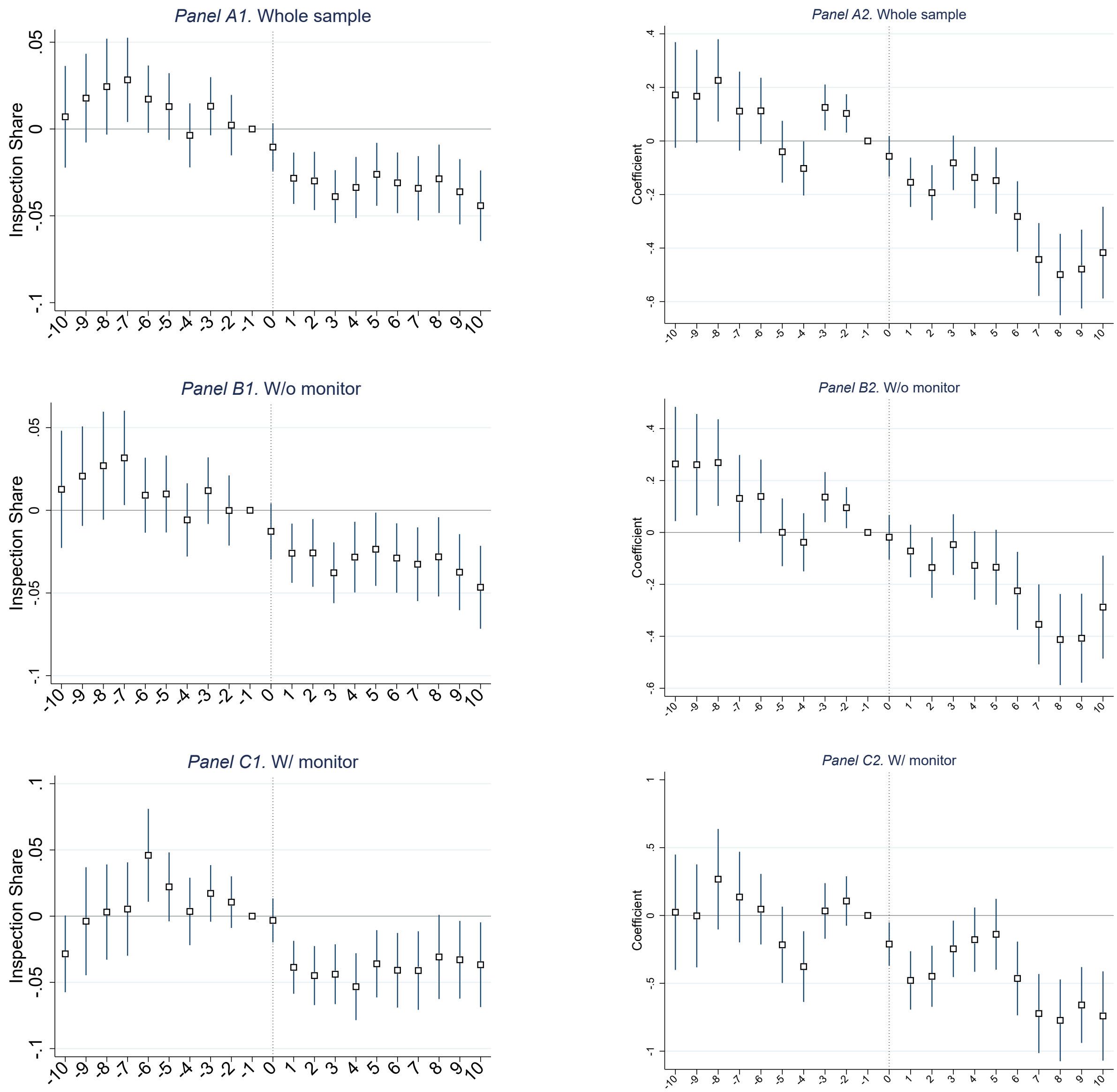


Figure A-7 – Afro-American Treatment Event Study.

Notes: The figure above shows the results of equation 1 for different subsamples. The treatment is defined as a 0.5 percentage point increase in the share of the Afro-American population. Panels A1 and A2 present the outcomes for the share of inspections and for remote sensed $PM_{2.5}$ for the whole sample. Panels B1 and B2 for the share of inspections and for remote sensed $PM_{2.5}$ for counties without monitors. Finally panels C1 and C2 show the results for the share of inspections and for remote sensed $PM_{2.5}$ for counties with monitors.

Asian Population

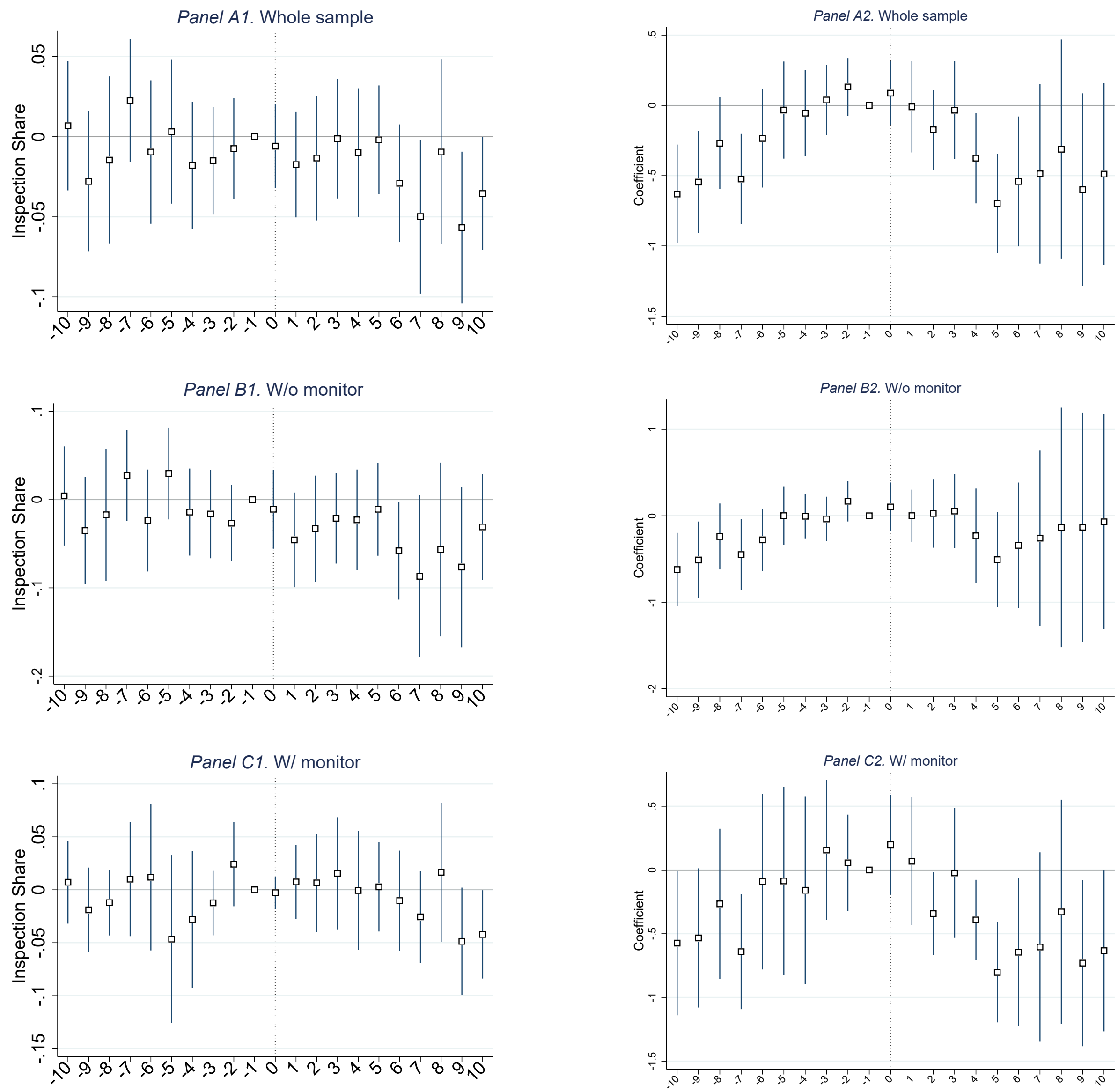


Figure A-8 – Asian Treatment Event Study.

Notes: The figure above shows the results of equation 1 for different subsamples. The treatment is defined as a 0.5 percentage point increase in the share of the Asian population. Panels A1 and A2 present the outcomes for the share of inspections and for remote sensed $PM_{2.5}$ for the whole sample. Panels B1 and B2 for the share of inspections and for remote sensed $PM_{2.5}$ for counties without monitors. Finally panels C1 and C2 show the results for the share of inspections and for remote sensed $PM_{2.5}$ for counties with monitors.

Hispanic Population

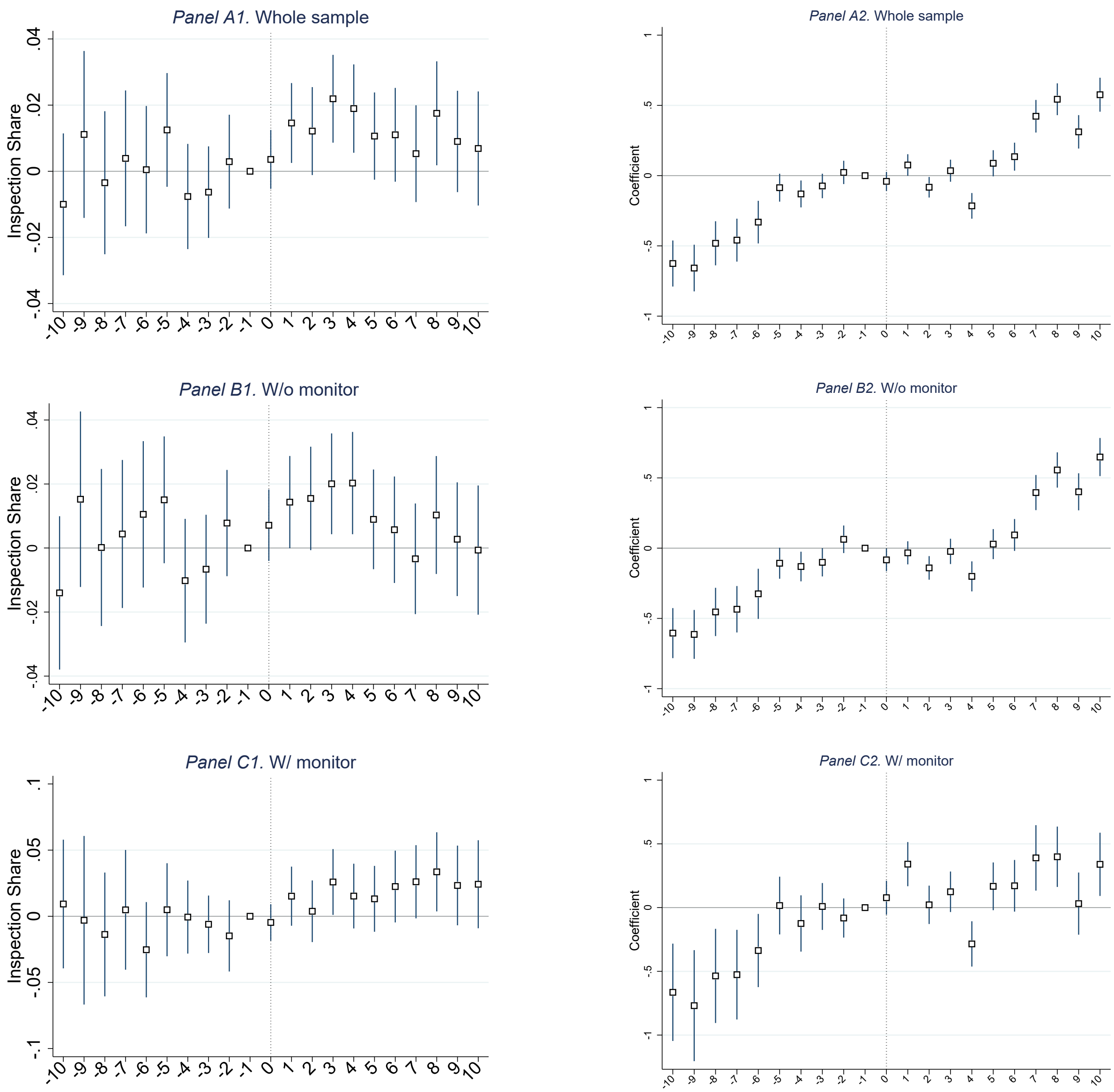


FIGURE A-9 – HISPANIC TREATMENT EVENT STUDY.

Notes: The figure above shows the results of equation 1 for different subsamples. The treatment is defined as a 0.5 percentage point increase in the share of the Hispanic population. Panels A1 and A2 present the outcomes for the share of inspections and for remote sensed $PM_{2.5}$ for the whole sample. Panels B1 and B2 for the share of inspections and for remote sensed $PM_{2.5}$ for counties without monitors. Finally panels C1 and C2 show the results for the share of inspections and for remote sensed $PM_{2.5}$ for counties with monitors.

D. Weight Matrix Choice

In general, the spatial weights matrix can take a variety of different forms. Choosing the correct spatial weights matrix is vital to the validity of the outcomes of the spatial models. While rook and queen contiguity weights[12] are often used in a pollution context; both matrices do not reflect the spatial behavior expected in the data, as solely neighboring counties would have a spatial impact on the $PM_{2.5}$ level in the county of interest. Hence, it seems more appropriate that counties further away have a less pronounced influence on the "base" cell. The standard weight matrix is given as follows:

$$W = \begin{pmatrix} w_{11} & w_{12} & \dots & w_{1n} \\ w_{21} & w_{22} & \dots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \dots & w_{nn} \end{pmatrix}, \text{ with } w_{ii} = 0 \tag{4}$$

In this paper, the elements of the weights matrix will be defined as the inverse distance d between two cells i and j:

$$w_{ij} = \begin{cases} d_{ij}^{-\alpha} & , \text{ if } d_{ij} \leqslant x \\ 0 & , \text{ if } d_{ij} > x \end{cases} \tag{5}$$

As equation 5 shows, the weights matrix contains two additional parameters next to the distance d. x is included as a threshold that determines the distance to which cells are considered having spatial influences on each other. Ascertain the adequate value of x remains difficult and strongly depends on the theoretical assumptions made beforehand. Considering that $PM_{2.5}$ can stay in the atmosphere over extended periods of time and travels up to 2000 miles in a few days (Wang et al., 2017), setting $x = \infty$ seems well justified for the purpose of this study. With regard to the theoretical spatial dependencies of NTL and health, this specification of x seems acceptable, too. However, to test the robustness of the spatial analysis, additional weight matrices are constructed for $x = 100$, 250, 500, 750, 1000, 1500, and 2000 miles, and the impact on the spatial autocorrelation statistics is investigated.

Additional to the threshold parameter x, the power parameter α ($\in [1; \infty)$) is included in the generation process of the spatial weights matrix. It can be interpreted as the speed at which the spatial dependencies decline. Most commonly, α is chosen to be 1. However, to check again for the robustness of that assumption, additional weight matrices with α

[12] Rook and queen contiguity matrices are named after the chess pieces and reflect spatial dependency based on their respective moves. Hence, rook contiguity defines neighbors on joint edges, and the queen contiguity on common edges and corners.

ranging from 2 to 10 will be constructed.[13] After the construction, all matrices above are additionally *minmax*-normalised.[14]

Finally, we also constructed a placebo weight matrix, to check that our results are indeed driven by spatial dependencies and no underlying structural issues. For this matrix we draw a random weight out of a uniform distribution $w_{ij} \sim U[0,1]$, keeping $w_{ii} = 0$.

[13] No cut-off will be introduced when looking into different variations of α, as well as α is kept constant to 1 when changing x.

[14] That is, each element is divided by the minimum of the largest row sum and column sum of the matrix. By doing so, the symmetry of the matrix is contained. Another more frequently used normalization approach is row normalization. Importantly, this technique does not keep the symmetry of the matrix and can lead to "a misspecified model," according to Kelejian and Prucha (2010, p. 56).