

Environmental Regulation, Residential Sorting, and Pollution Exposure among Senior Americans

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February 10, 2025

Abstract

We investigate how environmental regulation under the U.S. Superfund program and Clean Air Act affected exposures to fine particulate air pollution and hazardous waste for Americans over age 65 during the 2000's. Our research design uses quasi-random features of how the two programs enforce regulations and provide information to estimate their causal effects on migration and pollution exposure. We show that senior Americans' average pollution exposures declined substantially. We also show that spatially heterogeneous improvements in environmental quality had little-to-no effect on residential sorting. This led to relatively large reductions in pollution for seniors living in the dirtiest areas.

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1 Introduction

People over the age of 65 are the fastest growing age group in many countries and the primary beneficiaries of national policies targeting health and environmental quality. In the United States, senior citizens account for approximately 18% of the population and 75% of premature deaths avoided by regulating air pollution (EPA, 1999a, 2011b)). Yet relatively little is known about how environmental regulations affect pollution exposure among senior Americans.

Prior research on the distributional effects of regulation focused primarily on understanding the causes and consequences of heterogeneity in pollution exposure for subpopulations that differ by race and income, irrespective of age (Banzhaf et al., 2019). It is important to develop similar knowledge for seniors because they are believed to be particularly sensitive to pollution due to a combination of biological and behavioral factors (EPA, 1999b, 2003, 2011a, 2019). Equally important is the fact that seniors are less likely than younger adults to have constraints on their spatial mobility due to jobs and school-age children. In principle, this could increase the rates at which seniors respond to changes in environmental quality by moving (Graves and Waldman, 1991; Banzhaf and Walsh, 2008; Mathes, 2024). Migration matters for evaluating the distributional consequences of environmental regulation because residential sorting can redirect benefits from the incumbent residents of neighborhoods targeted for cleanup to non-residents who move in as neighborhoods gentrify (e.g. Sieg et al., 2004; Depro et al., 2015; Staiger et al., 2024).

This study investigates how environmental regulation under the U.S. Superfund program and Clean Air Act affected senior citizens' exposures to hazardous waste and fine particulate air pollution from 2000 through 2013. We develop pollution exposure histories for nearly 13 million seniors that incorporate changes in exposure caused by their individual migration decisions. Then we leverage quasi-experimental features of each regulatory program to estimate how environmental regulation affected migration and pollution exposure among seniors in general, and

among subpopulations that differ in their pollution sensitivities, according to the U.S. Environmental Protection Agency (EPA), due to differences in race, wealth, and health.

Our analysis combines data from several sources. We extract annual information on individuals' precise residential locations from administrative records for a random 20% sample of all U.S. Medicare beneficiaries over age 65. These data also allow us to observe each individual's birth year, death year, gender, race, if and when they were first diagnosed with various chronic medical conditions, and whether they claimed Medicaid benefits that are primarily restricted to individuals with low wealth. We measure their residential exposure to fine particulate air pollution smaller than 2.5 microns in diameter ($PM_{2.5}$) using data from Di et al. (2017) on annual average concentrations in a one square kilometer grid spanning the nation. Then we measure the Euclidean distance from each individual's residence to the nearest Superfund hazardous waste site, using the universe of sites that were on the EPA's National Priority List (NPL) (commonly known as Superfund) from its inception in 1980 through 2022. These data include key milestones in both the timing of exposure to hazardous waste, and the timing of information about that exposure. Specifically, we track the date that EPA proposed adding each site to the NPL (publicly identifying the site as a potentially significant health risk for nearby residents) and the dates that EPA deleted sites from the NPL (publicly certifying that the risk is no longer significant).

We use these data to document several new facts about senior Americans' pollution exposures. First, we show that average exposure to both $PM_{2.5}$ and known hazardous waste sites declined substantially from 2000 to 2013. Average exposure to $PM_{2.5}$ declined by 35% and the share of seniors living less than three kilometers of a Superfund site declined by 21%. Second, the sizes of these reductions differed, on average, by race and wealth. Black (or African-American) seniors experienced relatively larger reductions in $PM_{2.5}$ than White (non-Hispanic) seniors. On the other hand, the Black-White gap in exposure to hazardous waste sites grew during

the study period. We observe analogous trends when we use the receipt of Medicaid benefits to divide individuals into wealthier and poorer groups. The wealth gap in exposure to $PM_{2.5}$ declined whereas the wealth gap in exposure to hazardous waste sites increased. In contrast, we see virtually no difference in average pollution exposure between individuals who have been diagnosed with cardiopulmonary conditions that increase their sensitivity to pollution, and those who have not. Finally, we see a large decline in exposure to “hidden” pollution, which we define as yet-to-be discovered hazardous waste sites and $PM_{2.5}$ grid cells where ambient concentrations violate federal regulatory standards in areas without federal air quality monitoring stations.

Next, we estimate the effects of each regulatory program on migration and pollution exposure. For the Clean Air Act (CAA) we analyze the EPA’s enforcement of the National Ambient Air Quality Standard for $PM_{2.5}$ starting in 2005. Specifically, we follow prior literature in using each county’s non-attainment status interacted with baseline $PM_{2.5}$ concentrations to develop an instrument for changes in air pollution exposure during the decade (e.g. Bento et al., 2015; Bishop et al., 2023; Sager and Singer, 2025). The results from our instrumental variables estimator show that CAA-induced reductions in air pollution had virtually no effect on seniors’ migration patterns. We also demonstrate that enforcement of the EPA’s $PM_{2.5}$ standard was directly responsible for a large share of the reduction in seniors’ exposure to air pollution after 2005, as well as the concomitant reductions in exposure gaps by race and wealth.

For the Superfund program, we leverage the staggered timing of proposal and deletion dates for different sites to develop a spatial differences-in-differences estimator for how seniors’ residential sorting behaviors are affected by new information about environmental contamination. We find virtually no effect of information shocks about land contamination on seniors’ migration patterns. While information about land contamination does not appear to systematically affect migration, we observe that the individuals who choose to move in to neighborhoods around Su-

perfund sites are more likely to be Black and to receive Medicaid benefits. These immigration patterns help to explain the observed widening of race and wealth gaps in Superfund site exposure from 2000 to 2013.

Thus, our findings from the Superfund program and the Clean Air Act suggest that senior Americans' residential location decisions are relatively insensitive to regulatory-induced changes in the spatial distribution of pollution. This implies that younger adults' residential location decisions will tend to have long-lasting effects on their lifetime pollution exposures. It also suggests that residential sorting and environmental gentrification do not substantially unravel the benefits of regulation for seniors living in improved areas. This is important for measuring the benefits of regulation because seniors are known to be sensitive to local pollution (e.g. Schlenker and Walker, 2016; Deryugina et al., 2019; Bishop et al., 2023, 2024).

Our analysis and findings contribute to three distinct literatures. First, we add to literature examining the distributional consequences of environmental regulation for pollution exposure. Prior studies focused on how environmental regulations produce heterogeneous effects on exposure for demographic groups that differ in race and income (e.g. Banzhaf and Walsh, 2013; Depro et al., 2015; Banzhaf et al., 2019; Bakkensen and Ma, 2020; Hausman and Stolper, 2021; Cassidy et al., 2022; Currie et al., 2023; Cain et al., 2024; Sager and Singer, 2025). We extend this literature by focusing on seniors. Conditional on advanced age, we also examine how exposures differ based on other demographic characteristics that the EPA associates with greater pollution sensitivity. In addition to conventional measures of race and wealth, we examine how exposures vary based on biological sensitivity caused by the presence of cardiopulmonary diseases.

Second, our study adds to literature on the economics of residential sorting. Theoretical models of Tiebout sorting predict that some households will respond to changes in the spatial distribution of environmental quality by moving (e.g. Sieg et al., 2004; Banzhaf and Walsh, 2013; Kuminoff et al., 2013) and there is substantial evidence that local quality changes do cause housing prices to adjust and people

to move (e.g. Banzhaf and Walsh, 2008; Bento et al., 2015; Haninger et al., 2017; Ma, 2019; Bakkensen and Ma, 2020; Guignet et al., 2023; Guignet and Nolte, 2024; Cheng et al., 2024; Sager and Singer, 2025). We add to this literature by providing direct evidence on the extent to which senior citizens respond to environmental quality changes by moving. While their overall migration rate is not trivial—21% move at least once during our study period—it appears to be relatively insensitive to environmental quality changes.

Finally, we add to literature on the role of environmental information in consumer choice. Provision of information about ambient pollution has been shown to modify the consumption of housing and other goods (e.g. Haninger et al., 2017; Bakkensen and Ma, 2020; Christensen and Timmins, 2022; Guignet et al., 2023; Guignet and Nolte, 2024; Barwick et al., 2024; Cheng et al., 2024; Sager and Singer, 2025). One hypothesis for the existence of socioeconomic gaps in pollution exposure is that it is driven by heterogeneity in attention or access to information (Ma, 2019; Hausman and Stolper, 2021). Our analysis of hidden pollution is consistent with this hypothesis in the sense that we find Black seniors and those whose wealth is sufficiently low to receive Medicaid benefits are more likely to live near not-yet-discovered Superfund sites in 2000, and more likely to choose to move into neighborhoods around those sites between 2001 and 2013.

2 Data

2.1 Medicare Sample of Individuals Over Age 65

The Medicare program provides near universal health insurance for Americans over age 65. The U.S. Centers for Medicare and Medicaid Services (CMS) maintains records on each individual’s birth date, residential location history, medical history, and death date. It also records information on race and annual Medicaid enrollment. Medicaid enrollment provides a binary proxy for wealth because eligibility is generally limited to individuals whose income and assets fall below federal thresh-

olds for receiving supplemental security income.¹ For example, in the year 2000, the eligibility threshold on assets was \$2,000 for individuals and \$3,000 for couples.

We start with a random 20% sample of age-65-and-above full-year Medicare enrollees in the year 2000. The sample contains approximately 6 million individuals. We follow them through 2013, or until they die, and add a 20% random sample of new 65 year old enrollees each year. These data allow us to follow the year-2000 cohort as it aged, or to analyze a random sample of the over-65 population as it evolved from 2000 through 2013.

We use CMS administrative records from Medicare Chronic Condition Warehouse Files to identify if and when each individual was first diagnosed with heart or lung diseases that are thought to increase the sensitivity to particulate air pollution (EPA, 2003). Specifically, we create an indicator for the first year that each individual was diagnosed with any of the following conditions: acute myocardial infarction (i.e. nonfatal heart attack), asthma, chronic obstructive pulmonary disease (COPD), congestive heart failure, heart disease, or lung cancer.

Importantly, the CMS files include ZIP+4 codes for each individual’s sequence of residential addresses from 2000 through 2013. Each ZIP+4 code corresponds to a unique mail delivery point, such as a house, one floor of an apartment building, or one side of a street on a city block. This information is close to street address in terms of spatial precision. We use ZIP+4 centroids to track migration patterns and determine each individual’s annual residential exposure to air pollution and proximity to Superfund sites.

2.2 Air Pollution Exposure, Regulation, and Information

The EPA’s most recent benefit-cost analysis of the Clean Air Act indicates that the benefits of regulating air pollution in the United States are driven by reducing exposure to fine particulate matter smaller than 2.5 microns in diameter (i.e. PM_{2.5}) (EPA, 2011b). Moreover, Deryugina et al. (2019) and Bishop et al. (2023) provide

¹States can adjust these thresholds.

casual evidence that elevated residential exposure to $\text{PM}_{2.5}$ increases the risks of morbidity and mortality among the over-65 population. Therefore, we focus on measuring seniors' residential exposure to $\text{PM}_{2.5}$.

The data we use are from Di et al. (2017). They describe annual average concentrations of $\text{PM}_{2.5}$ on a 1km by 1km grid covering the United States. Concentrations in each grid cell were predicted using an artificial neural network that incorporated information from a variety of sources including satellite-based measurements, EPA air quality monitoring station records, a chemical transport model, land use data, and meteorological data. We used latitude and longitude coordinates for grid cell centroids and residential ZIP+4 centroids to assign each individual to a grid cell each year from 2000 through 2013.

In 2005, the EPA started to enforce a National Ambient Air Quality Standard on $\text{PM}_{2.5}$. Counties were required to report annual average $\text{PM}_{2.5}$ concentrations at each air quality monitoring station from 2001-2003. Counties containing monitors with annual average concentrations exceeding $15.05 \mu\text{g}/\text{m}^3$ were classified as “nonattainment” and required to work with local regulators to reduce emissions. Counties in which all monitoring stations reported concentrations below $15.05 \mu\text{g}/\text{m}^3$ were classified as “attainment” and counties without air quality monitoring stations were designated “unclassifiable”. Attainment and unclassifiable counties were generally not subjected to additional regulation.² This regulatory approach led to larger reductions in $\text{PM}_{2.5}$ for nonattainment counties compared to attainment counties over the following years (Bishop et al., 2023; Currie et al., 2023). We use the EPA's Greenbook and AirNow files to identify which counties were designated as attainment, nonattainment, and unclassifiable.

²An exception would be if such counties were believed to contribute to nonattainment designations in other counties due to air pollution transport.

2.3 Superfund Site Exposure, Regulation, and Information

The EPA’s Superfund Program identifies hazardous waste sites that pose a risk to human health and the environment, and remediates them.³ Exposure pathways are site-specific and may include ground water migration, surface water migration, air migration, and soil contamination. The EPA identifies the elderly, and minority and low-income individuals, as specific sub-populations that can be disproportionately affected by exposure (EPA, 2011a).

We use EPA data on the universe of 1,819 sites that were ever proposed for cleanup as of March 18, 2022. These data include latitude and longitude coordinates for each site, an index of health risk, and the dates for three milestones in the cleanup process: *proposal*, *listing*, and *deletion*. We use this information to measure how each individual’s proximity to the nearest Superfund site evolved over time as the individual did or did not move and as sites were or were not remediated. The remediation process can take decades to complete. While 80% of the sites were proposed prior to the beginning of our study period in 2000, only 21% were remediated by the end of our study period in 2013.

The *proposal*, *listing*, and *deletion* milestones delineate both the timing of exposure and the timing of information about exposure. After a potential hazardous waste site is discovered it is inspected and assigned a Hazard Ranking System (HRS) score that is designed to index the threat to human health and the environment.⁴ If the HRS score is sufficiently high, the EPA will *propose* adding the site to the National Priority List (NPL) of sites scheduled for cleanup and invite the public to

³In the 1970s, two significant environmental events – the ‘Love Canal Emergency’ in New York and ‘Valley of Drums’ in Kentucky – led to the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA). It was responsible for mitigating environmental dangers caused by the unregulated hazardous waste landfills and later became commonly known as the Superfund Program. The federal government has been the main source of funding, with annual appropriations from \$1 to \$2 billion between 1999 and 2013. The other potential funding sources are state governments, which pay 10% of cleanup costs, and private parties who contributed to the creation of the hazardous waste sites.

⁴A site is discovered when a private citizen, state agency, or EPA regional office notifies the EPA of the potential release of hazardous waste.

comment.⁵ After the public comment period, the EPA decides whether or not to add the site to the NPL. *Listed* sites are scheduled for long-term remediation. After a site is remediated, it is *deleted* from the NPL.

At each of these three milestones, the EPA provides the public with information about the site via local news media and interaction with community advisory groups.⁶ It also holds formal public comment periods. By *proposing* a site for the NPL, the EPA signals that it believes there is a significant health risk that may justify future mitigation effort. This may be an information shock to local residents because it is the first point of the mitigation process at which the EPA necessarily engages the public.⁷ *Listing* a site on the NPL confirms the presence of that risk and signals that the site will be remediated in the future, though remediation may take decades. *Deleting* a site from the NPL indicates that the EPA judges the site to no longer pose a significant threat to human health or the environment.

3 Descriptive Evidence

3.1 Analysis Sample

Prior to analyzing the data, we dropped 8% of individuals whose administrative records lacked ZIP+4 codes for one or more years. Their residential locations are often defined by coarser 5-digit ZIP codes that do not allow us to determine the precise distance to Superfund sites. We also dropped 1.3% of individuals who were ever missing information on Medicaid enrollment, 0.6% who were missing information on race, and 0.02% who were born before 1900. These data cuts left us with an unbalanced panel sample of 12.9 million individuals [henceforth, the “all 65+” sample]. We observe their residential exposure to PM_{2.5} and proximity to Superfund sites from the year 2000 (or when they turned 65) through 2013 (or when they died). The subset of 6.2 million individuals who were born before 1935 comprise a

⁵The threshold HRS score is 28.5, but cleanup efforts are contingent on funding availability.

⁶Appendix Figure A.1 provides an example of public notice for a proposed site.

⁷The EPA may or may not inform the public when it inspects a site.

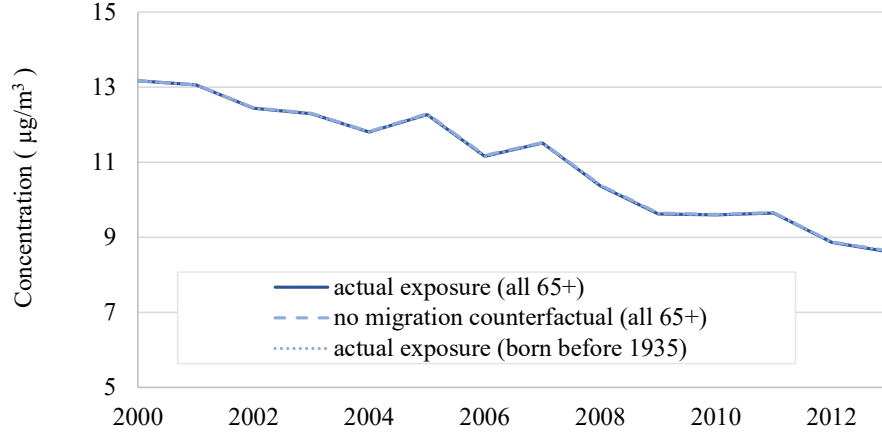
year-2000 senior Medicare cohort sample that we follow through 2013 or until they died [henceforth, the “born before 1935” sample].

The average individual in the all 65+ sample was born in 1933. Approximately 81% are coded as Non-Hispanic White, 9% as Black (or African-American), 7% as Hispanic, and 2% as Asian. Turning to measures of wealth and health that align with EPA-defined pollution-sensitive groups, we observe 13.4% of individuals receiving Medicaid benefits in at least one year after they turned 65, and 43% who were ever diagnosed with one or more heart or lung diseases by 2013 (asthma, COPD, heart failure, heart disease, lung cancer). Finally, 21% of individuals moved at least once during our study period, which underscores the potential for residential sorting to modify pollution exposure.

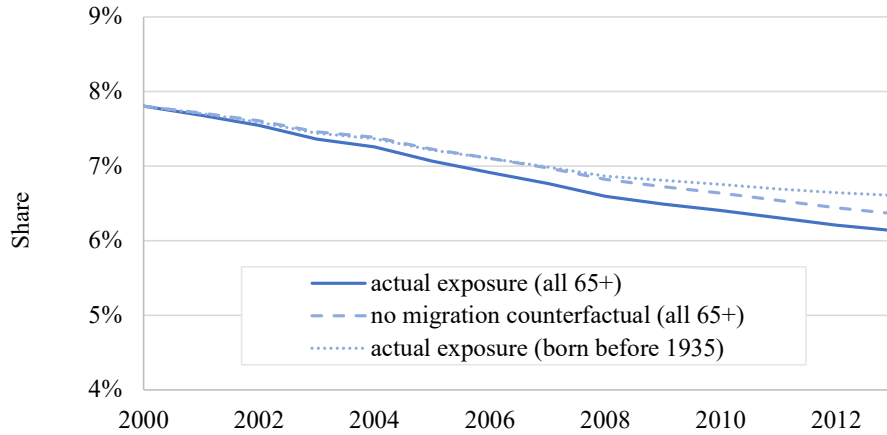
3.2 Seniors’ Exposure to Air Pollution and Hazardous Waste, 2000-2013

Figure 1 documents new facts about seniors’ residential exposure to air pollution and hazardous waste during the 2000’s. The solid line in Figure 1a shows that annual average exposure to $PM_{2.5}$ among the 65+ sample declined from about $13 \mu g/m^3$ in 2000 to less than $9 \mu g/m^3$ in 2013. This downward trend reflects the net effect of changes in emissions, weather, migration, and sample composition caused by differences in residential sorting among older individuals who died before the end of 2013 and younger individuals who turned 65 after 2000.

To start to explore how residential sorting affected seniors’ air pollution exposure, we construct a counterfactual “no migration” exposure measure. Specifically, for the 21% of individuals who ever moved in our data, we replace their actual post-move exposure with the exposure they would have experienced had they not moved. This counterfactual measure is shown by the dashed line in Figure 1a. The third line in the figure, which is dotted, reports actual exposure for the year-2000 cohort only, thus purging the effect of differences in residential sorting among younger and older seniors. Strikingly, the three lines are visually indistinguishable. Thus, while individuals may have substantially increased or decreased their exposure to $PM_{2.5}$



(a) Annual average residential exposure to $PM_{2.5}$



(b) Share living within 3km of a current or future NPL Site

Figure 1: Annual Average Exposure to Air Pollution and Hazardous Waste

Note: Panel (a) shows three measures of annual average residential exposure to $PM_{2.5}$ among Americans over age 65. The solid line reports actual exposure for the random Medicare sample of 12.9 million individuals. The dashed line shows their counterfactual exposure had there been no migration after the year 2000. The dotted line shows actual exposure among the subset of 6.2 million individuals who were over age 65 in 2000. Panel (b) shows the fraction of individuals living within 3 kilometers of a current or future NPL site each year. The solid, dashed, and dotted lines are defined the same as in Panel (a).

by moving, the population of seniors did not systematically move toward cleaner or dirtier locations during the 2000's. While this annual evidence for seniors is new, it is unsurprising in light of evidence in Currie et al. (2023) that migration had a relatively small effect on changes in $PM_{2.5}$ exposure among White and Black subsets of the general population (all ages) between 2000 and 2015.

Figure 1b presents comparable evidence for seniors' annual residential exposure to hazardous waste sites. We focus specifically on sites that that EPA judged to pose a significant risk to human health and environment. Each year, this includes the subset of sites that the EPA ever proposed adding to the NPL and that had not been deleted by the start of the year. This includes sites that were proposed in future years (and potentially unknown at the time we measure exposure) as well as sites with planned or ongoing mitigation efforts. To quantify exposure, we follow prior literature in using a binary variable for whether an individual lived near a site, specifically whether they lived within 3 kilometers based on Euclidean distance. The 3km distance falls near the middle of the range of distances commonly used to measure how exposure to NPL sites and other localized sources of land contamination affect human health and property values (Currie et al., 2011; Haninger et al., 2017; Persico et al., 2020; Klemick et al., 2020; Cassidy et al., 2022; Guignet et al., 2023; Cheng et al., 2024; Guignet and Nolte, 2024).⁸

135 sites were deleted from the NPL between 2000 and 2013, reducing exposure for nearby residents. The share of the all 65+ sample that lived near a site declined from 7.8% to 6.1%. Figure 1b decomposes this aggregate trend into three mechanisms. First, the dotted line shows that the exposure rate among the born before 1935 cohort declined by 1.2 percentage points, a 15% decline. This is the combined effect of remediated sites being deleted from the NPL, migration away from remaining sites, and sample attrition due to slightly higher mortality near those sites. Most of the decline is through the first two channels; higher mortality near sites only explains a 0.09 percentage point reduction in exposure. The role of migration away from sites is reinforced by comparing the solid and dashed lines in 2013. Had the all 65+ sample not moved, its exposure rate would have been 4% higher. Finally, comparing the dashed and dotted lines suggests that younger cohorts that entered the sample after 2000 were slightly less likely to live near NPL sites.

⁸Our qualitative findings are similar if we instead focus on larger or smaller distances.

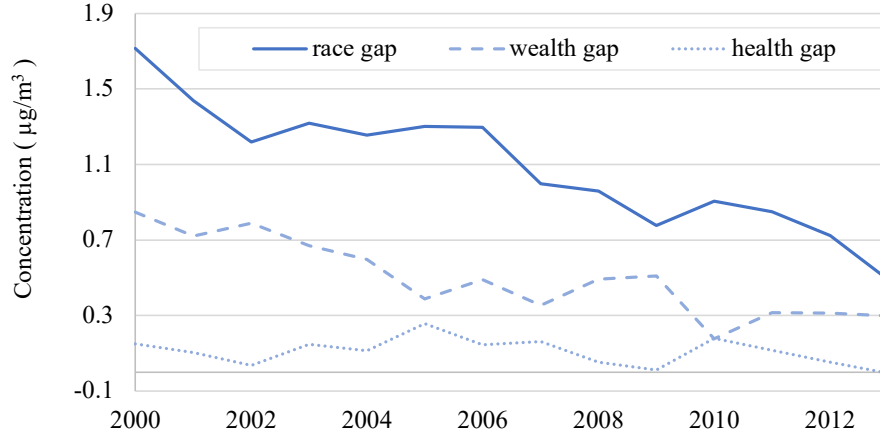
3.3 Demographic Gaps in Pollution Exposure

Figure 2 summarizes how exposure to particulate matter and hazardous waste differed among groups that the EPA classifies as being more or less vulnerable to pollution for reasons other than age, specifically race, wealth, and health (EPA, 2011a, 2019, 2022). First, as a baseline for comparison to prior literature, we follow Currie et al. (2023) in measuring the “race gap” in $PM_{2.5}$ exposure between the average individual coded as Black (or African-American) in Medicare administrative files and the average individual coded as White (non-Hispanic). These two groups account for 90% of the all 65+ population during our study period and they have been the focus of much of the economic literature on environmental justice (Banzhaf et al., 2019; Currie et al., 2023).⁹ Figure 2a shows that average exposure among Black seniors was $1.7 \mu g/m^3$ higher than among White seniors in 2000. This race gap declined by 71% between 2000 and 2013, which is similar to the 65% decline that Currie et al. (2023) report for all age groups between 2000 and 2015.

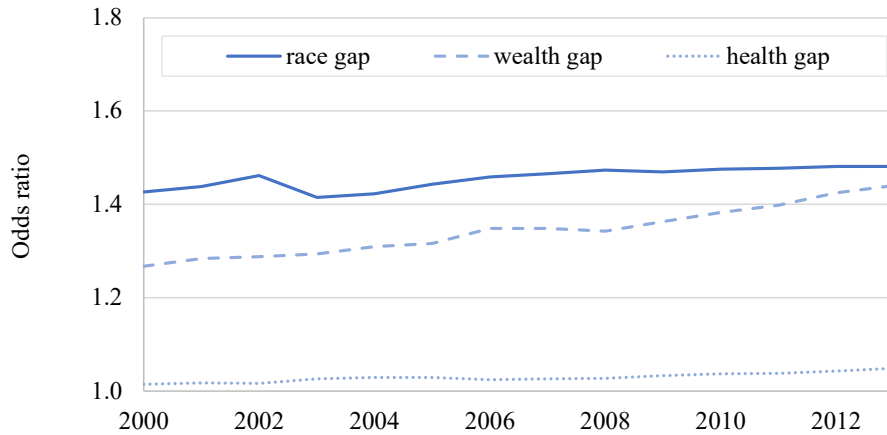
The dashed line in Figure 2a provides a measure of the “wealth gap” in air pollution exposure by comparing exposure levels for individuals who did or did not receive Medicaid benefits. Exposure was $0.85 \mu g/m^3$ higher among the lower-income group of Medicaid beneficiaries in 2000, and this gap declined by 65% by 2013. Finally, the dotted line shows that the “health gap” in exposure was closer to zero and comparatively flat during the 2000’s. Average decadal exposure to $PM_{2.5}$ among individuals who were more sensitive to air pollution due to pre-existing heart and/or lung diseases was $0.1 \mu g/m^3$ higher compared to those without cardiopulmonary diseases.

In contrast, Figure 2b shows that the demographic gaps in exposure to hazardous waste sites increased during the 2000’s. Since the probability of living within 3 km of an NPL site is low, we report the exposure gaps as odds ratios. They imply

⁹It would be interesting to examine groups coded as Hispanic, Asian / Pacific Islander, and American Indian / Alaska Native, but we exclude them here due to space constraints and smaller samples.



(a) Demographic gaps in residential exposure to $PM_{2.5}$



(b) Demographic gaps in residential exposure to NPL sites

Figure 2: Demographic Gaps in Exposure to Air Pollution and Hazardous Waste

Note: Panel (a) shows differences in annual average residential exposure to $PM_{2.5}$ between demographic groups. The solid line reports the difference between Black and White individuals. The dashed line reports the difference between individuals who did and did not receive Medicaid benefits each year. The dotted line reports the difference between individuals who had and had not been previously diagnosed with cardiopulmonary diseases (see text for details). All three lines are based on the all 65+ sample of 12.9 million individuals. Panel (b) makes the same demographic comparisons as Panel (a) and reports odds ratios for the probability of living within 3 kilometers of a current or future NPL site.

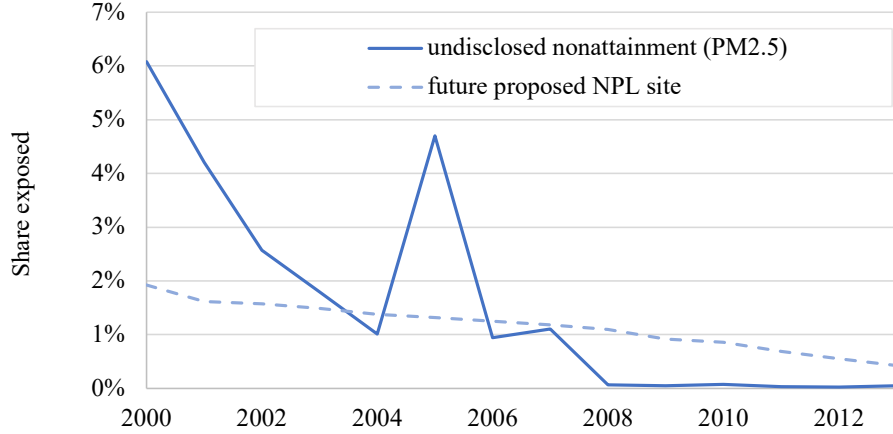
that, in 2000, the probability of living near an NPL site was 43% higher for Black individuals, 27% higher for individuals receiving Medicaid benefits, and 1% higher for individuals with cardiopulmonary illnesses. These gaps trended up during the 2000's, increasing to 48%, 44%, and 5% respectively by 2013. In Sections 4 and 5 we

test whether the trends in Figure 2 can be explained by differences in the extent to which each demographic group responded to changes in air quality and the EPA’s public disclosures about NPL sites by moving.

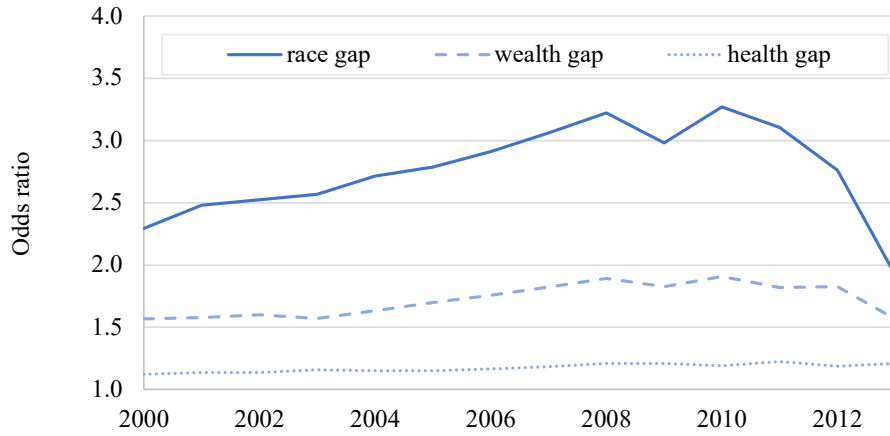
3.4 Information Frictions in Pollution Exposure

Figure 3a summarizes trends in exposure to undisclosed levels of $\text{PM}_{2.5}$ and hazardous waste. The solid line shows the share of individuals who lived in counties that were not regulated for $\text{PM}_{2.5}$, but whose annual average residential exposure to $\text{PM}_{2.5}$ nevertheless exceeded the EPA’s regulatory threshold of $15.05 \mu\text{g}/\text{m}^3$ based on the data in Di et al. (2017). This occurs in counties that lack monitoring stations for $\text{PM}_{2.5}$, and in pollution “hot spots” located within counties that were classified as attainment in 2005 based on monitor readings. The share declined from 6% in 2000 to 0.05% in 2013. The spike in 2005 is partly due to higher pollution in unmonitored counties during that year (also visible in Figure 1a) and partly due to violations of the regulatory threshold at locations within newly classified attainment counties. While the downward trend is striking, we interpret it as a potentially noisy measure due to the caveat that satellite-based measures for predicting pollution may tend to have greater measurement errors at locations far from monitoring stations (Fowlie et al., 2019).

The dashed line in Figure 3a shows the share of people living within 3 km of a hazardous waste site that the EPA had yet to propose to the NPL. Since exposure predates the EPA’s release of public information about site contamination, individuals living near the site may have been unaware of the associated health risks. The odds ratios in Figure 3b show that the probability of exposure was substantially higher for Black and Medicaid-recipient groups. Moreover, these demographic odds ratios are higher than for the broader set of NPL sites in Figure 2b. Overall, the evidence on NPL sites in Figure 3 is consistent with the hypothesis in Ma (2019) and ? that lower-income and minority groups are more likely to live in more polluted neighborhoods, in part, because they have less information about local environmen-



(a) Prevalence of undisclosed exposure to air pollution and hazardous waste



(b) Demographic gaps in exposure to future NPL sites

Figure 3: Information Frictions in Residential Pollution Exposure

Note: In Panel (a) the solid line shows the share of individuals with annual average residential exposure to $PM_{2.5}$ that exceeds the EPA’s regulatory threshold of $15.05 \mu g/m^3$ but who live in counties that are unmonitored or designated as attainment in 2005. The dashed line reports the share of individuals living with 3 kilometers of a hazardous waste site that was first proposed for the NPL in a future year. Both lines are based on the all 65+ sample of 12.9 million individuals. Panel (b) uses odds ratios for the probability of living within 3 kilometers of a future NPL site to report gaps in exposure for the same demographic groups as Figure 2.

tal quality. The upward trend in the odds ratios during the 2000’s and the steep decline in the race gap from 2010 to 2013 could be explained by residential sorting and/or by the timing of when sites were discovered in neighborhoods with higher shares of Black seniors and Medicaid recipients. We investigate the role of migration in Section 5.

4 Effects of PM_{2.5} Regulation on Exposure and Migration

The trends in PM_{2.5} exposure shown in Figures 1a–3a reflect the combined effect of several factors. These include the EPA’s direct regulation of PM_{2.5} under the Clean Air Act (CAA) starting in 2005, residential sorting, compositional changes in the 65+ population due to mortality and new 65-year-old entrants to Medicare, and national trends in emissions driven by technology and other regulations. For example, some of the decline in exposure was likely due to regulation of automobile emissions and fuel switching from coal to natural gas. We estimate the extent to which the trends in Figures 1a–3a can be explained specifically by enforcement of the EPA’s PM_{2.5} standard, and the extent to which the casual effect of CAA regulation on exposure was weakened or strengthened by residential sorting.

4.1 Effects on Clean Air Act Regulation on Exposure

We first estimate how enforcement of the EPA’s PM_{2.5} standard affected exposure among the 65+ population. Specifically, we estimate how much of the change in seniors’ PM_{2.5} exposures between 2001-2003 and 2011-2013 can be attributed to the EPA’s designations of nonattainment areas in 2005. Our econometric approach adapts the quasi-experimental design in Bishop et al. (2023) and Currie et al. (2023).

Our focal outcome is $y_{it} = PM_{it} - basePM_i$, the difference between individual i ’s annual average residential exposure to PM_{2.5} in year t and a measure of baseline concentrations at the location where the individual lived at the time nonattainment designations were made. We define $basePM_i$ as the annual average concentrations of PM_{2.5} from 2001-2003. This provides a counterfactual measure for exposures that would have occurred in year $t \geq 2005$ had PM_{2.5} not been directly regulated and had individual i not moved. As we noted in Section 2.2, year 2005 nonattainment designations were based on annual average concentrations recorded at monitoring stations from 2001-2003.

Equation (1) shows how we estimate the effect of CAA regulation on exposure.

$$y_{it} = f(Z_i, basePM_i; \beta_t) + \delta_{jt} + \epsilon_{it}. \quad (1)$$

We regress y_{it} on a function of baseline concentrations and an indicator, Z_i , for whether the individual lived in a county in 2005 that was designated as a nonattainment area. Fixed effects for core business statistical areas (CBSAs) $j = 1, \dots, J$ absorb changes in $PM_{2.5}$ exposure that are common to both attainment and nonattainment counties in different parts of the country. Importantly, nonattainment status can vary between counties within a CBSA (Bishop et al., 2023). Finally, we allow the regression parameters (β_t, δ_{jt}) to evolve flexibly over time by estimating separate regressions each year.

The parameter vector β_t measures how regulation caused exposure to differ for people who lived in nonattainment counties in 2005 compared to those who lived in attainment counties, conditional on baseline exposure. We follow Bishop et al. (2023) in specifying $f(Z_i, basePM_i; \beta_t)$ as linear function of Z_i and interactions between Z_i and a fourth-order polynomial function of $basePM_i$. This specification allows the regression to capture how treatment effects of regulation vary within and between counties as a function of baseline exposure. In particular, this feature is designed to capture the fact that local regulators are incentivized to target known pollution hot spots within counties because a county’s nonattainment status is determined by the annual average concentrations recorded at its dirtiest monitoring station (Auffhammer et al., 2009).

We estimate Equation (1) using individuals who were over age 65 at the time nonattainment designations were made in January 2005 and who survived through the end of year $t > 2005$. There is sample attrition after 2005 due to mortality, but no entry.¹⁰ For this sample, β_t measures the net effect of three mechanisms. First,

¹⁰We exclude people who entered Medicare in 2006 or later because we are generally unable to verify where they lived in 2005.

it captures the “intent-to-treat” effect of regulation on exposure for non-movers. Second, it captures changes in exposure caused by migration after 2005. Finally, it captures compositional changes in exposure among the surviving sample due to mortality. Thus, the estimator embeds any causal effects of regulation on migration and mortality, though it does not isolate those effects from the direct effect of regulation on exposure.

We aggregate the heterogeneous marginal effects from Equation (1) to calculate average treatment effects for specific groups according to Equation (2).

$$\frac{1}{N_\tau} \sum_{i \in \tau} f(Z_i, basePM_i; \beta_t), \quad (2)$$

where N_τ denotes the number of individuals who belong to group τ , based on their age, race, wealth, or health. Then we calculate differences between groups. This approach captures how regulation affected demographic groups differently based on the rates at which they lived in attainment versus nonattainment counties, and how they sorted themselves over cleaner and dirtier neighborhoods within those counties before and after regulation.

Table 1 reports our estimate for the effect of CAA regulation on $PM_{2.5}$ exposure among seniors in general, as well as our estimates for the effects of regulation on gaps in exposure by race, wealth and health. These estimates are calculated by averaging equation (2) over year-specific estimates for 2011, 2012, and 2013. This three-year averaging smooths over idiosyncratic shocks and yields a measure that is comparable with the measure of baseline exposure in 2001-2003.

We find that nonattainment designations reduced seniors’ exposure to $PM_{2.5}$ by $1.59 \mu g/m^3$ in 2011-2013 relative to 2001-2003. This a 13% reduction relative to baseline exposure. It is also equivalent to 45% of the total decline in average exposure during that period, suggesting that CAA regulation of $PM_{2.5}$ was a substantial driver of the overall reduction in exposure during the 2000’s. Our $1.59 \mu g/m^3$ estimate for seniors is similar to prior estimates for the effects of regulating $PM_{2.5}$ on exposure

Table 1: Effect of Nonattainment Designations on PM_{2.5} Exposures

	exposure (age 65+)	race gap in exposure	wealth gap in exposure	health gap in exposure
Change from 2001-2003 to 2011-2013	-1.595*** (0.039)	-0.639*** (0.033)	-0.239*** (0.031)	-0.017 (0.012)

Note: The table shows estimates for causal changes in residential exposure to fine particulate air pollution, measured in micrograms per cubic meter. Estimates are calculated by aggregating Equation (2) over year-specific estimates of Equation (1) for 2011, 2012, and 2013. These regressions use data on 2,393,960 individuals who were over age 65 and enrolled in Medicare at the time nonattainment designations were made in 2005 and survived through the end of 2011. Sample sizes decline slightly in 2012 and 2013 due to mortality. Standard errors are calculated using 1,000 bootstrap repetitions, clustered by Census tract.

among the general population (all ages) in Currie et al. (2023) and Sager and Singer (2025).

We also find that CAA regulation reduced the gap in exposure between Black and White seniors by $0.64 \mu\text{g}/\text{m}^3$. This reduction explains virtually all of the decline shown in Figure 2a. Interestingly, this finding differs from the evidence in Currie et al. (2023) and Sager and Singer (2025) that CAA regulation explains closer to 60% of the decline in the race gap when all age groups are pooled together. A potential explanation for this difference is that seniors were less likely to move in response to CAA-induced changes in air quality than younger adults. Indeed, Section 4.2 provides evidence consistent with this hypothesis.

The second-to-last column in Table 1 shows that our point estimate for the effect of regulation on the wealth gap in exposure is $-0.24 \mu\text{g}/\text{m}^3$. This accounts for most of the reduction between 2001-2003 and 2011-2013. Finally, our estimate of a near zero effect of regulation on the health gap is unsurprising since the gap itself was close to zero throughout the decade.

4.2 Effects on Clean Air Act Regulation on Migration

We use an instrumental variables estimator to measure the effect of changes in air pollution exposure, caused by CAA regulation, on the probability of moving.

Specifically, we instrument for the change in an individual’s exposure to $PM_{2.5}$ using an indicator for whether the individual lived in a nonattainment county when CAA enforcement started in 2005. Instruments based on county nonattainment status are used extensively in research on the economic consequences of air pollution exposure (Aldy et al., 2022) and our implementation is similar to Bishop et al. (2023).

Equation (3) shows the second-stage regression, where the outcome, m_{it} , is an indicator for whether individual i moved to a new location in year $t + 1$.

$$m_{it} = \beta_t y_{it} + \delta_{jt} + \gamma_t X_{it} + f(\text{base}PM_i; \nu_t) + \xi_{it} \quad (3)$$

We continue to use y_{it} to measure the change in pollution experienced by an individual between year t and the baseline period (2001-2003). The covariates include CBSA dummies, a vector of individual characteristics that includes dummies for integer age, gender, race, Medicaid take up, and whether the individual had ever been diagnosed with one or more cardiopulmonary illnesses, and a fourth-order polynomial function of baseline exposure during 2001-2003.

A threat to identifying β from OLS regression of (3) is that unobserved individual characteristics that affect the probability of moving to a new location in year $t + 1$ could be correlated with the change in $PM_{2.5}$ exposure experienced between the baseline period and year t . We address this threat by instrumenting for y_{it} using an indicator for nonattainment status of the county where the individual lived at the time enforcement began in 2005, interacted with a fourth-order polynomial function of $\text{base}PM_i$:

$$y_{it} = g(Z_i, \text{base}PM_i; \pi_t) + \delta_{jt} + \omega_t X_{it} + f(\text{base}PM_i; \eta_t) + \epsilon_{it}, \quad (4)$$

The validity of the IV estimator in (3)-(4) relies on the maintained assumption that county nonattainment status, Z_i , is independent of ξ_{it} conditional on the covariates. Intuitively, β is identified by variation in $PM_{2.5}$ exposures from 2006-2012 among

seniors of the same age, race, gender, Medicaid take-up and observed health, who lived in the same CBSA and sorted themselves into neighborhoods with similar baseline concentrations of $\text{PM}_{2.5}$ prior to enforcement of the regulatory standard in 2005 but lived in areas that were regulated differently under the Clean Air Act. We do not impose any restrictions on how the regression parameters evolve over time. The t subscripts on regression parameters in Equations (3) and (4) reflect the fact that we estimate those equations separately for each year from 2006 through 2012. In addition, we repeat estimation of Equation (1) for each of the three subpopulations that the EPA characterizes as being more sensitive to $\text{PM}_{2.5}$ exposure (EPA, 2019).

Figure 4 summarizes our IV results. Each panel shows time-varying estimates for the effect of CAA-induced changes in $\text{PM}_{2.5}$ on the probability of moving, along with 95% confidence bands.¹¹ The vertical axes measure percentage point changes in the migration probability. The results in each panel show precisely-estimated near-zero effects of air pollution changes on migration.

These results imply that the EPA’s regulation of $\text{PM}_{2.5}$ did not induce seniors to move in general (Figure 4a). Nor did the regulation appear to cause subpopulations that are thought to more vulnerable to pollution exposure to move out of areas that experienced larger reductions in pollution (Figures 4b,4c,4d). The 95% confidence bands allow us to rule out causal changes in migration greater than one percentage point for all groups and years.

The lack of a migratory response is important for at least three reasons. First, it implies that residential location choices made prior to age 65 have long-lasting effects on pollution exposure. Second, it can explain why we find that CAA regulation explained virtually all of the decline in the race gap among people over age 65 whereas Currie et al. (2023) and Sager and Singer (2025) find that it explains closer to 60% when all age groups are pooled. Specifically, Currie et al. (2023) find that race-based migration undid part of the causal decline in the race gap as White

¹¹The instruments have adequate statistical power with Kleibergen-Paap rk Wald F-statistics between 41 and 415. These results are shown in Appendix Table B.1

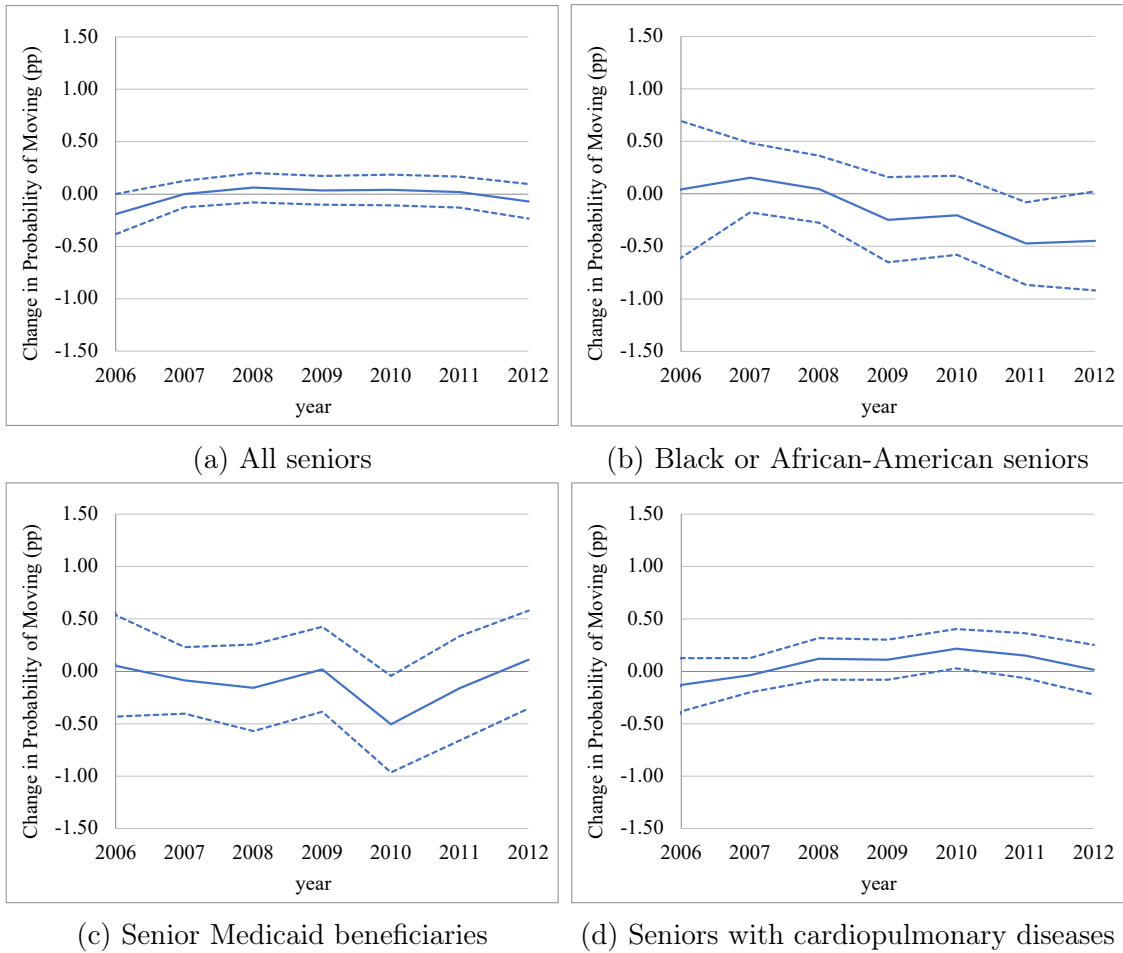


Figure 4: Estimated Effects of $PM_{2.5}$ Exposure on the Probability of Moving

Note: The figure shows IV estimates for the effect of changes in air pollution exposure on the probability of migration. 95% confidence bands are based on clustering standard errors at the Census tract level.

(Black) population shares increased (decreased) the most in areas that had the largest reductions in $PM_{2.5}$. Our results suggest that this race-based sorting was concentrated among people under age 65. Finally, the lack of a similar migratory response among seniors implies that CAA regulation produced a relatively larger reduction in the race gap in exposure for seniors, whom the EPA classifies as being more vulnerable to air pollution based on age.

5 Effects of Superfund Cleanup on Migration

The trends in Superfund site exposure shown in Figures 1b–3b reflect the combined effects of migration, compositional changes in the 65+ population, and remediation activities. Of these three channels, migration is the primary channel for modifying Superfund site exposure among a given cohort of seniors because, compared to CAA regulation of $PM_{2.5}$, the time from regulatory action to measurable changes in exposure is relatively long for non-movers. Most seniors who live near newly discovered Superfund sites will have died before those sites are deleted from the NPL. For example, at the midpoint of our study period, the average individual is 70 years old with a remaining life expectancy of 14 years. In comparison, the median time from proposal to deletion for sites proposed since 2000 is at least 15 years.¹²

Against this background, we estimate the extent to which the exposure trends in Figures 1b–3b can be explained by seniors moving to reduce their exposure to contaminated sites. Specifically, we estimate how proposal and deletion of sites affects short-term migration. As we noted in Section 2.3, the EPA publicizes proposal and deletion events through local news media and community advisory groups. By proposing a site for the NPL, the EPA informs nearby residents that the site may pose a significant risk to their health. By deleting a site, the EPA signals that it believes the risk is no longer significant. The heterogeneous timing of these events provides an opportunity to study how information shocks about environmental health risks affect migration.

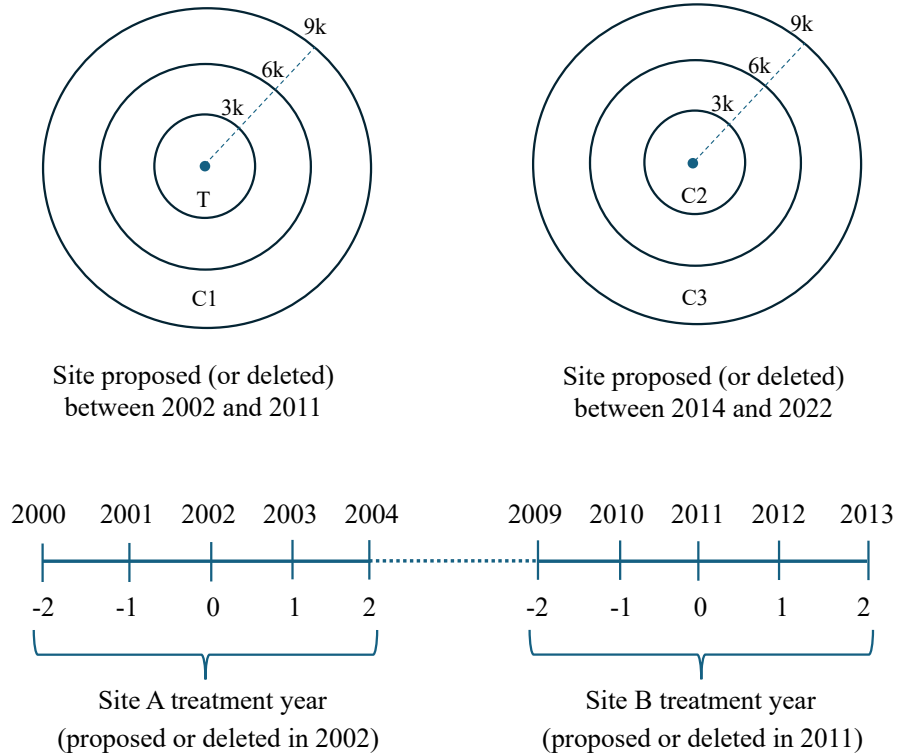
5.1 Spatial Difference-in-Differences Design

Figure 5 provides a stylized illustration of the spatial and temporal sources of variation that motivate our empirical design. We focus on “treatment” sites that the EPA either proposed for the NPL between 2002 and 2011, or deleted from the NPL during that period, and for which we observe individuals living within 9 kilometers

¹²This is a weak lower bound on remediation time because it relies on an extreme assumption that all sites are fully remediated just after our study period. If we repeat the calculation including sites proposed before 2000, the lower bound median cleanup time is 30 years.

of the treated site and no other site.¹³ The sets of proposed and deleted sites are mutually exclusive; that is, all of the proposed sites that we examine were still on the NPL at the end of 2013. We define the treatment window to be a subset of our 2000-2013 study period in order to utilize variation in migration within a five-year window around the year each site was proposed or deleted. For a site that was proposed in 2002, for example, we examine pre-trends in 2000 and 2001 and post-trends in 2003 and 2004, whereas we examine trends from 2009-2013 for a site proposed in 2011.

Figure 5: Spatial Difference-in-Differences Design



The concentric circles in Figure 5 illustrate the spatial delineation of treatment and control areas. We define the treatment area, T , by a 3 kilometer radius around each treated site. As we noted in Section 3.1, the 3 kilometer distance lies near

¹³These sample criteria drop 35 sites that were proposed in 2002-2011 and 9 sites that were deleted in 2002-2011.

the middle of the range commonly used to estimate effects of hazardous waste and other localized sources of land contamination on property values and the health of nearby residents. The control area $C1$ is a donut defined by 6 and 9 kilometer rings around the newly proposed or deleted site. We exclude the smaller 3k-to-6k donut due to ambiguity around the fact that distances within this range are included as part of the treatment group in some studies of health effects and property values (e.g. Cassidy et al., 2022; Guignet et al., 2023; Persico et al., 2020) and as part of the control group in others (e.g. Currie et al., 2011; Haninger et al., 2017; Klemick et al., 2020; Guignet and Nolte, 2024). Variation in emigration from areas T and $C1$ before and after a site is proposed or deleted can identify a spatial difference-in-differences estimator for the effect of proposal or deletion on emigration from surrounding neighborhoods.

The spatial difference-in-difference (DID) estimator embeds the maintained assumption of common trends in emigration between areas T and $C1$. Our empirical design provides two years of pre-trend data to test this assumption. As an additional sensitivity check we also estimate specifications that include data from control areas $C2$ and $C3$ around sites that the EPA proposed (or deleted) after our study period, specifically between 2014 and 2022. Adding these sites to the control group allows for the possibility that emigration time trends differ with spatial proximity to sites regardless of when those sites were proposed or deleted. This could occur, for example, if the shares of single-family and multi-family housing units varied with distance from sites and were differently affected by boom-bust cycles in the housing market.

Thus, the estimation samples are comprised of seniors who lived in neighborhood types T , $C1$, $C2$, and $C3$ each year and who did not live within 9 kilometers of any other current or future site.¹⁴ We define the outcome of interest, m_{ijt} , as an indicator for whether individual i who lived in neighborhood j at the beginning of year t moved outside their neighborhood by the beginning of year $t + 1$. This

¹⁴Individuals may live within 9k of sites that had been remediated and removed from the NPL.

definition treats within-neighborhood moves (e.g. moves within area T in Figure 5) as being equivalent to not moving because both possibilities leave the individual’s proximity to their nearest site approximately unchanged.

Equation (5) shows the basic spatial differences-in-differences regression.

$$m_{ijt} = \beta_1 Post_{jt} + \beta_2 T_{ijt} + \beta_3 Post_{jt} \times T_{ijt} + \alpha_t + \gamma_j + \delta X_{it} + \epsilon_{ijt} \quad (5)$$

T_{ijt} is an indicator for whether individual i lived within 3k of site j at the beginning of year t , and $Post_{jt}$ is an indicator for whether t is the first or second year after the EPA proposed adding that site to the NPL (or deleting it from the NPL). We normalize $Post_{jt} = 0$ for the year during which sites were proposed or deleted because we do not observe the precise timing of moves relative to proposal/deletion dates during the calendar year. The covariates include year fixed effects, α_t , site fixed effects, γ_j , and the following individual characteristics: indicators for integer age, gender, race, receipt of Medicaid benefits, and past diagnosis of one or more cardiopulmonary illnesses.

Thus, the coefficient of interest, β_3 , is identified by differences in emigration between treatment and control neighborhoods around sites before and after they were proposed for the NPL conditional on time trends, site-specific effects, and the demographic compositions of neighborhood populations. Importantly, treatment occurs at the same time for all individuals living around each site. This feature, combined with the fact that sites do not transition back to untreated status during our estimation window, makes our econometric framework similar to a stacked DID design, which is one of several designs for data with staggered treatment windows (Roth et al., 2023).¹⁵ We also estimate specifications that add time-varying treatment effects and that interact treatment with individual characteristics.

¹⁵Guignet and Nolte (2024) provide another example of this approach in the context of hazardous waste and home values.

5.2 Effects of Superfund Site Proposal and Deletion on Emigration

Table 2 reports results from four specifications of Equation (5). Regression coefficients are multiplied by 100 and can therefore be interpreted as approximate percentage point (pp) changes. The first two columns use data from near and far neighborhoods around 135 sites that the EPA proposed adding to the NPL between 2002 and 2011 (i.e. neighborhoods T and $C1$ in Figure 5). Column (1) indicates that new information about environmental contamination had virtually no effect on the rates at which seniors moved out of surrounding neighborhoods.

Table 2: Effect of Site Proposal on Emigration

	(1)	(2)	(3)	(4)
proposal	0.007 (0.187)	0.039 (0.247)	0.006 (0.188)	0.037 (0.247)
<u>proposal interacted with:</u>				
Black or African-American		-0.389 (0.514)		-0.388 (0.512)
Medicaid recipient		-0.568 (0.580)		-0.579 (0.579)
Cardiopulmonary disease		0.127 (0.287)		0.133 (0.287)
number of person-years	348,600	348,600	857,846	857,846
number of sites	135	135	208	208
includes future sites	no	no	yes	yes

Note: The outcome is an indicator for whether an individual moved out of their neighborhood. Coefficients are multiplied by 100 and can therefore be interpreted as approximate percentage point changes. Standard errors are clustered by site-year.

Column (2) shows results from a specification that interacts the information treatment with indicators for whether a nearby resident is Black, a Medicaid recipient, or previously diagnosed with a cardiopulmonary disease. The interaction terms suggest that Black seniors and Medicaid recipients are slightly less likely to move out of neighborhoods around newly proposed sites. However, these effects are statistically indistinguishable from zero and 95% confidence intervals rule out reductions greater than 1.8pp.

Finally, the null effects shown in columns (1)-(2) of Table 2 persist in columns (3)-(4) when we add data from near and far neighborhoods around 73 sites that were proposed for the NPL after the end of our study period (i.e. neighborhoods *C2* and *C3* in Figure 5). These additional “control” sites were proposed between 2014 and 2022. The similarity in results suggests that the null effects reported in the first two columns are not simply attenuated by differential trends in migration between neighborhoods closer and further from hazardous waste sites that may differ in their stock of housing.

Table 3: Effect of Site Deletion on Emigration

	(1)	(2)	(3)	(4)
deletion	0.354*	0.160	0.340	0.146
	(0.211)	(0.245)	(0.212)	(0.243)
<u>deletion interacted with:</u>				
Black or African-American		0.974		0.988
		(0.703)		(0.704)
Medicaid recipient		-0.462		-0.481
		(0.512)		(0.512)
Cardiopulmonary disease		0.211		0.211
		(0.320)		(0.320)
number of person-years	266,024	266,024	450,752	450,752
number of sites	94	94	158	158
includes future sites	no	no	yes	yes

Note: The outcome is an indicator for whether an individual moved out of their neighborhood. Coefficients are multiplied by 100 and can therefore be interpreted as approximate percentage point changes. Standard errors are clustered by site-year.

Table 3 reports estimates for the effect of deleting a Superfund site from the National Priority List on emigration from surrounding neighborhoods. The first two columns use data from neighborhoods around 94 sites that were deleted between 2002 and 2011, and the last two columns add another 64 “control” sites that were deleted between 2014 and 2022. The average effects in columns (1) and (3) imply that during the first two full years after a site is deleted from the NPL, the probability of moving out is approximately 0.35 percentage points higher. However, the 95%

confidence intervals include zero. The interaction terms suggest a higher probability of emigration for Black seniors and a lower probability for Medicaid recipients. While these effects are imprecisely estimated, confidence intervals rule out effects larger than 2.4pp in absolute magnitude.

Overall, the results in Tables 2 and 3 suggest that new information about exposure to health risks from local sources of land contamination generates little to no residential sorting response among incumbent over-65 populations living in the affected areas.¹⁶ Their non-response parallels the nationwide evidence on the insensitivity of migration to air quality changes in Section 4.2. This reinforces our observation that earlier-in-life location choices have long-lasting consequences for later-in-life pollution exposures. A remaining question is why the race and wealth gaps in Superfund site exposure increased during the 2000’s (Figure 2b) while overall exposure declined (Figure 1b). We find that immigration to Superfund site neighborhoods can help to explain this pattern.

5.2.1 Immigration to Superfund Site Neighborhoods

We measure how the probability that movers choose to live near Superfund sites varies with information, race, wealth, and health. The sample we use for this final exercise is comprised of all individuals who we observe moving from locations that are not within 9k of any Superfund site to new locations that are either less than 3k from the nearest site or 6k-to-9k from the nearest site. Given that these movers choose to live within 9k of a site, we ask how the probability of living closer (0-to-3k) or further (6k-to-9k) varies with mover demographics, before and after sites are proposed for the NPL or deleted from it.

The first three columns of Table 4 show descriptive estimates from linear proba-

¹⁶Appendix B shows that this conclusion persists when we extend the econometric specification in Equation (5) to allow for additional forms of treatment effect heterogeneity across time and space. First, Appendix Figure B.1 provides visual evidence that there are no discernible pre-trends or post-trends when we repeat estimation of the specification in column (1) of Tables 2 and 3 after interacting treatment with indicators for each of the two years before and after the treatment year. Second, Appendix Table B.2 shows that we continue to find null effects when we interact treatment with the Hazardous Ranking System score of site toxicity.

Table 4: Immigration to Superfund Sites

	(1)	(2)	(3)	(4)	(5)
Black or African-American	5.162*** (1.076)	1.917*** (0.478)	-0.280 (1.041)	-2.744 (2.188)	3.584 (2.902)
Medicaid recipient	2.13*** (0.555)	1.813*** (0.275)	6.048*** (0.686)	2.061 (1.294)	5.554** (2.169)
Cardiopulmonary disease	0.040 (0.505)	0.404** (0.171)	0.792** (0.355)	0.590 (0.964)	1.75* (0.963)
proposal (or deletion)				0.849 (1.751)	3.441 (2.109)
<u>proposal (or deletion) interacted with:</u>					
Black or African-American				2.726 (2.495)	2.621 (5.157)
Medicaid recipient				1.158 (2.096)	1.832 (2.853)
Cardiopulmonary disease				-1.273 (1.702)	-1.914 (1.419)
number of person-years	22,715	152,545	56,402	8,653	7,074
number of sites	210	1,139	309	118	86
site type	future proposed	proposed	deleted	proposed	deleted

Note: The outcome is an indicator for whether an individual moved to a new location within 3 kilometers from a Superfund site. The sample is comprised of individuals who moved from a location that was at least 9 kilometers from the nearest Superfund site to a location that was either within 3 kilometers of a site or between 6 kilometers and 9 kilometers from a site. Coefficients are multiplied by 100 and can therefore be interpreted as approximate percentage point changes. Standard errors are clustered by site-year.

bility regressions. The dependent variable is an indicator for whether the individual moved within 3k of a site and the covariates include indicators for year, site, integer age, gender, race, Medicaid take-up, and cardiopulmonary illness. The first two columns show that Black seniors and those receiving Medicaid benefits are significantly more likely to move near Superfund sites that were previously proposed for the NPL, as well as sites that will be proposed in the future. For example, column (1) implies that, conditional on moving within 9k of a site, Black seniors are 5 percentage points more likely to move within 3k of the site. We also estimate a relatively large 6pp differential for Medicaid recipients moving near deleted sites.

Overall, the signs and relative magnitudes of the coefficients in columns (1) and (2) suggest that immigration to Superfund neighborhoods contributes to the trends in the race, wealth, and health gaps in exposure shown in Figure 2b.

The last two columns of Table 4 examine whether the demographic trends in immigration to Superfund neighborhoods change before and after proposal and deletion events. Our econometric approach is a pooled event study design focused on five-year windows around the years when sites were proposed or deleted. This specification is equivalent to the spatial DID regression in Equation (5) with the restriction that $\beta_2 = \beta_3 = 0$. While the relatively small mover sample reduces statistical precision relative to our prior analysis of incumbent residents' emigration patterns, we still fail to reject the null hypothesis that new information about Superfund site proposal and deletion has no effect on how seniors sort themselves across residential neighborhoods.

6 Conclusion

This study examined how environmental regulation under the U.S. Superfund program and Clean Air Act affected exposure to hazardous waste and fine particulate air pollution among the over-65 population from 2000 through 2013. We found that regulatory-induced changes in the spatial distribution of pollution did not substantially change seniors' residential sorting behavior. This implies that environmental gentrification did not unravel the benefits of lower pollution exposure for seniors living in areas improved by regulation.

We also showed that regulation caused seniors' exposure to Superfund sites and air pollution to decline substantially, as did differences in air pollution exposure by race and wealth. Race and wealth gaps in exposure to hazardous waste sites grew, partly due to differential rates of migration into neighborhoods around those sites. However, we found that these differences were unaffected by EPA regulatory actions that publicly identified new sites as potential health risks and publicly certified other sites as having been cleaned. Finally, we showed that there was virtually no

difference in pollution exposure between people with and without chronic diseases that increase their sensitivity to air pollution.

Overall, these findings imply that residential location decisions made by younger adults are likely to have long-lasting effects on their lifetime pollution exposure. This underscores the need to advance research on the life cycle dynamics of residential sorting and pollution exposure (Bayer et al., 2016; Bishop and Murphy, 2019; Kuminoff and Mathes, 2024; Mathes, 2024).

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Supplemental Appendix


A Background

Figure A.1 provides an example of a notice to the public that the EPA proposed adding a site to the National Priority List.

Figure A.1: Example of a Superfund Site Proposal Notice

D4 THURSDAY, APRIL 07, 2016

PUBLIC NOTICES

 **EPA** United States Environmental Protection Agency

**NOTICE OF PUBLIC COMMENT OPPORTUNITY
BONITA PEAK MINING DISTRICT**

**THE UNITED STATES ENVIRONMENTAL PROTECTION AGENCY (EPA)
ANNOUNCES THE PROPOSAL TO ADD THE
BONITA PEAK MINING DISTRICT IN SAN JUAN COUNTY, COLORADO
TO THE NATIONAL PRIORITIES LIST (NPL)**

The NPL is the list of national priorities among the known releases or threatened releases of hazardous substances, pollutants, or contaminants throughout the nation, commonly known as Superfund sites. The public is invited to comment on the proposal during a 60-day comment period beginning April 7, 2016.

Please reference Docket # EPA-HQ-OLEM-2016-0152 in all submitted comments. Comments may be submitted using one of the three following methods:

Go to www.regulations.gov and follow the online instructions for submitting comments using Docket # EPA-HQ-OLEM-2016-0152.

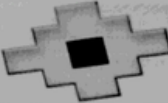
Mail comments to the following address: Docket Coordinator, Headquarters U.S. Environmental Protection Agency CERCLA Docket Office (Mail Code 5305T) 1200 Pennsylvania Avenue, NW Washington, DC 20460

Hand deliver comments or send comments via express mail to the following address: Docket Coordinator, Headquarters U.S. Environmental Protection Agency CERCLA Docket Office 1301 Constitution Avenue, NW EPA West, Room 3334 Washington, DC 20004 (8:30 a.m. – 4:30 p.m. Mon – Fri)

Specific documents supporting the proposal to add the Bonita Peak Mining District to the NPL are available at www.regulations.gov as describe above. Copies of all documents, including references, are available at <https://cumulis.epa.gov/supercpad/cursites/csitinfo.cfm?id=0802497> and at the following locations:

Silverton Library 1117 Reese Street, Silverton, CO 81433	Durango Public Library 1900 East Third Ave., Durango, CO 81301
Farmington Public Library 2101 Farmington Ave., Farmington, NM 87401	EPA Superfund Records Center 1595 Wynkoop Street, Denver, CO 80202-1129 To request copies of documents call: 303-312-7273 800-227-8917 ext. 312-7273 (toll free Region 8 only)
Office of the Navajo Nation Library Arizona Highway 264, Post Office Loop Road Window Rock, AZ 86515	

For questions or additional information, contact:
Rob Parker, Site Assessment Manager, at 800-227-8917, ext. 312-6664
Cynthia Peterson, Community Involvement Coordinator, at 800-227-8917, ext. 312-6879

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B Additional Results

Table B.1 reports point estimates from an instrumental variables regression of migration on the change in residential exposure to $PM_{2.5}$

Table B.1: Effects of $PM_{2.5}$ Regulation on Migration

Group	year	sample size	point estimate	confidence interval		Kleibergen-Paap rk Wald F statistic
All seniors	2006	3,080,831	-0.19	-0.38	0.00	96.78
	2007	2,900,742	0.00	-0.13	0.13	104.94
	2008	2,730,307	0.06	-0.08	0.20	113.01
	2009	2,561,116	0.04	-0.10	0.17	41.54
	2010	2,393,948	0.04	-0.11	0.19	176.04
	2011	2,231,022	0.02	-0.13	0.17	119.98
	2012	2,071,106	-0.07	-0.23	0.09	99.31
Black or African American seniors	2006	286,870	0.04	-0.61	0.69	235.80
	2007	269,295	0.15	-0.18	0.48	284.66
	2008	252,978	0.05	-0.27	0.36	342.31
	2009	236,860	-0.25	-0.65	0.16	234.14
	2010	221,270	-0.20	-0.58	0.17	397.86
	2011	206,038	-0.47	-0.87	-0.08	414.51
	2012	191,217	-0.45	-0.92	0.02	379.21
Senior Medicaid beneficiaries	2006	363,151	0.05	-0.43	0.54	128.70
	2007	345,492	-0.08	-0.40	0.23	130.85
	2008	327,648	-0.16	-0.57	0.26	157.61
	2009	308,094	0.02	-0.39	0.43	107.08
	2010	295,283	-0.50	-0.96	-0.04	144.56
	2011	280,479	-0.16	-0.66	0.34	185.66
	2012	263,018	0.11	-0.35	0.58	130.71
Seniors with cardiopulmonary illnesses	2006	1,393,420	-0.13	-0.38	0.13	96.78
	2007	1,375,993	-0.04	-0.20	0.13	131.81
	2008	1,345,998	0.12	-0.08	0.32	126.83
	2009	1,303,508	0.11	-0.08	0.30	44.95
	2010	1,246,804	0.22	0.03	0.41	181.04
	2011	1,185,164	0.15	-0.07	0.37	138.82
	2012	1,118,248	0.02	-0.22	0.25	105.43

Note: The outcome is an indicator for whether an individual moved. Coefficients are multiplied by 100 and can therefore be interpreted as approximate percentage point changes. Standard errors are clustered by county.

Figure B.1 shows time-to-treatment effects of proposal and deletion. The specifications used to generate the figures correspond to column (1) of Tables 2 and 3 after

interacting the treatment dummy with indicators for the two years before and after treatment. The treatment effect is normalized to zero in the year when treatment occurs.

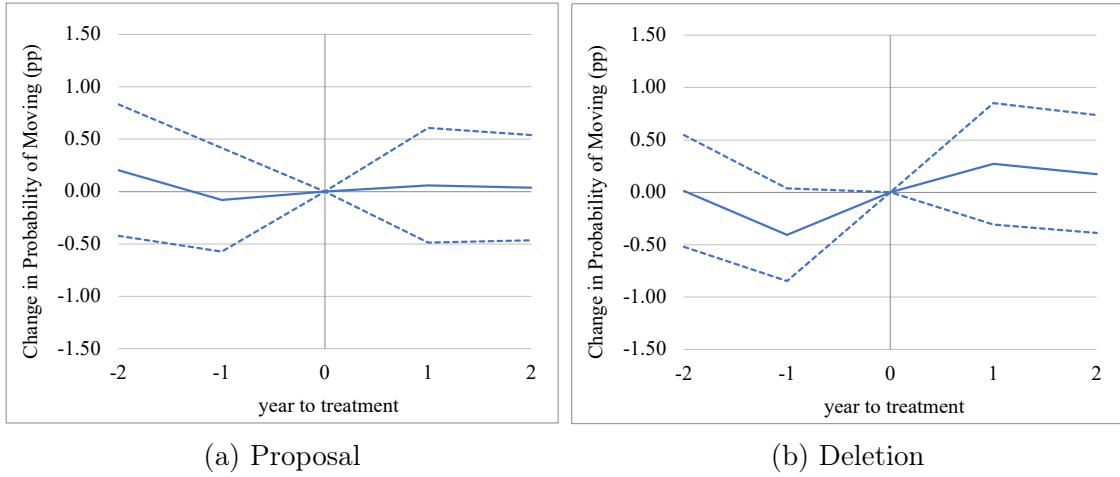


Figure B.1: Time-to-Treatment Effects

Note: The figure shows Spatial DID estimates for time-varying treatment effects of Superfund site proposal and deletion on the probability of emigration.

Table B.2 shows results from repeating estimation of the specifications in columns (1) and (3) of Tables 2 and 3 after adding an interaction between treatment and the Superfund site's Hazardous Ranking System score. Sample sizes are slightly smaller than in Tables 2 and 3 because a small number of sites are missing data on HRS score.

Table B.2: Proposal and Deletion Interacted with HRS Score

	(1)	(2)	(3)	(4)
proposal	0.075 (0.9934)	-0.013 (0.9971)		
<u>proposal interacted with:</u>				
Hazard Ranking System Score	-0.0015 (0.0204)	0.0002 (0.0204)		
deletion			0.1743 (0.8048)	0.2550 (0.8072)
<u>deletion interacted with:</u>				
Hazard Ranking System Score			0.0011 (0.0184)	-0.0011 (0.0185)
number of person-years	338,375	799,893	255,226	434,134
number of sites	126	192	90	153
includes future sites	no	yes	no	yes

Note: The outcome is an indicator for whether an individual moved out of their neighborhood. Coefficients are multiplied by 100 and can therefore be interpreted as approximate percentage point changes. Standard errors are clustered by site-year.