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Disproportionate Environmental Risks: An Analysis of Chemical Facilities and Accidents in the U.S.

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Disproportionate Environmental Risks:
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Abstract:

A key objective of the environmental justice movement is to identify and address situations where environmental risks and harms are shouldered disproportionately by historically underserved populations, often based on race, ethnicity, and low-income status. This study examines a unique dataset of chemical facilities that use extremely hazardous substances and subsequent chemical accidents involving fires, explosions, and/or toxic vapors. Using nationwide data on the U.S. Environmental Protection Agency's Risk Management Plan (RMP) program, we examine the proportions of underserved populations living near these facilities both before and after a chemical accident. We find that the proportions of residents who are Black, Hispanic, Asian, and living in poverty are substantially greater in communities near these facilities. Such inequities are exacerbated after a chemical accident occurs, with the results suggesting that the proportion of Black individuals in these fenceline communities is almost triple that compared to the rest of the U.S.; and the proportion of households living in poverty is over 45% higher.

JEL Classification: D63; Q53; Q56

Keywords: accident, chemical, environmental justice, equity, toxic, Risk Management Plan, RMP

I. INTRODUCTION

Communities living near facilities that use hazardous substances in their production processes face risks from potential accidental releases. Such chemical releases can result in fires, explosions, and drifting clouds of toxic vapors. The United States Environmental Protection Agency's (EPA) Risk Management Plan (RMP) program is in place to protect the public from accidental releases at facilities using extremely hazardous substances. The RMP program was authorized by Section 112(r) of the 1990 Clean Air Act Amendments, which established a "general duty" for owners and operators of "stationary sources" holding extremely hazardous substances to identify potential hazards, take steps to prevent releases, and minimize the consequences of accidental releases that do occur.[1] The RMP program regulates almost 12,000 facilities, and there are multiple RMP facilities located in every U.S. state. There are close to 150 million people in communities located within 3 miles (about 4.8 km) of these regulated facilities (U.S. EPA 2023). Despite the sheer number and ubiquity of RMP facilities across the United States (U.S.), there are few studies focused on the surrounding "fenceline" communities.

Understanding the demographic characteristics of communities facing risks of chemical accidents will shed light on the RMP program's distributional impacts, and the impacts of other policies aimed at reducing the risk of exposure to chemical accidents and toxic releases from chemical facilities. Multiple Executive Orders, including *E.O. 14096: Revitalizing Our Nation's Commitment to Environmental Justice for All,* called for Federal agencies to consider environmental justice (EJ) issues. EPA routinely considered the demographic characteristics of neighborhoods affected by environmental regulations. However, as pointed out by an EPA Science Advisory Board report, the Agency's distributional analyses of community demographics often did not clarify whether any identified disparities are *statistically significant* (U.S. EPA Science Advisory Board 2024). Consider, for example, the EPA's recently finalized 2024 "Safer Communities by Chemical Accident Prevention" rule, which includes provisions to further reduce the probability and magnitude of future chemical accidents at RMP facilities. An EPA analysis of the rule's potential distributional impacts compared average percentages of racial, ethnic, and income groups in communities near RMP facilities to nationwide population averages further away, but failed to include evidence of whether any differences were statistically significant (U.S. EPA 2023). Such an omission may be due to concerns of multicollinearity among the variables used to characterize population groups across numerous dimensions (e.g., race, ethnicity, financial well-being).

We propose a simple regression-based analytical framework that can be used to quantify any environmental disparities, and assess whether such disparities are statistically significant. Our approach circumvents multicollinearity concerns by examining each demographic variable separately. We demonstrate our analytical approach using nationwide data on facilities regulated by the U.S. EPA's RMP program and on accidents that occurred at those facilities from 2004 to 2019. We spatially and temporally link the RMP data to Census tract-level demographic data from

[1] 42 U.S.C. § 7412(r)(1).

the U.S. Census Bureau's American Community Survey for the years 2006-2015, and employ multivariate regression models to statistically examine (i) whether industrial facilities regulated under the RMP program are more likely to be located near communities where a greater proportion of residents are White, Black, American Indian, Asian, Hispanic, and/or living below the poverty line; (ii) whether facilities near such communities pose a greater risk in terms of an accident occurring and the severity of an accident; and (iii) how community demographics shift after an accident occurs. In addition, we investigate heterogeneity in community demographics based on whether the U.S. EPA versus the state administers and enforces the RMP program. Ultimately, we wish to characterize the environmental justice (EJ) implications posed by the locations and risks of chemical accidents at these industrial facilities.

Demonstrating the existence and extent of any environmental inequities is particularly important given the U.S. federal government's recent shift away from environmental justice and equity related initiatives under President Trump's Executive Order "Ending Radical and Wasteful Government DEI Programs and Preferencing" (U.S. EPA 2025a; U.S. Whitehouse 2025). In addition, the U.S. EPA is now considering whether to roll back some of the safeguards implemented under the 2024 Safer Communities by Chemical Accident Prevention rule (U.S. EPA 2025b; Younes and Grist 2025).

Our results suggest glaring inequities. Facilities are more often located near communities where a greater proportion of people are Black, Asian, Hispanic, and living in poverty. Such inequitable patterns seem to intensify for some groups, with the results suggesting that the proportions of Black individuals and poverty-stricken households living near these facilities roughly double after a chemical accident. These positive associations are robust to alternative model variants, such as the inclusion of state fixed effects and the use of alternative distance bins to define proximity to a facility (i.e., five, three, and one kilometer(s)). We find little evidence that these sociodemographic patterns differ with respect to *a priori* risks of an accident or severity. Finally, we find no statistically significant patterns suggesting that these inequities systematically differ across the nine states that are delegated authority to implement all or part of the RMP program themselves, compared to the rest of the country where the program is implemented federally by the U.S. EPA.

Overall, this nationwide analysis provides objective information to aid discussions with government, industry, and community stakeholders as part of the regulatory development process. It introduces a straightforward approach for determining whether disparities across population groups are statistically significant. Better understanding inequities across racial, ethnic, and income groups in neighborhoods affected by environmental regulations provides a deeper understanding of how environmental risks (and reductions in those risks) are distributed across the population.

The remainder of this paper provides additional background on the RMP program and related literature. The empirical data and methodology are then discussed, followed by the results. We conclude by discussing the implications and importance of our findings.

II. BACKGROUND AND LITERATURE

The original RMP regulation promulgated by the U.S. EPA in 1996 requires that any stationary source that uses, stores, manufactures, or handles, more than a threshold quantity of one or more of 140 listed substances must undertake accident prevention steps and submit a ‘‘risk management plan’’ to various local, state, and federal planning entities.[2] The purpose of the RMP program is to protect the public and the environment from accidental chemical releases that can result in escaped toxic clouds, fires, and explosions. While onsite worker safety is regulated by the U.S. Occupational Safety and Health Administration, the U.S. EPA's RMP program is specifically meant to reduce risks to populations in the surrounding communities.

The RMP program covers a wide range of industry categories, from large multi-process manufacturing plants, such as petroleum refineries and chemical manufacturers, to smaller facilities, such as agricultural chemical distributors, water and wastewater treatment systems, and cold storage facilities. In between there are a variety of other manufacturers, energy production facilities, chemical storage terminals and warehouses, natural gas processing plants, and food manufacturers, among others, regulated under the RMP program.

When a chemical accident occurs, an RMP facility must report it to regulators within 6 months if the accident resulted in death, injury, property damage, evacuations or sheltering-in-place of people, and/or environmental damage (e.g., fish or animal kills, water contamination, tree defoliation). In most cases any reportable accident impacts are onsite, meaning that the extent of harm is limited to what occurred at the regulated facility and on its property. However, in several cases, reportable accidents involved *offsite* impacts such as deaths, injuries, property damage, evacuations, sheltering-in-place, and/or environmental damage to the surrounding communities. In recent years, 27% of reportable accidents have involved offsite impacts (U.S. EPA 2023).

The spatial distribution of RMP facilities and reportable chemical accidents could be considered inequitable if they tend to be located near communities where a greater share of the population is a historically underserved racial or ethnic group, or living in poverty. If there are no inequities, then proximity to RMP facilities and accidents would be uncorrelated with the surrounding population demographics. To our knowledge, there are only three prior studies that have examined potential inequities around facilities and chemical accidents regulated under the RMP program. Elliott et al. (2004) studied facility data reported by an initial set of approximately 15,000 facilities regulated at the beginning of the RMP program, covering accidents from 1994 to 2000. Looking only at counties with RMP facilities, they examined correlations between county-level demographic information and measures of the riskiness of RMP facilities, including the frequency of chemical accidents. Elliott et al. found that larger and more chemical-intensive facilities are in counties with greater Black populations, and although these counties had higher median incomes, they also had greater levels of income inequality. Using data for the same set of facilities and time period as Elliot et al., Kleindorfer et al. (2004) examined the relationship between RMP facilities' propensities for accidents and the financial conditions, capital structures, regulatory environments, and demographic characteristics of the county where the facility is located. They found that

[2] CAA section 112(r) (3)–(5) and (7)(B).

counties with greater Black populations are more likely to have RMP facilities with higher quantities of chemicals (and other measures of riskiness); and that the risk of accidents, and of accidents with more severe outcomes (including injuries and property damage), is greater in counties with larger proportions of Black residents. More recently, Guignet et al. (2023a) used census tract-level data to examine population demographics near RMP facilities in Michigan (MI), Ohio (OH), and Pennsylvania (PA). They found that RMP facilities and accidents are more often located near neighborhoods where a greater proportion of the population is Black, Hispanic, and living in poverty.

Our current study includes populations near RMP facilities nationwide, and examines a wider set of racial groups (including American Indian and Asian). We also investigate how demographics in communities near a facility might shift after an accident occurs, and assess whether any disparities are greater among states that manage their own RMP programs directly, as opposed to implementation by the federal government. Such states must set standards at least as strict as those set by the federal program (42 U.S. Code 7412(I)); for example, they may have increased frequency of facility inspections or lower chemical quantity thresholds for triggering program participation. Data on differences in RMP facility requirements between federal EPA and delegated states is sparse. The U.S. Government Accountability Office (2022) offers one useful comparison. In 2019, EPA inspected approximately 2% of RMP facilities nationwide, whereas in the delegated state of Florida, the Division of Emergency Management inspects an average of 12% of RMP facilities each year. Other examples of greater stringency include lower threshold quantities on many chemicals in Delaware and additional planning, auditing, and notification obligations in New Jersey (JJ Keller Compliance Network, 2024). At the same time, in delegated states there is less federal oversight and state regulators may have closer relationships with regulated entities, which could lead to more relaxed enforcement.

Although not exclusively focused on EJ, studies by Guignet et al. (2023a; 2023b) examined how RMP facilities and accidents affect residential property values. They found that the value of homes near RMP facilities in general is lower, all else constant. This is important given that for many families their home is their single most important financial investment.[3] At the same time, Guignet et al. (2023a; 2023b) find that accidents with direct offsite impacts lead to an additional decrease in the value of homes (looking at distances of either 5 or 5.75 km, respectively).

Our current study aims to enhance understanding of the demographic composition of communities near RMP facilities and accidents, and how that composition might change in response to a chemical accident. Doing so sheds light on which historically underserved populations are most affected by housing value depreciations. More importantly, our study provides insight as to what demographic groups are exposed to the potential health and safety risks; as well as to other negative impacts (such as evacuations and road closures) from living near hazardous chemical facilities, and to the associated increases in adaptation costs to mitigate or avoid those impacts and risks. In doing so, our results demonstrate who experiences the benefits of RMP program requirements, including provisions like third party inspections and analyses of safer alternative technologies. On

[3] As of Quarter 4, 2025, the overall homeownership rate in the U.S. is 65.5 percent (seasonally adjusted); the rate for Black Alone households is 44.2 percent; for Asian, Native Hawaiian and Pacific Islander Alone is 63.1 percent, and for Hispanic households is 48.7 percent (Federal Reserve Bank of St. Louis 2026).

the other side of that same coin, it also reveals what demographic groups may be harmed by the removal or reduction of such provisions, as recently proposed by the U.S. EPA (U.S. EPA 2025b; Younes and Grist 2025). Finally, our analysis sheds light on how the general trajectory of a community may shift in response to an environmental disaster.

Outside of just the RMP program, a wide variety of studies have examined disparate exposures to toxic air emissions, some at the national level and others focused on smaller regions. Data and measures of toxic air exposures that have been examined include the Toxic Release Inventory (TRI), the National Emissions Inventory, the Air Quality System, satellite/remote sensing information, proximity to polluters, and more (Davis, 2011, Mikati et al. 2018, Gillingham and Huang 2021, Currie et al. 2023, Madrigal et al. 2024; Sheriff 2024). There is a long history of related studies that find disproportionate exposures among historically underserved populations near contaminated sites (Bullard et al. 2007, Burda and Harding 2014, Solatyavari et al. 2022, Brodin and Guignet 2024). A recent review by Cain et al. (2024) synthesizes the economics-oriented EJ research that has been published over the past decade and categorizes the primary contribution of each study. Forty percent of the papers reviewed are categorized as primarily "documenting and quantifying" population disparities in exposures to, or damages from, environmental risks. Of the 40 papers falling into this category, some compare differences in exposure and damages faced by Black and White populations. Others include additional racial and ethnic groups, as well as income groups, sometimes using the poverty line as a demarcation. Two main findings from the broader literature are that communities with higher percentages of Blacks, Hispanics, and Asian populations face higher pollution exposures, and that low-income communities face higher pollution burdens (as reflected in impacts on morbidity and mortality, for example). Documenting baseline disparities in exposures and harms from environmental risks is important to help inform policy intended to prioritize and address the largest disparities. Our current paper contributes to this literature by examining disparities associated with proximity to chemical facilities and accidents of different severities, and how any disparities shift after an accident occurs. As is often the case, there are no direct measures of risks and exposure available, and so we use proximity and accident severity as surrogates (U.S. EPA 2023).

III. DATA

Information on the location of RMP facilities and chemical accidents was obtained from the U.S. EPA's Office of Emergency Management and used to create variables denoting the presence and count of RMP facilities, and different accident severities. Based on varying proximities, we spatially and temporally link these data to Census tract-level community demographics from the IPUMS data of the U.S. Census Bureau's 2006-2015 American Community Surveys (ACS).

III.A. RMP Facility and Accident Data

Risk Management Plans (or RMPs) are required to be submitted by regulated facilities every five years. Submissions include information about the facility, its location, the chemical processes used, and emergency response plans. All submissions are required to include a facility's prior five-year history of reportable accidents (those that resulted in deaths, injuries, significant property damage, evacuations, shelter-in-place orders, or environmental damage).[4] The U.S. EPA maintains a national database of all submitted RMPs. As shown in Figure 1, our analysis focuses on the 17,437 facilities in the contiguous U.S. that were regulated under the RMP program for at least a portion of time from 2004 through September 2021. This includes all facilities who submitted at least one RMP to the program during this period, as well as seven facilities who submitted an earlier RMP, but did not deregister from the program until after 2004.[5]

In addition to examining the demographic characteristics of communities surrounding these facilities, we examine the demographics surrounding reportable accidents. Among the 17,437 facilities, there were 2,275 reportable accidents from 2004 through 2019.[6] These reportable accidents occurred at 1,428 different facilities, with most facilities (1,061) experiencing just one accident, 202 facilities experiencing two accidents, 70 experiencing three accidents, and 95 experiencing four or more accidents. The number of reportable accidents fluctuates from year to year, but has been trending downward over time (see Figure A1 in Appendix A). Among the reportable accidents, 789 resulted in offsite impacts to the surrounding community, including an offsite mortality (1 accident), offsite injuries (260 accidents), property damage (89), evacuations (312), and sheltering-in-place events (222). Among the 260 accidents with offsite injuries, the number of reported injuries ranged from one to 15,020 people being injured or hospitalized, with an average of 64 injuries. The upper end of that range is an outlier, with 111 being the next highest number of reported injuries. The median value is a single injury, and the 75th and 95th percentiles are two and 16 injuries, respectively. Among the 312 accidents where people in the surrounding community had to evacuate, the average number of people evacuated was 307, with a range from one person to 50,000 people being evacuated. Again, the upper end is an outlier. The median number of evacuees was 35 people, and the 75th and 95th percentiles were 102 and 575 individuals. Similar variation is reported among the accidents where the surrounding community had to shelter in place. Among those accidents, an average of 2,379 people were sheltered in place, and this ranged from just one person to 55,000 people. The median, 75th, and 95th percentiles were 65 people, 390 people, and 11,972 people being ordered to shelter-in-place.

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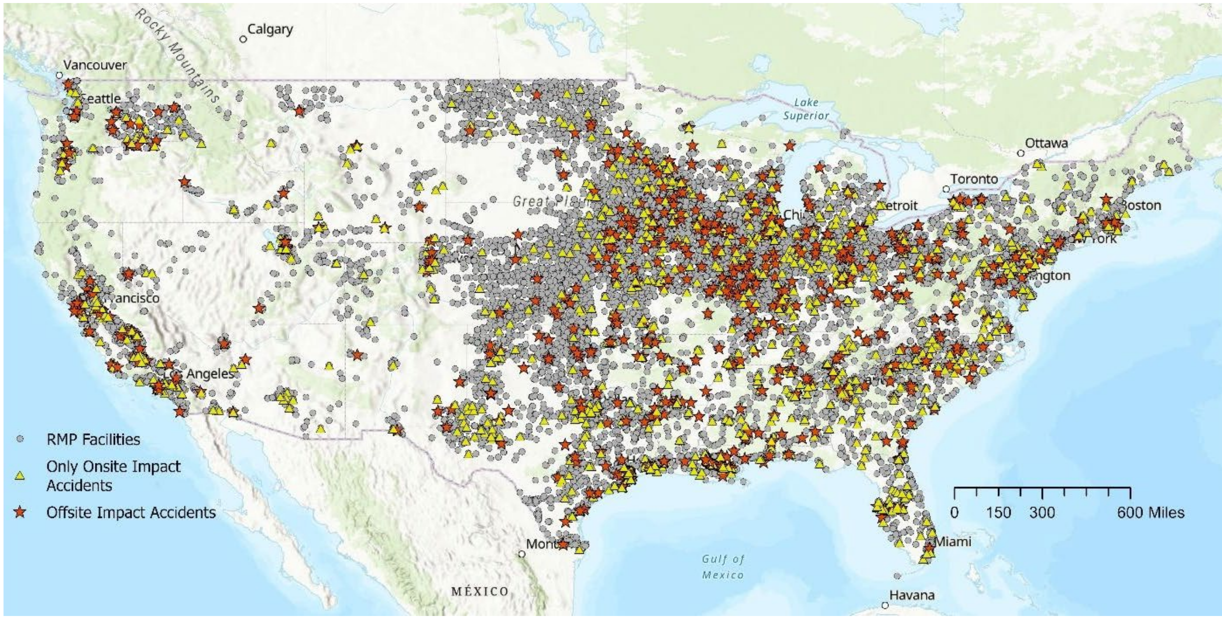
[4] See 40 CFR 68.42.

[5] The RMP dataset started with 20,758 facilities in the contiguous U.S. who submitted an RMP since the program's inception in 1999 through September 2021. We then excluded 3,292 facilities where the coordinates or coordinate system were missing, and another 29 facilities where the coordinates were likely incorrect, placing facilities in other countries or over open water, leaving 17,437 facilities. To match the available data of RMP chemical accidents examined by Guignet et al. (2023b), we sought to exclude any facilities that exited the RMP program prior to 2004. Although seven facilities did not submit an RMP since prior to 2004, they are maintained in our analysis because they did not deregister from the program until a later date.

[6] This is the same set of 2,275 reportable accidents examined by Guignet et al. (2023b) in their nationwide hedonic property value analysis. Further details regarding the RMP data can be found there.

Figure 1. RMP facilities and accidents.



III.B. Community Demographic Data

We conduct a community-level analysis, defining communities according to the 2010 census tract boundaries. The data was obtained from IPUMS, which provides historic and current ACS data.[7] Based on these data, we calculate the proportion of the population in each census tract that is White, Black, American Indian, Asian, Hispanic, and living below the poverty line.[8] The panel dataset started with annual observations for each of the 72,335 tracts within the contiguous U.S., over a period of 10 years from 2006-2015; implying a dataset of 723,350 tract-by-year observations.[9] We then dropped 6,026 observations where the proportion of White, Black, or Hispanic individuals was missing, and another 1,789 observations where information for inferring the poverty rate in a given year was missing. Such missing values are likely instances where there was a small number of individuals in a tract in a given year, and thus where confidentiality concerns may have emerged. This suggests a final sample size of n=715,535 tract-by-year observations.

As shown in Table 1, the average tract has a population that is approximately 73% White, 14% Black, and less than one-percent American Indian and Asian. Almost 16% of the population in a

[7] IPUMS National Historic Geographical Information System (NHGIS), Accessed 17 Nov 2024, https://www.nhgis.org/.
[8] For a family of four, this corresponds to an annual income less than or equal to $22,050 (2010$ USD) for 2006-2010 ACS data, and an annual income less than or equal to $24,250 (2015$ USD) for 2011-2015 ACS data.
[9] The 179 tracts in Washington, D.C. were excluded.

tract is Hispanic, on average.[10] The average tract consists of a population where approximately 15% of households are living in poverty.

The census tract data are spatially merged to the RMP data, and then indicators denoting the presence of an RMP facility, reportable accidents, and offsite impact accidents are derived. Unfortunately, there are no direct measures of risk or exposure generally available for RMP facilities, and so proximity is often used as a surrogate (U.S. EPA 2023). In an analysis of potential risk exposure for the 2024 Safer Communities by Chemical Accident Prevention rule, the U.S. EPA examined community demographics within one- and three-mile distances. The three-mile distance (about 4.8 km) was intended to capture worst-case release scenarios (U.S. EPA 2023). The U.S. EPA's EJ screening and mapping tool (EJScreen) builds an indicator of potential health and environmental hazard impacts from RMP facilities using a five-kilometer distance (U.S. EPA 2024). Hedonic studies have found adverse effects on surrounding home values out to about five kilometers (Guignet et al. 2023a; 2023b), suggesting that households perceive RMP risks out to this distance. Overall, the evidence suggests that five kilometers is a reasonable distance when identifying communities potentially affected by RMP facility and accident risks. We adopt five kilometers for our main analysis, and then examine the sensitivity of our findings when using alternative one- and three-kilometer distance bins. The five-kilometer distance also allows for direct comparison to an earlier cross-sectional analysis of demographics at a five kilometer distance from RMP facilities in MI, OH, and PA (Guignet et al. 2023a).

As shown in Table 1, more than half of the tracts in the contiguous U.S. (52%) are within five kilometers of an RMP facility.[11] The average tract has 1.5 RMP facilities within five kilometers, but there is notable variation, ranging from 0 to 47 facilities. About 11% of tracts are within five kilometers of a reportable accident, and only 6% of tracts are within five kilometers of an offsite impact accident that directly affected the surrounding community.

Table 1. Descriptive Statistics.

	Obs	Mean	Std. dev.	Min	Max
% White	715,535	73.392	25.148	0	100
% Black	715,535	13.709	22.062	0	100
% American Indian	715,535	0.860	4.459	0	100
% Asian	715,535	0.118	0.598	0	61.165
% Hispanic	715,535	15.792	21.278	0	100
% Poverty	715,535	14.861	11.446	0	100
RMP Facility w/in 5km	715,535	0.522	0.500	0	1

[10] As defined in the 2010 ACS, Hispanic describes a person's ethnicity, which is separate from race. People who identify as Hispanic may also identify as White, Black, Asian, or American Indian in these data.

[11] Geodesic distances were calculated within a Geographic Information System (GIS) and are based on the population-weighted centroid for each 2010 census tract (https://www.census.gov/geographies/reference-files/time-series/geo/centers-population.html, accessed 13 Feb 2024).

# RMP Facilities w/in 5km	715,535	1.471	2.373	0	47
RMP Accident w/in 5km	715,535	0.111	0.314	0	1
# RMP Accidents w/in 5km	715,535	0.224	0.938	0	36
Offsite Impact Accident w/in 5km	715,535	0.059	0.236	0	1
# Offsite Impact Accidents w/in 5km	715,535	0.080	0.377	0	16

IV. METHODS

Our objective is to identify whether different socioeconomic groups make up greater proportions of the population in communities near RMP facilities and accidents. To achieve this, we estimate a series of multivariate regression models that allow us to quantify the extent to which RMP facilities are in communities where a greater proportion of residents are White, Black, American Indian, Asian, Hispanic, and/or living in poverty, relative to the rest of the contiguous U.S. population. Additionally, we evaluate whether the share of residents in these different demographic groups is even greater near facilities that pose a greater risk in terms of an accident occurring and the severity of an accident. Finally, we analyze how community demographics shift after an accident occurs. The dependent variable in our models is the percent of the population in census tract j in state s, as of time t $\left(\%pop_{jst}\right)$ that is White, Black, American Indian, Asian, Hispanic, or living in poverty.

A separate regression model is estimated for each of these groups, where only the dependent variable is different across the models. In our base models, the independent variables include a binary indicator RMP_{js} that equals one if there is an RMP facility located within, for example, five kilometers of the population-weighted centroid of tract j in state s, and zero otherwise. Similar indicator variables denoting whether an RMP accident ever occurred within that distance bin (Acc_{js}), and whether an accident yielding offsite impacts ever occurred (Off_{js}) are also included as independent variables. The formal regression models to be estimated are of the following form:

$$\%pop_{jst} = \alpha_0 + \alpha_1 RMP_{js} + \alpha_2 Acc_{js} + \alpha_3 Off_{js} + \delta_t + e_{jst} \quad (1)$$

where e_{jst} is an unobserved disturbance term that is allowed to be correlated across all tracts within each county of state s, and δ_t is a year-specific fixed effect meant to capture broader population trends across the country.

Although $\%pop_{jst}$ is the outcome variable in equation (1), we emphasize that our interest is not in explaining the overall demographic composition in a tract. We are trying to establish statistical associations between different demographic groups and the presence of RMP facilities and chemical accidents. We are not attempting to identify causal mechanisms of why populations near RMP facilities may consist of a greater composition of Black individuals, for example. Instead, we are simply attempting to identify population groups that tend to be near RMP facilities and accidents.

An alternative empirical approach would be to flip the model and include demographic information on the right-hand side and RMP activity variables on the left-hand side (for example, see Brodin and Guignet 2024), but we prefer the model in equation (1) for two reasons. First, we are interested in accounting for the incremental associations between RMP variables and the demographic composition of surrounding communities. The coefficient α_1 allows us to identify the percentage point change in the corresponding demographic group when an RMP facility is nearby (e.g., within five kilometers). This association is relative to tracts where there are no nearby RMP facilities. For example, if $\%pop_{jst}$ corresponds to the percent of the population that is Black, then α_0 will capture the average percent of the population that is Black for tracts where no RMP facility is nearby. The coefficient α_1 captures the incremental difference in the share of the population that is Black among tracts where an RMP facility is nearby.

The next coefficient α_2 captures the incremental difference between tracts near an RMP facility with a reportable accident, compared to tracts near an RMP facility with no reportable accidents. Thus, the model allows us to identify any additional inequitable patterns associated with chemical accidents, conditional on the presence of an RMP facility. Similarly, α_3 captures the incremental association between the share of the population that is of a specific demographic group near facilities where a more severe, offsite impact accident has occurred, or will occur within our data timeframe. This latter association is relative to tracts where there was a reportable accident that did not result in offsite impacts to the surrounding community. Both α_2 and α_3 examine whether there are greater inequities near riskier RMP facilities. Acc_{js} and Off_{js} are time-invariant, meaning that the estimated associations capture differences in the prevalence of different population groups that tend to be near these riskier facilities.

Our main analysis focuses on an extension of equation (1), where we include indicators denoting tracts where an accident has occurred within five kilometers as of year *t* ($PostAcc_{jst}$), and where an accident yielding offsite impacts to the surrounding community has occurred ($PostOff_{jst}$).

$$\%pop_{jst} = \alpha_0 + \alpha_1 RMP_{js} + \alpha_2 Acc_{js} + \gamma_2 PostAcc_{jst} + \alpha_3 Off_{js} + \gamma_3 PostOff_{jst} + \delta_{st} + e_{jst} \quad (2)$$

In this model, the estimates of α_2 and α_3 capture how demographics near RMP facilities where an accident will eventually occur during our study period are different compared to tracts near an RMP facility where no accident occurs. The added coefficients to be estimated are γ_2 which captures how the demographic composition of a neighborhood shifts after an accident occurs, and γ_3 which reflects any incremental difference in this shift if that accident yields offsite impacts that directly affect the surrounding community.

Equation (2) represents our most thorough model, which includes state-by-year fixed effects, as denoted by δ_{st}. To investigate the robustness of the results, in some models building up to this, we include just year, or separate year and state, fixed effects. State fixed effects account for any factors associated with $\%pop_{jst}$ that are common across all tracts within a state, and in such cases the estimates of α and γ reflect only *within* state inequities. The state-by-year fixed effect takes this a step further by flexibly allowing for state-specific trends over time.

In later models, we re-estimate equation (2) separately for delegated versus non-delegated states. Doing so allows us to examine heterogeneity in potential inequities based on whether the EPA administers the RMP program versus when states have delegated authority. States with (full or partial) delegated authority to implement and enforce the RMP program include DE, FL, GA, MS, NJ, NC, ND, OH, and SC (see Appendix B for details). In delegated states, there is less federal oversight, but at the same time standards must be at least as stringent as the EPA's federal program. Any identified heterogeneity could reflect pre-existing inequities in the spatial distribution of RMP facilities and population groups that differ on average, across states that do and do not have delegated authority; or alternatively, could reflect patterns that have developed after state delegation.

V. RESULTS

In this section, we present and discuss the main regression model results following equations (1) and (2). This is done separately for each socioeconomic group, including the proportion of a community's population that is White, Black, Hispanic, Asian, and American Indian, as well as the percent of households living in poverty. We then investigate potential heterogeneity in the distributional characterization of RMP facilities and accidents based on whether the corresponding state, as opposed to the U.S. EPA, is delegated to administer the RMP program and requirements.

V.A. Primary Regression Model Results

We first examine the association between the percent of the population in a census tract that is White and the presence of an RMP facility and accident risks. The constant term in Model 1 of Table 2 suggests that the average tract not near an RMP facility has a population that consists of 79.6% White individuals. The presence of an RMP facility within 5 km of a tract, however, is associated with a 10.0 percentage point decrease in that proportion. The percent of the population that is White drops an *additional* 10.0 percentage points, on average, when focusing on tracts near the riskiest facilities – i.e., where a chemical accident has or will take place. Communities near RMP facilities tend to consist of a lower percent of White individuals, and this decrement is greater around sites with a higher risk of a chemical accident, suggesting a cumulative difference of 20.0 percentage points. Put another way, the average community in the U.S. has a population where about 80% of individuals are White, but the average community near an RMP facility where a chemical accident occurs has a population where only about 60% of the individuals are White. We see no additional differences in the proportion of the population that is White when examining more severe accidents yielding offsite impacts to the surrounding community and environment.

Model 2 in Table 2 examines how the percent of White individuals changes after an accident occurs. We still find that the proportion of the population that is White is lower near sites where an accident occurs. This decrement is partly present prior to an accident, but then the proportion of the population that is White decreases an additional 4.1 percentage points after an accident. The occurrence of an accident seems to exacerbate existing demographic differences, suggesting an increased out-migration of White residents from a community. Again, we see no additional shift in demographics associated with more severe offsite impact accidents, compared to chemical accidents in general.

Model 3 adds state fixed effects, which better identifies within-state population differences. Model 4 includes state-by-year fixed effects to flexibly account for state-specific factors and trends. The results are largely the same, again suggesting that communities near an RMP site tend to have 10.6 percentage point less White individuals. Communities facing a higher risk, where an accident does eventually occur, tend to have an even lower proportion of White individuals – an additional 5.6 percentage points less. And after an accident occurs, we again see that more White individuals move out, as suggested by the additional 4.8 percentage point decrease in the proportion of the population that is White. The largest difference is in comparing the average community in the U.S. that is not near an RMP facility, which is about 80% White (as suggested by the constant term), to a community near an RMP facility where a chemical accident has already occurred, which is only about 59% White, on average (about 21 percentage points less).

Table 2. Primary Regression Models: Percent White.

	(1)	(2)	(3)	(4)
	% White	% White	% White	% White
RMP Site w/in 5km	-10.0174***	-10.0174***	-10.5667***	-10.5667***
	(1.0307)	(1.0307)	(0.7255)	(0.7257)
RMP Accident Site w/in 5km	-9.8785***	-6.5727***	-5.6391***	-5.6268***
	(1.8092)	(2.4304)	(1.8518)	(1.8609)
× Post Accident		-4.1029*	-4.8105**	-4.8257**
		(2.2342)	(2.0727)	(2.0897)
Offsite Impact Accident Site w/in 5km	1.1651	0.5712	0.6473	0.6170
	(2.4139)	(2.5135)	(2.3608)	(2.3623)
× Post Accident		1.0764	0.8758	0.9164
		(2.8693)	(2.4624)	(2.4857)
Constant	79.6432***	79.6432***	79.8963***	79.8964***
	(0.9668)	(0.9668)	(0.6791)	(0.6793)
Fixed Effects				
Year	X	X	X	X
State			X	X

State × Year				X
Observations	715,535	715,535	715,535	715,535
Adjusted R-squared	0.069	0.070	0.200	0.200

Note: Cluster robust standard errors in parentheses, clustered at the county level. * p<0.10, ** p<0.05, *** p<0.01. All variables are binary indicators.

The next question is, given that these fenceline communities consist of lower proportions of White individuals, then what socioeconomic groups are more prevalent, and thus experience increased risks of exposure? To investigate this, we next examine how the proportion of Black individuals within a census tract varies depending on the presence of RMP facilities and the associated chemical accidents.

The results in Table 3 overwhelmingly suggest that communities near RMP facilities and those that face greater accident risks have populations that consist of a much greater proportion of Black individuals. The constant term in Model 1 of Table 3 demonstrates that the average tract not near a RMP facility has a population where about 9.8% is Black. Within 5 km of a chemical facility, we see an increase in this population – by nearly 6.0 percentage points. The proportion increases further by about 7.1 percentage points when looking at facilities where accidents have or will occur. At the same time, we find no significant difference based on the severity of the accident (i.e., the offsite impact accident coefficient is insignificant). Considering the cumulative association, Model 1 suggests that communities near higher risk RMP facilities tend to have a population that is about 23% Black, a 13 percentage point increase compared to the average tract not near an RMP facility.

Models 2, 3, and 4 in Table 3 account for the temporal dynamics, examining how the proportion of the population that is Black changes after an accident occurs. All three models suggest similar results, and so we focus here on the most thorough specification – Model 4, which includes state-by-year fixed effects. Model 4 suggests that populations surrounding RMP facilities tend to have more Black individuals – 7.7 percentage points more. Although the proportion of the population that is Black tends to be 2.0 percentage points greater when focusing on tracts within five kilometers of an RMP facility where a chemical accident does eventually occur, this association is statistically insignificant. After an accident occurs, however, we see that more Black individuals are remaining, or perhaps even moving into these areas, leading to an incremental increase in composition of about 6.0 percentage points, on average. Considering the cumulative association, the average community within five kilometers of an RMP facility after an accident occurs has a population that is about 24.6% Black. The rate of Black individuals living in these fenceline communities is almost triple that compared to the rest of the U.S. In general, we find small and statistically insignificant differences associated with more severe offsite impact accidents, compared to more typical chemical accidents where any identified adverse physical effects remain onsite.

Table 3. Primary Regression Models: Percent Black.

	(1) % Black	(2) % Black	(3) % Black	(4) % Black
RMP Site w/in 5km	6.0088***	6.0088***	7.7218***	7.7218***
	(0.7187)	(0.7187)	(0.6438)	(0.6440)
RMP Accident Site w/in 5km	7.1300***	2.1835	2.0315	1.9921
	(2.5801)	(2.1003)	(1.5463)	(1.5488)
× Post Accident		6.1395**	5.8867***	5.9357***
		(2.8362)	(2.1543)	(2.1713)
Offsite Impact Accident Site w/in 5km	0.0425	-0.4558	-0.4558	-0.2197
	(2.7766)	(2.7329)	(2.7329)	(2.2747)
× Post Accident		0.1969	0.1969	-0.2755
		(3.7959)	(3.7959)	(2.7899)
Constant	9.7818***	9.7818***	8.9359***	8.9359***
	(0.5351)	(0.5351)	(0.4327)	(0.4328)
Fixed Effects				
Year	X	X	X	X
State			X	X
State × Year				X
Observations	715,535	715,535	715,535	715,535
Adjusted R-squared	0.038	0.039	0.201	0.200

Note: Cluster robust standard errors in parentheses, clustered at the county level. * p<0.10, ** p<0.05, *** p<0.01. All variables are binary indicators.

We also assessed the potential for any systematic inequities associated with other racial groups, namely the percent of the population that consists of American Indian and Asian individuals. In general we find that there tends to be a small but statistically significant increase in the proportion of Asian individuals among tracts within 5 km of a RMP facility (about 0.03%), and otherwise find no statistically significant differences in Asian populations near riskier or more severe accident sites, nor based on the timing of an accident. In contrast, being near an RMP facility is associated with a small, but statistically significant decrease in the proportion of the population that is American Indian (about 0.40%), likely reflecting that RMP facilities tend to be in less rural areas. But again, we otherwise find no statistically significant differences in the percent of American Indian individuals. The full regression model results are presented in Tables A1 and A2 in Appendix A.

We now turn to ethnicity, namely the percent of Hispanic individuals in a community. As seen in Table 4, tracts in the broader U.S. and that are not near a chemical facility tend to have a population that is about 11-12% Hispanic, on average. The results are robust across models, with the most comprehensive model (Model 4) suggesting that communities within five kilometers of a RMP facility tend to have more Hispanic individuals, about 5.6 percentage points greater. In other words, the average tract near an RMP facility has a population that is about 17.9% Hispanic, compared to just 12.3% among tracts in the rest of the contiguous U.S. We find no statistically significant differences in the proportion of a community's population that is Hispanic based on accident risk, severity, or timing, at least not when examining the coefficient estimates individually. However, when considering the coefficients corresponding to the RMP Accident variable and the subsequent post-accident interaction term together, we see a statistically significant 5.2 percentage point increase in the proportion of Hispanic individuals (p = 0.02). This suggests that, not only is the proportion of Hispanic individuals greater among communities near an RMP facility, but also that this increase in the composition of Hispanic individuals is twice as great among communities near riskier RMP facilities and after an accident occurs.

Table 4. Primary Regression Models: Percent Hispanic.

	(1) % Hispanic	(2) % Hispanic	(3) % Hispanic	(4) % Hispanic
RMP Site w/in 5km	8.1028***	8.1028***	5.6318***	5.6318***
	(1.1213)	(1.1213)	(0.4457)	(0.4459)
RMP Accident Site w/in 5km	4.2115	1.6648	1.1849	1.1750
	(2.8761)	(2.6431)	(1.9260)	(1.9485)
× Post Accident		3.1608	4.0403	4.0523
		(5.3073)	(3.7564)	(3.7858)
Offsite Impact Accident Site w/in 5km	0.2535	2.5297	2.8286	2.8338
	(2.4238)	(5.9801)	(4.0501)	(4.0694)
× Post Accident		-3.1994	-2.5626	-2.5701
		(8.4678)	(5.4467)	(5.4762)
Constant	11.0834***	11.0834***	12.2975***	12.2975***
	(0.6586)	(0.6586)	(0.5032)	(0.5033)
Fixed Effects				
Year	X	X	X	X
State			X	X
State × Year				X
Observations	715,535	715,535	715,535	715,535
Adjusted R-squared	0.049	0.050	0.364	0.363

Note: Cluster robust standard errors in parentheses, clustered at the county level. * p<0.10, ** p<0.05, *** p<0.01. All variables are binary indicators.

Table 5 examines the relationship between the poverty rate – i.e., the percent of households with an income below the poverty line – and the presence of RMP facilities and accidents. The results are largely the same across specifications, and so we again focus on the most comprehensive model, Model 4. The results indicate that in tracts not near an RMP facility, about 12.3% of the population is impoverished. This rate is 4.2 percentage points higher among tracts within 5 km of an RMP facility. There is no difference across sites where an accident does or does not eventually occur, but after an accident does occur we see an incremental increase in the poverty rate – an *additional* 3.4 percentage points. Chemical accidents seem to trigger further environmental "de-gentrification” in these fenceline communities, where relatively wealthier households move out, leaving a greater composition of poverty-stricken households. It is also possible that economic factors may cause lower-income households to move in. “Gentrification” is the process where wealthier households move into a neighborhood, and then due to economic factors, lower-income households move out. In contrast, “de-gentrification” refers to the process in which the dynamics of gentrification reverse causing a downward trajectory in neighborhood wealth (Lees and Bondi 2013; Han et al. 2021; Fong et al. 2019). After a chemical accident occurs, a tract within five kilometers has a poverty rate of 20.7%; this is an almost 70% increase in poverty compared to the average tract in the U.S. that is not near an RMP facility.

Table 5. Primary Regression Models: Percent Poverty.

	(1) % Poverty	(2) % Poverty	(3) % Poverty	(4) % Poverty
RMP Site w/in 5km	3.7006***	3.7006***	4.2133***	4.2133***
	(0.2547)	(0.2547)	(0.2500)	(0.2501)
RMP Accident Site w/in 5km	3.6770***	0.4657	0.7937	0.7958
	(0.8274)	(1.0951)	(1.1369)	(1.1417)
× Post Accident		3.9857***	3.4037***	3.4009***
		(0.9880)	(1.0428)	(1.0518)
Offsite Impact Accident Site w/in 5km	0.3212	1.4870	1.2216	1.2265
	(1.0404)	(1.5752)	(1.6942)	(1.6951)
× Post Accident		-1.8130	-1.5040	-1.5102
		(1.5867)	(1.7269)	(1.7300)
Constant	12.5042***	12.5042***	12.2560***	12.2560***
	(0.2100)	(0.2100)	(0.1757)	(0.1758)
Fixed Effects				
Year	X	X	X	X
State			X	X
State × Year				X
Observations	715,535	715,535	715,535	715,535
Adjusted R-squared	0.051	0.053	0.101	0.101

Note: Cluster robust standard errors in parentheses, clustered at the county level. * p<0.10, ** p<0.05, *** p<0.01. All variables are binary indicators.

As shown in Tables 2 through 5 above, it is reassuring that the revealed patterns are robust across the inclusion of state, year, and even state-by-year fixed effects. In addition, although the primary analysis above is based on five kilometers serving as a reasonable distance to proxy for perceived and actual risks (see Section III.B), the general patterns found are robust when alternative distance bins of three kilometers and one kilometer are used (see Tables A3 and A4 in Appendix A).

V.B. Implications of State Delegation

In most areas of the U.S. the RMP program is implemented and enforced by the Federal government, and in particular, by the U.S. EPA. In some cases, however, individual states (and sometimes counties) request and receive authority to run the RMP program in their jurisdictions.[12] States may apply for delegation for a variety of reasons, including that they already had a preexisting program that they wanted to retain when EPA started the federal program; or they prefer having a high degree of control over their own jurisdictions. Appendix B lists the nine states and four counties with delegated authority to oversee the RMP program (as of 2024). All but one of these jurisdictions received delegated authority prior to the start of our study period.[13]

We next investigate whether the spatial patterns and demographic disparities discussed above systematically vary across states that have or have not been delegated to implement and enforce (all or some of) the RMP program. We do so by dividing the sample by tracts in delegated versus non-delegated states, and separately estimating equation (2). We estimate variants of the Model 4 specification to maintain the state-by-year fixed effects and ensure all broader state-specific differences and trends are controlled for.

As seen in Table 6, we find no statistically significant differences in population patterns across non-delegated states versus states delegated the authority to manage their RMP program. The magnitudes and signs of the parameter estimates are generally similar.

VI. CONCLUSION

This study contributes to a growing literature that has revealed significant environmental disparities in the U.S. across different racial, ethnic, and income groups. Policymakers who wish to address inequities in environmental exposures need to understand where such disparities occur, their magnitudes, and whether such differences are statistically significant (U.S. EPA Science Advisory Board 2024). Focusing on the U.S. EPA's Risk Management Plan (RMP) program, we demonstrate a straightforward approach to statistically identify and quantify environmental disparities, as well as how demographics shift following a chemical accident.

Starting with Bullard's (2007) seminal paper, the old saying – what came first, the chicken or the egg – has been a common metaphor in the EJ literature. Much debate has been around whether the environmental disamenity is placed in underserved communities, or if individuals in different socioeconomic groups sort into such locations (Cain et al., 2023). In the context of chemical accidents at RMP facilities, we find that it is a little bit of both. Our findings show that communities nationwide that are located near facilities using extremely hazardous substances are indeed disproportionately populated with Black, Asian, Hispanic, and low-income residents. For example, considering the cumulative association, the average community within five kilometers of an RMP

[12] In a couple of cases the delegation is partial, and the state only has authority over a subset of facilities. See Appendix B for details.

[13] North Dakota received delegated authority in 2014. The findings discussed next are robust when excluding North Dakota from the analysis.

facility, after an accident occurs, has a population that is 24.7% Black. The rate of Black individuals living in these fenceline communities is almost triple that compared to the rest of the U.S. These results are consistent with an earlier cross-sectional regional analysis of RMP facilities and accidents in MI, OH, and PA (Guignet et al. 2023a).

In addition, we find that these disproportionate spatial distributions widen after a chemical accident involving fires, explosions, and/or toxic vapors occurs, particularly in terms of Black individuals and low-income households. Our results highlight how environmental disasters can exacerbate existing inequities, leading to increased de-gentrification in fenceline communities. Two caveats are important to keep in mind when interpreting these results. First, we do not firmly claim that the demographic shifts after a chemical accident are causal. Our results could also reflect general trends in fenceline communities that are more likely to experience a chemical accident. Either way, there are clear equity implications. More research is needed to identify the underlying mechanisms and propose potential solutions. Second, our estimates reflect a compositional change in demographics. An increase in the proportion of poverty-stricken households or Black individuals, for example, can reflect both other demographic groups moving out, and/or greater numbers of those subgroups moving in. As shown in Table A5 in Appendix A, it is a little bit of both. We re-estimate variants of our most thorough specification (Model 4) but use population counts (instead of proportions) as the dependent variable. The results illustrate that after an accident, total population in a tract is generally decreasing, with a particularly notable decrease in White individuals. In contrast, we see small but statistically significant increases in the number of Black individuals and households living in poverty after a chemical accident. This suggests that on average there is a net loss in population in these fenceline communities, but both outward and inward migration are driving de-gentrification after a chemical accident.

Our findings that Black and low-income households face greater inequities after a chemical accident remain robust across many specifications, such as to the inclusion of state, year, and state-by-year fixed effects, and when using alternative 1 km and 3 km distance bins, rather than the 5 km distance assumed in the main analysis. We also find little evidence of systematic heterogeneity in these sociodemographic patterns based on the severity of an accident (i.e., yielding offsite impacts), or across states with or without delegated authority to implement and enforce their own RMP program.

Guignet et al. (2023b) examine property value impacts of RMP facility accidents nationwide and find that accidents with direct offsite impacts involving deaths, injuries, evacuations, sheltering-in-place, or property or environmental damage have a significant negative impact on home values. For many families, their home is their single most important financial investment. Our findings demonstrate that those negative property value effects occur disproportionately to low income and historically underserved populations, thus further fueling the increased disparities associated with exposure to these hazardous chemicals and related environmental harms.

The U.S. EPA's RMP program is in place to reduce the risk of chemical facility accidents and, when one occurs, ensure that facilities have procedures in place to minimize damages. Given the location of many industrial facilities, the risk of chemical accidents may well increase as we face more frequent extreme weather caused by climate change (Flores et al. 2021; U.S. Chemical Safety

Board, 2017; Chemical Industries Association, 2015; Asadi et al. 2024). An analysis by the U.S. Government Accountability Office examined nationwide data on flooding, storm surge, wildfire, and sea level rise (all of which could be made worse by climate change), and concluded that almost a third of the over 10,000 RMP facilities they analyzed were located in areas susceptible to these natural hazards (U.S. Government Accountability Office 2022). At the same time, the U.S. EPA in recent years has taken steps to dismantle regulations on greenhouse gases (U.S. EPA 2026), potentially rollback recent safeguards put in place for RMP facilities (U.S. EPA 2025b; Younes and Grist 2025), and disregard distributional concerns (U.S. EPA 2025a; U.S. Whitehouse 2025). Our results highlight how historically underserved populations living in these fenceline communities will be impacted.

Table 6. Primary Regression Models: Delegated vs. Non-Delegated States.

	(1) % White Delegated	(2) % White Non-Delegated	(3) % Black Delegated	(4) % Black Non-Delegated	(5) % Hispanic Delegated	(6) % Hispanic Non-Delegated	(7) % Poverty Delegated	(8) % Poverty Non-Delegated
RMP Site w/in 5km	-11.4565***	-10.2811***	9.1499***	7.2721***	3.9554***	6.1457***	4.0307***	4.2568***
	(1.0163)	(0.8860)	(1.0758)	(0.7690)	(0.5378)	(0.5465)	(0.4816)	(0.2908)
RMP Accident Site w/in 5km	-8.0515*	-5.2809***	4.7381	1.6255	1.0023	0.8285	3.1815**	0.0823
	(4.3966)	(1.9625)	(4.4881)	(1.4991)	(2.3794)	(2.5755)	(1.4165)	(1.4377)
× Post Accident	-6.0331	-4.1598**	7.7074	5.0490***	0.2168	5.5002	1.8714	3.8894***
	(5.5822)	(1.9377)	(5.6938)	(1.9267)	(2.2468)	(4.8106)	(1.6070)	(1.3357)
Offsite Impact Accident Site w/in 5km	-3.7974	2.9593	4.8896	-2.9876*	-0.7725	4.9371	1.1401	1.1913
	(7.0372)	(2.1633)	(7.1725)	(1.6754)	(2.5766)	(5.3813)	(3.0743)	(2.0946)
× Post Accident	4.8672	-1.7108	-3.6100	2.6375	-1.2598	-4.6810	-0.1653	-1.6494
	(6.0726)	(2.3007)	(5.9893)	(2.4161)	(1.8585)	(7.1200)	(2.6549)	(2.1986)
Constant	78.1190***	80.3528***	14.8509***	7.3605***	9.7182***	12.9600***	13.1754***	12.0067***
	(0.8777)	(0.8297)	(0.7717)	(0.5057)	(1.5958)	(0.4568)	(0.2480)	(0.2138)
Observations	153751	561784	153751	561784	153751	561784	153751	561784
Adjusted R-squared	0.176	0.207	0.172	0.185	0.206	0.384	0.113	0.097

Note: Cluster robust standard errors in parentheses, clustered at the county level. * p<0.10, ** p<0.05, *** p<0.01. All variables are binary indicators.

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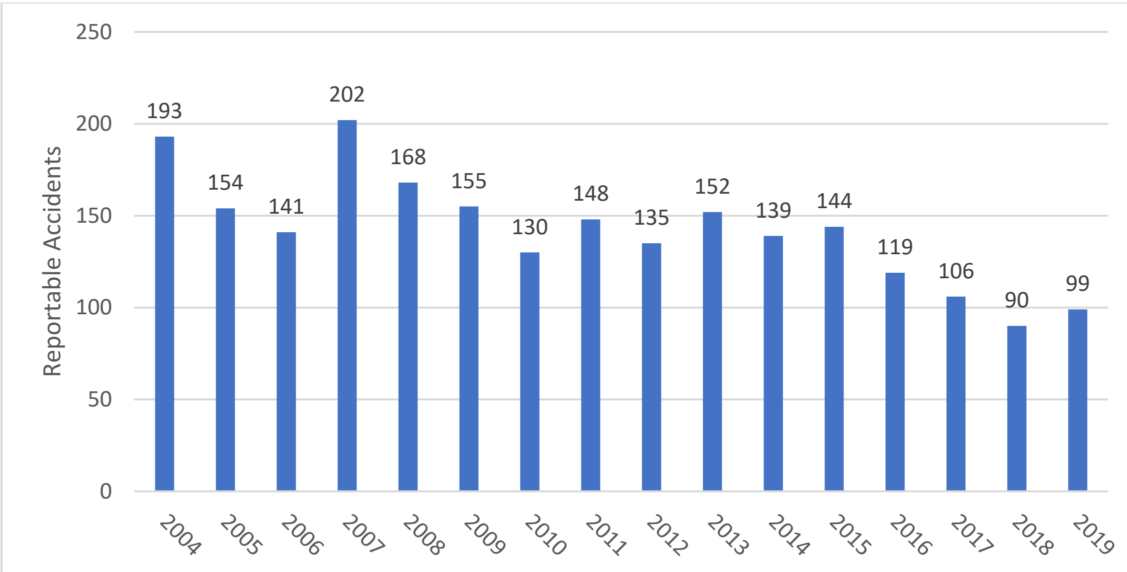
APPENDIX A. Supplemental Descriptive Statistics and Model Results.

Figure A1. Number of Reportable Accidents by Year.



Note: Study time period spanned from 2004 through September of 2019, so the count of reportable accidents for the final year may be incomplete.

Table A1. Primary Regression Models: Percent Asian.

	(1) % Asian	(2) % Asian	(3) % Asian	(4) % Asian
RMP Site w/in 5km	0.0370***	0.0370***	0.0259***	0.0259***
	(0.0093)	(0.0093)	(0.0069)	(0.0070)
RMP Accident Site w/in 5km	-0.0008	0.0330	0.0246	0.0246
	(0.0219)	(0.0284)	(0.0191)	(0.0193)
× Post Accident		-0.0420	-0.0307	-0.0307
		(0.0373)	(0.0242)	(0.0244)
Offsite Impact Accident Site w/in 5km	0.1010**	0.0707	0.0544	0.0544
	(0.0470)	(0.0544)	(0.0386)	(0.0385)
× Post Accident		0.0425	0.0425	0.0425
		(0.0548)	(0.0373)	(0.0375)
Constant	0.0927***	0.0927***	0.0993***	0.0993***
	(0.0088)	(0.0088)	(0.0051)	(0.0051)
Fixed Effects				
Year	X	X	X	X
State			X	X
State × Year				X
Observations	715,535	715,535	715,535	715,535
Adjusted R-squared	0.003	0.003	0.069	0.069

Note: Cluster robust standard errors in parentheses, clustered at the county level. * p<0.10, ** p<0.05, *** p<0.01. All variables are binary indicators.

Table A2. Primary Regression Models: Percent American Indian.

	(1) % AmInd	(2) % AmInd	(3) % AmInd	(4) % AmInd
RMP Site w/in 5km	-0.5037***	-0.5037***	-0.3809***	-0.3809***
	(0.0834)	(0.0834)	(0.0743)	(0.0743)
RMP Accident Site w/in 5km	-0.0299	-0.0458	0.0708	0.0680
	(0.0590)	(0.0663)	(0.0469)	(0.0466)
× Post Accident		0.0197	0.0052	0.0086
		(0.0763)	(0.0414)	(0.0412)
Offsite Impact Accident Site w/in 5km	0.1291*	0.0698	0.1134	0.1113
	(0.0686)	(0.1017)	(0.0732)	(0.0726)
× Post Accident		0.0759	-0.1131	-0.1106
		(0.1058)	(0.0954)	(0.0944)
Constant	1.1189***	1.1189***	1.0492***	1.0492***
	(0.0922)	(0.0922)	(0.0716)	(0.0716)
Fixed Effects				
Year	X	X	X	X
State			X	X
State × Year				X
Observations	715,535	715,535	715,535	715,535
Adjusted R-squared	0.003	0.003	0.107	0.107

Note: Cluster robust standard errors in parentheses, clustered at the county level. * p<0.10, ** p<0.05, *** p<0.01. All variables are binary indicators.

Table A3. Regression model results: Alternative three-kilometer distance bin.

	(1) % White	(2) % Black	(3) % Hispanic	(4) % Asian	(5) % AmInd	(6) % Poverty
RMP Facility w/in 3km	-9.5163***	6.8672***	6.3664***	0.0230***	-0.1954***	5.1281***
	(0.6296)	(0.5980)	(0.4821)	(0.0078)	(0.0433)	(0.2908)
RMP Accident w/in 3km	-4.0497**	1.3396	0.9814	0.0110	0.0651	0.5281
	(1.9176)	(1.7115)	(1.3780)	(0.0254)	(0.0543)	(1.0301)
x Post Accident	-3.1740	4.2656**	3.2807	-0.0117	0.0003	2.3677**
	(2.0780)	(2.1041)	(2.9625)	(0.0254)	(0.0603)	(1.0007)
Offsite Impact Accident w/in 3km	2.6155	-2.0833	1.1864	0.1161*	0.1617*	0.2251
	(2.7475)	(2.6450)	(2.3963)	(0.0614)	(0.0895)	(1.6144)
x Post Accident	-1.7993	1.2056	0.3266	-0.0246	-0.0996	0.5614
	(2.8014)	(2.7693)	(4.0438)	(0.0465)	(0.1115)	(1.6183)
Constant	76.4940***	11.4813***	13.6758***	0.1089***	0.9161***	13.1853***
	(0.7821)	(0.5478)	(0.5454)	(0.0059)	(0.0615)	(0.2108)
Fixed Effects						
Year	X	X	X	X	X	X
State	X	X	X	X	X	X
State × Year	X	X	X	X	X	X
Observations	717,324	717,324	717,324	717,324	717,324	715,535
Adjusted R-squared	0.169	0.177	0.359	0.068	0.106	0.098

Note: Cluster robust standard errors in parentheses, clustered at the county level. * p<0.10, ** p<0.05, *** p<0.01. All variables are binary indicators.

Table A4. Regression model results: Alternative one-kilometer distance bin.

	(1) % White	(2) % Black	(3) % Hispanic	(4) % Asian	(5) % AmInd	(6) % Poverty
RMP Facility w/in 1km	-7.3133***	5.2591***	6.9835***	0.0240*	-0.0283	5.7638***
	(0.7586)	(0.6897)	(0.6226)	(0.0127)	(0.0495)	(0.4001)
RMP Accident w/in 1km	-0.0435	-2.7568	6.7902**	0.1912	0.3297	0.8603
	(2.5323)	(2.2313)	(2.8270)	(0.1530)	(0.2068)	(1.5303)
x Post Accident	-4.9567*	6.6140**	-2.9908	-0.0586	-0.3853**	1.1803
	(2.8437)	(2.6684)	(2.5189)	(0.1633)	(0.1844)	(1.6628)
Offsite Impact Accident w/in 1km	1.9339	0.6954	-7.3990*	-0.0728	-0.1898	0.2270
	(4.2788)	(3.8864)	(3.8871)	(0.1608)	(0.1820)	(2.6056)
x Post Accident	-2.3359	-0.8134	7.8410*	-0.0585	0.4480	0.7989
	(4.6770)	(4.4393)	(4.1305)	(0.1716)	(0.3187)	(2.8500)
Constant	73.6997***	13.4947***	15.4607***	0.1167***	0.8632***	14.5849***
	(0.8138)	(0.5826)	(0.6080)	(0.0061)	(0.0582)	(0.2277)
Fixed Effects						
Year	X	X	X	X	X	X
State	X	X	X	X	X	X
State × Year	X	X	X	X	X	X
Observations	717324	717324	717324	717324	717324	715535
Adjusted R-squared	0.136	0.154	0.341	0.067	0.106	0.060

Note: Cluster robust standard errors in parentheses, clustered at the county level. * p<0.10, ** p<0.05, *** p<0.01. All variables are binary indicators.

Table A5. Regressions of Total Population and Population Counts by Group.

	(1) Total Population	(2) White	(3) Black	(4) Hispanic	(5) Asian	(6) AmInd	(7) Poverty
RMP Facility w/in 1km	-193.3611***	-551.1339***	246.7537***	238.8838***	1.0911***	-13.3060***	48.6669***
	(31.9399)	(37.7921)	(22.1013)	(22.7037)	(0.3501)	(2.7826)	(3.3866)
RMP Accident w/in 1km	-99.5978	-291.4086***	40.0041	58.8021	0.8342	1.4784	-2.8574
	(101.3422)	(103.0688)	(70.7558)	(79.5273)	(1.0172)	(1.7624)	(11.3813)
x Post Accident	-25.1504	-21.8560	28.6630	83.7462	3.1847	4.3644*	16.1414
	(109.2421)	(116.1896)	(96.0953)	(144.7963)	(2.0743)	(2.4770)	(12.8589)
Offsite Impact Accident w/in 1km	-286.3611***	-327.4002***	131.9418*	95.7656	-1.4746	-1.5812	23.9663***
	(96.7519)	(112.1817)	(73.9881)	(143.1405)	(1.3383)	(1.5114)	(9.2739)
x Post Accident	105.3720	96.5430	-3.1150	-46.3801	1.8970	-3.2798	-12.2853
	(119.9817)	(122.4404)	(109.1067)	(186.8241)	(2.0481)	(3.4882)	(12.0552)
Constant	4490.3163***	3563.1343***	400.8029***	599.0039***	4.7310***	41.1736***	195.3951***
	(30.6891)	(38.5513)	(15.8570)	(26.2421)	(0.2826)	(2.8578)	(2.7602)
Fixed Effects							
Year	X	X	X	X	X	X	X
State	X	X	X	X	X	X	X
State × Year	X	X	X	X	X	X	X
Observations	715,535	715,535	715,535	715,535	715,535	715,535	715,535
Adjusted R-squared	0.048	0.084	0.175	0.289	0.069	0.099	0.072

Note: Cluster robust standard errors in parentheses, clustered at the county level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

APPENDIX B. Regions and States with Authority to Directly Implement and Enforce the RMP program (as of 2024).

EPA Region 2

New Jersey

EPA Region 3

Delaware

EPA Region 4

Florida (partial – everything but propane facilities), Georgia, Mississippi, North Carolina, South Carolina,

Jefferson County (KY), Forsyth County (NC), Buncombe County (NC), and Mecklenburg County (NC)

EPA Region 5

Ohio

EPA Region 8

North Dakota (only Agricultural Ammonia facilities)

Source for list of delegated states: U.S. Environmental Protection Agency. 2024. States with authority to implement/enforce the risk management program rule. Accessed: https://www.epa.gov/rmp/states-authority-implement-enforce-risk-management-program-rule, 24 July 2024.

NOTE: From the above list, eight states received delegation from EPA in 1998, 1999, or 2000. North Dakota received it in 2014. Information on the year in which Mississippi received delegation is missing though believed to be in the 1998 to 2000 period.

Sources for years of delegation:

New Jersey and Delaware: Code of Federal Regulations: National Archives (2024) Title 40/Chapter I/ Subchapter C/ Part 63/ Subpart E. Subpart E – Approval of State Programs and Delegation of Federal Authorities https://www.ecfr.gov/current/title-40/chapter-I/subchapter-C/part-63/subpart-E

Florida: Burnaman, Ross Stafford. 1999. Florida's Accidental Release Prevention and Risk Management Planning Act. Environmental & Land Use Law. 73(5). https://www.floridabar.org/the-florida-bar-journal/floridas-accidental-release-prevention-and-risk-management-planning-act/

Georgia: Environment, Health and Safety Online. Risk Management Planning (RMP) Guide for Authorized States. https://www.ehso.com/RMP_states.htm

Mississippi: No information.

North Carolina: Letter from U.S. EPA dated Jul 27, 2000 to Mr. Bill Holman, North Carolina Department of Environmental and Natural Resources. Provided by email by delegated state program officials.

South Carolina: Jun 26, 1995 as reported by email from Kevin Daniel, RMP program U.S. EPA to Robin Jenkins, Office of Policy, U.S. EPA dated Aug 6, 2024.

Kentucky: April 13, 1999 as reported in Dec 1999 Letter from EPA: Region 4, Atlanta Federal Center to Mr. Arthur Williams, Director, Jefferson County Air Pollution Control District.

Ohio: Federal Register: The Daily Journal of the United States Government. National Archives. 1999. Approval of Delegation of the Accidental Release Prevention Requirements: Risk Management Programs Under Clean Air Act Section 112(r)(7): State of Ohio. https://www.federalregister.gov/documents/1999/11/03/99-28311/approval-of-delegation-of-the-accidental-release-prevention-requirements-risk-management-programs

North Dakota: January 19, 2014 as per North Dakota Department of Agriculture. Risk Management Program (RMP) for Agriculture Anhydrous Ammonia Facilities. https://www.ndda.nd.gov/divisions/pesticide-fertilizer-division/risk-management-program-rmp-agriculture-anhydrous-ammonia