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Layers of injustice: A distributional assessment of toxic chemical facilities, releases, and cleanups.

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Abstract:
The Resource Conservation and Recovery Act of 1976 (RCRA) is a cornerstone of environmental policy in the United States. The law regulates the generation, transportation, storage, and disposal of hazardous chemicals. Unfortunately, hazardous releases are known to occur due to flawed equipment, human error, and dated historical practices. Releases are investigated and remediated through what is collectively known as a Corrective Action (CA). Using Census data and a novel dataset of RCRA facilities across the contiguous US, we examine the possibility of systematic inequities with regards to the (i) siting of RCRA facilities, (ii) occurrence of releases and CAs, (iii) duration of CAs, and (iv) permanence of remediation methods. We find evidence of disproportionate impacts across racial, ethnic, and income dimensions. The results vary, however, depending on the different aspects of the siting and cleanup process, thus emphasizing the need for multi-layered analyses to identify and fully understand potential inequities associated with environmental programs.

JEL Classification: D63; Q53; Q56

Keywords: chemical, cleanup, environmental justice, equity, hazardous waste, RCRA

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I. INTRODUCTION

In the fall of 1982, the North Carolina state government disposed of 6,000 truckloads of PCB laced toxic soil in Warren County (NCDCR 2013). This poor, rural county was home to predominately Black populations. Residents from Warren County and surrounding communities took to the streets to physically block the unwelcomed dump trucks. Unfortunately, they were unsuccessful. Despite the unfavorable outcome, this and similar events laid the path for the environmental justice (EJ) movement, including the 1987 seminal study by the United Church of Christ Commission for Racial Justice (UCC), which was one of the first reports to clearly document and quantify environmental disparities in the siting of toxic waste sites.

The Resource Conservation and Recovery Act (RCRA) was first passed in 1976, and gave the U.S. Environmental Protection Agency (EPA) the authority to regulate hazardous material from "cradle-to-grave", including the generation, storage, transportation, and eventual disposal or neutralization of the material. Unfortunately, unintended releases of these hazardous chemicals do occur, often due to the degradation of equipment and structures over time, human error, and dated historical practices and land uses. RCRA was amended in 1984 to expand the cleanup provisions and give EPA the authority to require potential releases be investigated and, if necessary, subsequently remediated. Collectively these activities are referred to as a Corrective Action (CA). CA is required at a RCRA-regulated facility when there is an identified or suspected release. Approximately 113 million Americans live within three miles of a RCRA CA site (US EPA 2020).

For this study, focus is drawn to 41,361 RCRA sites in the contiguous US that are characterized as a large quantity generated (LQG) of hazardous material; and/or a treatment, storage, and disposal facility (TSDF).[1] These types of facilities deal with the largest quantity of chemicals and pose the highest risk. Among these facilities, 199 CAs were initiated within our 2000 to 2019 study period and involved actual contamination and subsequent remedial actions. Such cleanup actions can include physical removal and/or neutralization of pollution (e.g., excavating contaminated soil, pump-and-treat the groundwater); construction of physical controls (modification/addition of concrete caps over contaminated soil, physical barriers to minimize exposure/migration); and/or institutional controls (e.g., re-zoning the land as industrial use only to deter human exposure). Cleanup solutions— or a combination of cleanup solutions— are deemed appropriate, if they protect human health and the environment, attain cleanup objectives, and control the source (US EPA 2022a)

This study contributes to the EJ literature by examining whether various "layers" of regulated activities under RCRA are disproportionately associated with communities consisting of greater populations of racial and ethnic minorities, and lower income populations. More specifically, our four research questions are: (i) Do RCRA-regulated hazardous sites tend to be located in neighborhoods with a higher percentage of nonwhite, Hispanic, or lower income individuals? (ii) Is a release of contamination and a subsequent CA more likely to occur in such neighborhoods? (iii) Is the duration of investigation and cleanup activities systematically longer in certain communities? And (iv) Is the implementation of less permanent remedial solutions associated with neighborhoods consisting of higher proportions of nonwhite, Hispanic, and/or lower income populations?

[1] A large quantity generator (LQG) is defined as a facility that generates 1,000 kg or more of RCRA-regulated hazardous material in a single month, accumulates 1 kg or more of an acute hazardous material in a single month, or accumulates more than 100kg of spill material that contains an acute hazardous material (US EPA, 2021).

We find evidence that RCRA sites tend to be located in neighborhoods consisting of higher proportions of Nonwhite and Hispanic populations. Communities with higher proportions of Nonwhite and Hispanic populations also face significantly longer release investigation and cleanup times. We find some mixed evidence of disproportionate impacts to lower income populations in terms of the likelihood of a release and subsequent cleanup activities. And finally, there is little evidence of systematic injustices in terms of cleanup permanence; although this result is limited by a fairly small sample size. Overall, the occurrence of disproportionate impacts varies across the different aspects of the siting and cleanup process, thus emphasizing the need for multi-layered analyses to identify and fully understand potential inequities associated with far-reaching environmental programs.

The next section reviews the relevant literature and highlights the specific contributions of this study. Section III provides information regarding the source and content of the data that are used. The models and methods used for analysis can be found in section IV, followed by the regression results in section V. The paper concludes with section VI, where we summarize the primary results, and discuss the EJ implications and limitations of the study.

II. LITERATURE REVIEW

Most of the literature does not pertain specifically to RCRA regulated hazardous waste sites, but instead focuses on other environmental programs dealing with hazardous chemicals, including Superfund and the Toxic Release Inventory (TRI). Studies that do examine RCRA often focus on only a subset of sites, namely treatment, storage, and disposal facilities (TSDFs). Furthermore, much of the literature is very local in scope, and the results of such case studies cannot necessarily be extrapolated to the broader universe of sites regulated under national programs.

The overall evidence of potential inequities is mixed. Several studies have found environmental injustices with regards to the location of hazardous sites. For example, Boer et al. (1997) found Black and Latino communities in Los Angeles County were more likely to host a TSDF. Baben and Coursey (2002) analyzed 1990 census data and found Superfund sites in Chicago tend to be located in communities with low population density and higher proportions of Hispanic residents. Superfund sites are industrial facilities that are cleaned up through the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA), and often entail the most severe and notorious types of contaminated sites. In contrast to their findings based on 1990 data, when examining historical trends based on 1960s census data, Baben and Coursey (2002) found that hazardous sites were concentrated in poorer white neighborhoods with low population density. The dynamic nature of the socioeconomic factors correlated with hazardous site locations highlights the need to periodically revisit the issue.

It is important to emphasize that it is not necessarily the case that facilities handling hazardous materials are systematically placed in neighborhoods associated with these characteristics. It could also be that certain populations migrate to neighborhoods with these disamenities due to differences in preferences and income (Banzhaf and McCormick 2007). Been and Gupta (1997) attempted to disentangle these effects. They found that the percentage of Black and Hispanic individuals in a census tract were both significant predictors of whether a tract hosts a TSDF. They suggest that TSDFs tended to be placed in tracts where there is a higher proportion of Hispanics, whereas the proportion of Black individuals tended to increase in tracts where a TSDF was already sited.

Banzhaf et al. (2019) argue that the problem is more complex than a simple chicken-or-the-egg question. Changes in demographics that are correlated with changes in pollution could be obscured for a number of reasons. Initial household sorting due to pollution could have a domino effect of negative neighborhood characteristics that could reinforce the initial sorting patterns. For example, high pollution in an area could lead to decreases in property values and drive out high income earners. This could leave the community with fewer resources to ensure attractive retailers, public safety, and good school quality. Additionally, an area's reputation as "dirty' and "unsafe" due to pollution could lead to public stigma, which could remain even after the pollution issue is resolved (Messer et al., 2006).

Banzhaf et al. (2019) outline four mechanisms that can lead to disamenities being disproportionately located in different neighborhoods: (1) disproportionate siting on the firm side, (2) "coming to the nuisance" on the household side (Banzhaf and McCormick 2007; Been 1994, 1997; Hamilton 1995), (3) market-like coordination of the two, and (4) discriminatory politics and/or enforcement. Banzhaf et al. find the fourth mechanism to be unlikely and discuss how activists and non-economists alike agree that the observed injustices are likely not rooted in the desire to harm minority groups. However, they do find that firms tend to site in communities with higher minority populations. Such inclinations could be driven by economic incentives. Lack of coordination and protest among populations in some communities may imply lower costs to locate there (Hamilton, 1995). Land may be cheaper, and there could be increased access to labor pools and transportation infrastructure.

Other studies have found negligible evidence of disproportional impacts associated with the siting of hazardous sites. Anderton et al. (1994) did not find evidence that the percentage of minorities (Black, Hispanic, and foreign-born individuals) was a statistically significant predictor of the location of TDSFs. Davidson and Anderton (2000) expanded upon the study to include all urban RCRA-regulated sites, instead of only looking at TSDFs, and again found no correlation between race and ethnicity with regards to the siting of RCRA facilities. Been and Gupta (1997) did not find tracts with higher poverty levels to be any more or less likely to host a TSDF.

Hamilton (1993, 1995) looked at the capacity expansion plans of commercial TSDFs from 1987-1992. Hamilton (1993) found that communities with greater political engagement (measured by voter turnout) are less likely to be chosen for commercial waste processing expansion. He interpreted this finding to demonstrate the importance of collective action. He applied the Coase theorem (Coase 1960) to explain that facilities located in communities with low political engagement are more attractive expansion options because they pose lower costs and community backlash. Hamilton (1995) expanded the study and found that the zip codes targeted for expansion had 7% more nonwhite residents (1995). He maintains political engagement as a logical explanation for this difference, stating that "Under the current regulatory regime where communities differ in the degree they may engage in collective action to voice their environmental compensation demands, firms such as hazardous waste facilities will attempt to locate where, ceteris paribus, opposition is the least." (page 129). Hamilton suggests that this could be representative of institutionalized racism in terms of hazardous waste policy, as "differences in a neighborhood's tendency to engage in collective action may in part depend on expectations from the payoff of residents' activities and on their resources" (page 129).

Palmer (2003) investigated whether reductions in the use of toxic chemicals at manufacturing firms in Massachusetts was greater across communities with different sociodemographic characteristics. He found that manufacturers in low-income and high-minority communities tended to adopt fewer techniques to reduce their use of toxic chemicals.

Other studies examined emissions of toxic substances across neighborhoods with different demographics, rather than the siting of the facilities themselves. Focusing on air emissions reported to the TRI, Arora et al. (1998) found that racial composition of the surrounding population was only an important descriptor of the occurrence of a toxic release in the Southern United States, as opposed to other US regions.[2]

Elliot et al. (2004) investigated the relationship between community sociodemographic characteristics and accidental acute toxic air emissions at facilities regulated under the EPA's Risk Management Plan (RMP) program. They found that even after controlling for facility size, hazard score, number of employees, and chemical inventory, facilities located in counties that have a high percentage of Black residents and/or strong presence of income inequality are more likely to have a chemical accident. In a separate study using the same dataset Kleindorfer et al. (2003) found that intrinsically hazardous facilities (measured by the quantity of chemicals in inventory and their potential harm) are more likely to be located in minority and impoverished communities. Guignet et al. (2023) found that chemical facilities regulated under the RMP program tend to be in close proximity to neighborhoods where a greater proportion of the population is Black, Hispanic, and living in poverty. Furthermore, they found that conditional on the presence of a chemical facility, the occurrence of chemical accidents and subsequent air emissions are more likely to occur as the percentage of the population that is Black, Hispanic, and living in poverty increases.

A few studies also examined the distributional implications of cleanup duration. Lavelle and Coyle (1992) found that it took longer for sites to get approved CA plans in zip codes with predominantly minority populations. They found that in more than half of the programs across the 10 autonomous regions authorized to implement EPA programs, action on cleanup at Superfund sites starts 12% to 42% later for sites in minority neighborhoods compared to predominately White neighborhoods. Lavelle and Coyle (1992) also found inequities in terms of prevention, suggesting that regulation penalties were 500% higher in zip codes with the greatest White population. The implication is that enforcement of safe practices may have been more often carried out in predominately White neighborhoods.

Focusing on Superfund site cleanups, Solatyavari et al. (2022) found evidence of longer cleanup times in census tracts with a greater percentage of minority populations. Political involvement and percent owner-occupied housing were also correlated with faster cleanup times. Similarly, Sigman (2001) found that communities with higher voter turnout (a proxy for community coordination and engagement) experience faster Superfund site cleanups. Burda and Harding (2014) investigated the time between NPL listing and construction completion at Superfund sites and found that sites listed at the beginning of the program (early 1980s) had longer cleanup times associated with Black, high density, and lower educated populations. Their findings suggest that this association ceased for sites listed later in the Superfund program's history.

Finally, there is a small and fairly dated literature examining the implementation of various remedial methods and the permanence of cleanup. Lavelle and Coyle (1992) found that releases in minority communities are 7% more likely to be capped off/contained, as opposed to a more permanent remedy— i.e., removal and treatment of the chemicals. Gupta et al. (1996) examined the cleanup decisions from 110 wood-preserving and PCB contaminated Superfund sites, and

[2] We also note that there is a larger literature on environmental justice issues associated with air pollution more broadly, mainly in the context of particulate matter and other criteria air pollutants (e.g., Ard 2015, Clark et al. 2017, Currie et al. 2020).

found no evidence of less permanent cleanup solutions in areas with sizable minority or impoverished populations.

Our study contributes to the numerous branches of this literature by providing a comprehensive analysis of a national program and the multiple layers where disproportional impacts could occur. The bulk of the EJ literature on the siting of hazardous sites relied on data from the 1990s or earlier. We provide an updated assessment and go beyond just the siting of hazardous waste facilities. Although others have focused on the distributional implications of toxic air emissions and releases of hazardous chemicals into the air, we focus on releases of toxic chemicals into other media, namely land and groundwater. To our knowledge, the literature examining cleanup duration and permanence has largely focused on Superfund sites. We empirically analyze the duration and permanence of cleanup activities in the context of facilities regulated under RCRA. Although both programs deal with the cleanup of hazardous chemicals, Superfund sites remediated through CERCLA are often non-operating, usually abandoned facilities. In contrast, RCRA is targeted towards hazardous chemicals at facilities that are currently in operation, and where the owners and operators are known.

III. DATA

A cross-sectional dataset of all census tracts across the contiguous US was obtained from the United States Census Bureau's 2000 Decennial Population Census, which coincides with the beginning of our 2000-2019 study period. Focusing on demographics at the beginning of the study period, prior to any new Corrective Action (CA) activities, reduces endogeneity concerns due to reverse causality. We are interested, for example, in how the likelihood of a CA varies with socioeconomic characteristics of a neighborhood. At the same time, such demographics could later shift in response to CA activities. There is, in fact, a significant literature examining such demographic shifts in response to environmental quality shocks (e.g., Bakkensen and Ma 2020, Banzhaf et al. 2019, Been 1994, Cameron and McConnaha 2006, Hamilton 1993, 1995).

Data on race, ethnicity, poverty status, and median income were gathered at the census tract level.[3] The area of the census tract was calculated in a Geographic Information System (GIS) based on the 2000 census tract polygon borders from the US Census Bureau's TIGER/Line files.[4] The variables derived for later analysis include population density (measured in 1000s of people per square mile); median annual income (measured in $1000s, 2021 USD); and percentages of the population that are Nonwhite; of Hispanic, Latino, or Spanish descent; and living below the poverty line.[5] The census-tract level dataset of neighborhood characteristics was then spatially linked to data on RCRA sites and CAs across the contiguous US.

The RCRA and CA data were compiled from an extensive multi-relational (and publicly available) database collected and maintained by the EPA, known as RCRAInfo.[6] This database is organized into eight different "modules", each containing several data tables. The "Handler" module includes facility-level information like whether the facility operates as a TSDF, generates

[3] Median income was reported in 1999 USD and converted to 2021 USD based on the US Bureau of Labor Statistics' Consumer Price Index (https://www.bls.gov/cpi/tables/supplemental-files/historical-cpi-u-202204.pdf, accessed 13 Oct 2022).
[4] US Census Bureau, https://www.census.gov/, accessed 13 Oct 2022.
[5] The percent nonwhite variable was calculated based on the proportion of the population that identified as only a single race, which comprised 97.5% of the total population. The other socioeconomic variables are based on the total population.
[6] EPA, "RCRAInfo Public Extract", https://rcrapublic.epa.gov/rcra-public-export/, data downloaded in June 2019.

hazardous materials, handles specific types of hazardous materials, and industry classification. The "Corrective Action" module offers information on the timing and severity of CAs, including the start date and, if applicable, the type of remediation implemented and completion date of the CA. For purposes of this analysis we identify CAs as only those where the investigation revealed actual contamination that required clean up or active efforts to minimize exposure.[7]

The data we gathered from RCRAInfo starts with 129,670 RCRA sites in the United States as of 2019; among these sites, 1,610 had or have a CA that involved confirmed contamination requiring cleanup.[8] After limiting the data to the contiguous US and CAs that were initiated during our 2000-2019 study period, we are left with 127,846 RCRA sites; 234 of which had a CA initiated. Finally, we draw focus to the largest and potentially riskiest types of RCRA sites – large quantity generators (LQGs) and treatment, storage, and disposal facilities (TSDFs). Sites that were only reported as small quantity generators, recyclers, transporters, etc. are excluded. The final sample of RCRA facilities examined is n=41,668 RCRA sites, among which 199 had an active CA requiring eventual remediation.

Each research question required a slightly different dataset, based on the merged census tract and RCRA facility data. Following the theme of "layers of injustice", as the research questions progress attention is drawn to a narrower focus and smaller subsets of the data. To examine if the siting of these larger RCRA facilities is correlated with neighborhood demographics (Q1), we analyze a cross-sectional, tract-level dataset of all census tracts in the contiguous US. Analysis of whether CAs are systematically more or less likely to occur in different types of neighborhoods (Q2) requires a cross-sectional, facility-level dataset of all LQGs and TSDFs in the contiguous US. Duration analysis of whether time to cleanup completion varies systematically with respect to neighborhood characteristics (Q3) is conducted using a subset of the facility-level data, where only LQGs and TSDFs with an ongoing or completed CA are included. Lastly, focus is further drawn to only facilities with a completed CA, where we then examine whether permanence of cleanup is correlated with neighborhood socioeconomic characteristics (Q4).

III.A. Tract-level dataset to examine siting of RCRA sites (Q1).

There are 63,083 census tracts in the contiguous US (based on the 2000 Census tract definitions).[9] As shown in Table 1, 30.5% of tracts contained at least one LQG or TSDF, and the average tract contains 0.52 facilities. In 2000, the average tract population consisted of 23.6% Nonwhite and 11.2% Hispanic. About 13.3% of the population in a tract was living below the

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[7] These CAs are identified within RCRAInfo based on the following event codes: CA550RC (remedy construction); CA770GW and CA770NG (groundwater and non-groundwater controls); and CA772EP, CA772GC, CA772ID, and CA772PR (institutional controls). See Guignet and Nolte (2024) for further details.

[8] Our dataset excludes a small subset of facilities falling under the conditional subpart K exemptions, which apply to academic institutions, such as teaching hospitals and universities (US EPA, 2008), as well as that deal with international imports and exports of hazardous materials.

[9] We exclude outliers where the census tract had more than 7 LQGs or TSDFs (536 tracts), the population density was greater than 60,000 people per square mile or less than two people per square mile (637 and 636 tracts, respectively). These cutoffs roughly correspond to the top or bottom percentiles of the sample. Two additional tracts are excluded because the total population self-identifying as a single race was zero, and that value is used as the denominator in calculating our percent nonwhite variable. Our estimating dataset of 63,083 tracts maintains 97% of the total number of census 2000 tracts in the contiguous US.

poverty line, and the median income was $71,788, on average. The average population density was 4,343 people per square mile.

III.B. RCRA facility-level dataset to analyze risk of a Corrective Action (Q2).

A total of 41,361 RCRA facilities that are reported as a LQG and/or TSDF are analyzed. A CA is undertaken during our study period at 199 of these facilities (see Figure 1). As shown in Table 2, the population statistics corresponding to the tract where a RCRA site is located, compared to those in Table 1 for all tracts across the contiguous US, suggest greater proportions of the population that are Nonwhite, Hispanic, and living in poverty, as well as slightly higher median incomes. These statistics are not directly comparable, however, because the unit of observation here is a RCRA facility. We more formally test for such differences in later statistical regression models.

Comparison of the RCRA facility characteristics in Table 2 suggests that 97% of the sample of RCRA sites are a LQG, and about 4% are a TSDF. We also see that among the RCRA sites in our study sample, some are also reported as small quantity generators (5%), recyclers of hazardous material (1%), and/or accept hazardous waste from other offsite locations (0.07%). Note that these classifications are not necessarily mutually exclusive. , respectively. Finally, among the facilities where the corresponding North American Industry Classification System (NAICS) codes were available, we see that manufacturing, trade and transportation, and services industries are the most common.

III.C. Dataset to model duration of Corrective Action (Q3).

The duration of a CA is calculated as the amount of time from when an investigation and/or cleanup activities were first initiated, until the contamination issues were sufficiently addressed and the case closed.[10] The dataset used to model the duration of investigation and cleanup activities focuses on 196 (of the original 199) RCRA facilities where a CA involving actual contamination occurred. Two sites were dropped because they had a negative duration listed, likely due to clerical errors.[11] A third site had the same CA open and completion date, but given the remedial technologies implemented, those dates likely do not reflect the true CA duration.

The CA investigation and cleanup was completed during our study period at 77 of the 196 CA sites. Table 3 shows that the average duration of the 77 completed CAs was 7.07 years, but there is noticeable heterogeneity across cases, ranging from just two weeks, to over 17 years. For the remaining CAs, the investigation and cleanup activities were not yet complete, as of the time our data was acquired (June 5, 2019). These censored durations, however, still yield useful information and are maintained when estimating our CA duration models (see section IV.C). Among those 133 incomplete CA cases, the average censored duration was 14.42 years.

[10] We define the opening date for a CA as the earliest of the following three events: when regulators were first notified of contamination (CA060), the date an investigation was imposed (CA100), or when the initial assessment was complete (CA200). A CA is considered complete based on the earliest recorded date for one of the following events, and only when applicable to the entire site – when the CA was officially terminated (CA999, CA999NF, or CA999RM), or when the required performance standards were achieved (CA900CR or CA900NC).

[11] Although the start dates were listed as January 2004 and March 2000 for two of the CA sites, the CA completion dates for both were entered as January 1, 2000.

III.D. Dataset to analyze permanence of cleanup (Q4).

Focusing on the 77 completed CAs, we examine what factors are significantly associated with the permanence of cleanup. Permanence is approximated based on the type of remedy (or remedies) that was implemented at each CA site. We judge "remedy construction" to be the most permanent solution. This entails the construction and implementation of active remedial technologies (e.g., excavation of contaminated soil, pump-and-treat of groundwater). As shown in Table 3, active remediation techniques were used in 90% of the completed CA cases. The remediation types are not mutually exclusive, and may be used in conjunction, but in 25% of the cases we see less permanent physical and engineering controls being implemented to minimize exposure and the migration of contaminants. Such controls include routine monitoring and testing of groundwater, concrete caps over contaminated soil, and other physical barriers to prevent exposure and migration. Although cost-effective and perhaps sufficiently effective in many cases, we judge institutional controls (e.g., zoning requirements and restrictions on future land uses) to be the least permanent solution. Among the 77 completed CAs, 57% use institutional controls.

For our empirical analysis, we aggregate these measures into two indicator variables. The first denotes cases where the most permanent solution – "remedy construction" – is put in place. Other solutions may or may not be implemented in conjunction with these active contamination removal and treatment techniques. The second indicator is more comprehensive, reflecting cases where "remedy construction" and/or physical/engineering controls are put in place. The percentage of completed CA cases corresponding to each are 88% and 90%, respectively. The omitted category, and least permanent solution, entails the 10% of cases where *only* institutional controls are put in place. See Table 3 for details.

IV. METHODS

We next outline the empirical models that are estimated to examine each of our four research questions. The binary models used to analyze key neighborhood sociodemographic factors that are correlated with the siting of a RCRA site (Q1), the probability of a CA occurring (Q2), and whether a relatively more permanent remedial method is implemented (Q4), are estimated as three sets of Probit models. Models of the duration of the CA at individual facilities (Q4) are estimated as a series of Cox proportional hazard models (Cox 1972).

IV.A. Probit model of the siting of RCRA sites (Q1).

When answering our first research question, the outcome of interest is whether there are one or more RCRA sites located within a neighborhood. We estimate the probability that there is one or more RCRA sites within census tract *c* as:

$$Pr(site_c > 0) = F(\beta_0 + \boldsymbol{x}_c\boldsymbol{\beta}_1 + \varepsilon_c) \quad (1)$$

where $site_c$ is the number of RCRA sites within census tract *c*, and $\boldsymbol{x}_c$ is a vector of neighborhood characteristics based on the 2000 decadal census (e.g., percent of the population that is Nonwhite, of Hispanic or Latino origin, living in poverty; and median income and population density). ε_c is an assumed normally distributed disturbance term, and $F(\cdot)$ is a normal cumulative density function. The coefficients to be estimated are β_0 and $\boldsymbol{\beta}_1$. To ease interpretation, we present the average marginal effects in our main results tables.

IV.B. Probit model of the occurrence of a Corrective Action (Q2).

Although equation (1) is estimated at the neighborhood or tract-level, the remaining models are estimated at the RCRA site-level. The probability of a CA occurring at RCRA site *i* in census tract *c* is modelled as:

$$Pr(CA_{ic} = 1) = F(\alpha_0 + \boldsymbol{x}_c\boldsymbol{\alpha}_1 + \boldsymbol{z}_i\boldsymbol{\alpha}_2 + \varepsilon_{ic}) \quad (2)$$

where CA_{ic} is a binary dependent variable that equals one if a CA occurs at the site during our study period, and zero otherwise. The notation is similar to before; for example, $\boldsymbol{x}_c$ denotes the sociodemographic characteristics for the census tract where RCRA site i is located. If a tract contains more than one RCRA site, then each site is represented as a separate observation when estimating equation (2). The vector $\boldsymbol{z}_i$ represents characteristics of the facility, including indicators of whether the facility is a LQG, TSDF, and accepts offsite waste for disposal and treatment. In some models, indicators denoting the type of industry based on aggregated NAICS codes are also included. The vector $\boldsymbol{z}_i$ is included in some models to assess if CAs may be systematically more or less likely to occur in different types of neighborhoods, even after controlling for other facility-specific risk factors. Similar to before, we present the main results as the average marginal effects.

IV.C. Hazard model of duration of Corrective Action (Q3).

Another layer of potential inequities could occur in terms of the duration of investigation and cleanup activities. In other words, all else constant, do CAs take longer to complete in neighborhoods with greater populations of minorities or those living in poverty? Cox proportional hazard models (Cox 1972) are often used when examining how covariates impact the duration of the "spell" of interest, in this case of the CA investigation and cleanup activities. We estimate the hazard or probability that the CA for site *i* will be completed in time *t* as:

$$\lambda(t|\boldsymbol{x}_c, \boldsymbol{z}_i, risk_i) = \lambda_0(t)exp(\boldsymbol{x}_c\boldsymbol{\gamma}_1 + \boldsymbol{z}_i\boldsymbol{\gamma}_2 + \gamma_3 risk_i) \quad (3)$$

Similar to before, the probability of a CA being completed in a given year is estimated as a function of characteristics of the surrounding neighborhood $(\boldsymbol{x}_c)$ and of the facility itself $(\boldsymbol{z}_i)$. In later models we also include a coarse measure of contamination severity $(risk_i)$, which is a 1 to 3 ranking reflecting EPA's risk-based cleanup prioritization – 1=lowest risk and 3=highest risk.

The coefficients to be estimated are $\boldsymbol{\gamma}_1$, $\boldsymbol{\gamma}_2$, and γ_3. To facilitate interpretation, we present the corresponding hazard ratios in the main results. For example, the vector of hazard ratios corresponding to marginal changes in neighborhood characteristics $\boldsymbol{x}_c$, can be expressed as $exp(\boldsymbol{\gamma}_1)$. The magnitude of the hazard ratio has an intuitive interpretation. A marginal increase in the corresponding variable in $\boldsymbol{x}_c$, for example, suggests a $(exp(\boldsymbol{\gamma}_1) - 1) \times 100$ percentage point change in the probability of CA completion in a given year.[12] When the hazard ratio is greater than

[12] For details see, for example, Wooldridge (2010, Chapter 22) or Solatyavari et al. (2022).

one, it indicates an increase in the "hazard", or in our case, an increase in the probability of CA completion in a given year – i.e., a decrease in the CA duration. In contrast, a hazard ratio less than one indicates a lower probability of CA completion in time *t,* implying an increase in the duration of the CA.

IV.D. Probit model of implementation of more permanent cleanup approaches (Q4).

To answer our last research question, we estimate a Probit model of the probability that relatively more permanent remediation approaches are used at a CA site. We estimate this model using the subset of RCRA facilities where a CA occurred and was completed during our study period. Let $perm_{ic} = 1$ if a relatively more permanent cleanup approach was utilized, and zero otherwise. More formally:

$$Pr(perm_{ic} = 1) = F(\varphi_0 + \boldsymbol{x}_c\boldsymbol{\varphi}_1 + \boldsymbol{z}_i\boldsymbol{\varphi}_2 + \varphi_3 risk_i + \varepsilon_{ic}) \quad (4)$$

We measure $perm_{ic}$ using two alternative variables. The first denotes completed CAs where "remedy construction" was specified as part of the cleanup. This includes active cleanup efforts, such as excavation and removal of contaminated soil, pumping and treating polluted groundwater, etc. The second outcome measure is expanded to include not only remedy construction, but also cleanup approaches based on engineering and physical controls. This second measure is not mutually exclusive, as it includes sites where remedy construction and/or physical controls were implemented. The omitted category for this second measure is CA sites where only institutional controls (i.e., zoning and land use restrictions) are put in place. The coefficients to be estimated are φ_0, $\boldsymbol{\varphi}_1$, $\boldsymbol{\varphi}_2$, and φ_3.

V. RESULTS

The results for each research question and layer of analysis are presented next. The main results are discussed in terms of average marginal effects or risk ratios, depending on the model.

V.A. Probit results of the siting of RCRA sites (Q1).

Following equation (1), Model 1.1 in Table 4 is the simplest model of the probability of at least one RCRA site being located in a census tract, as a function of just the percent of the population that is Nonwhite and the percent of the population that is of Hispanic or Latino origin. The results suggest that, on average, a tract with a one-percentage point higher population of Nonwhites is associated with a 0.03 percentage point increase in the probability of a RCRA site being located there. A similar 0.10 percentage point increase in the likelihood of a RCRA site is associated with a one-percentage point increase in the proportion of the population that is Hispanic. These average effects are small but statistically significant.

To help put these findings into context, consider the average tract, one with a population that is 23.7% Nonwhite and 11.3% Hispanic. The predicted probability of a LQG or TSDF site being located in this neighborhood is 30.5%. The results in Model 1.1 suggest that if we compare this to a neighborhood with a 50-percentage point greater Nonwhite population (i.e., 73.7% Nonewhite), then the probability of a RCRA site in the community increases 1.4 percentage points.

Making this same illustrative 50-percentage point increase for the proportion of the population that is Hispanic, suggests a roughly 6 percentage point increase in the probability of a RCRA site.

In Models 1.2 and 1.3 we add alternative measures of wealth; both suggest a similar finding – that a tract is more likely to host a TSDF or LQG as median income increases, and less likely to as the proportion of the population living in poverty increases. Although we find no evidence of inequities being experienced by lower income communities with respect to the siting of RCRA sites, the small yet significant disproportional impacts associated with race and ethnicity are robust. The results are similar even when controlling for population density in Models 1.4 and 1.5, which also suggest that RCRA sites are more likely located in more urban areas with higher population densities.

V.B. Probit results of the occurrence of a Corrective Action (Q2).

The average marginal effect estimates from a series of Probit models of the occurrence of a CA are presented in Table 5. Model 2.1 is the simplest, estimating the probability of a CA as a function of the percent of the surrounding population that is Nonwhite and Hispanic. The results suggest that, if anything, facilities in tracts with higher proportions of racial and ethnic minorities are actually less likely to undergo a CA. At face value, this is positive news in terms of EJ. Perhaps contamination incidents are less likely to occur at facilities in these neighborhoods. At the same time, there could be situations where historical contamination exists, but state and federal regulators are less likely to be notified. Further research into the occurrence of contamination releases versus the reporting and initiation of a CA is needed to fully understand any potential EJ implications. In any case, this result remains fairly robust across most models in Table 5.

The next two models include alternative variables to control for household wealth. Model 2.2 suggests that a facility is less likely to have a release discovered, and subsequently undergo a CA investigation and cleanup activities, as median income increases. The average marginal effect suggests that a $1,000 increase in median income is associated with a 0.006% decrease in the probability that a CA occurs at that facility. Put another way, facilities in poorer neighborhoods are more likely to undergo a CA. For example, the probability of a CA at a facility in the "average" neighborhood, where median income is $74,070, is 0.41%.[13] If the median household income is $20,000 lower, then the model suggests that the probability of a CA increases by 0.11 percentage points, an almost 27% increase in the risk of a CA. Although this is suggestive of inequities in terms of household wealth, this finding is not robust to our alternative wealth measure. When controlling for household wealth based on the percentage of the population living in poverty, we see statistically insignificant effects. This pattern of mixed evidence holds in subsequent models that control for population density, and characteristics of the facilities.

Models 2.4 and 2.5 in Table 5 control for population density. The negative and significant estimates suggest that CAs are less likely to occur at facilities in more densely populated areas. All else constant, an increase of 1,000 people per square mile is associated with a 0.089 to 0.094 percentage point decrease in the probability of a CA. It is reassuring that riskier facilities tend to be located in less populated areas, just from the standpoint that less people are potentially exposed. Additionally, the results are counter to any beliefs that injustices may be systematically occurring

[13] More specifically, this is the predicted probability for a site in a neighborhood where the proportions of the population that are Nonwhite, Hispanic, and the median income, are evaluated at the sample average values (shown in Table 2).

in more urban neighborhoods. At the same time, the results could be interpreted as potential evidence of disproportionate impacts towards more rural communities. The probability of a CA predicted from Model 2.4 for the "average" site, with a population density of 8,512people per square mile, is 0.13%. All else constant, for a site in a more rural area where the population density equals the 25th percentile (456 people per square mile), the predicted risk of a CA increases to 0.65%, a more than 80% increase.

Models 2.6 and 2.7 control for additional characteristics of the RCRA facility, including industry categories. Even after controlling for facility-specific characteristics, the previous findings are generally robust. Facility characteristics are also generally in line with expectations, lending credibility to our results. For example, TSDFs are more likely to experience a CA. When compared to the omitted category of manufacturing, we see that facilities that are characterized as being in the trade and transportation industry or the services industry are less likely to endure a CA, on average. In contrast, facilities that handle hazardous chemicals for purposes of waste management are more likely to experience a CA.

V.C. Duration of a Corrective Action results (Q3).

We estimate a series of Cox proportional hazard models (Cox 1972) to examine whether the duration of CA investigation and cleanup activities systematically varies across facilities located in different types of neighborhoods. The estimated hazard ratios are presented in Table 6. As described in section IV.C, a hazard ratio greater than one implies an increase in the probability that the CA will be completed in a given year, and therefore suggests a shorter duration. In contrast, a hazard ratio less than one implies a decrease in the probability of completion, and thus a longer CA. The statistical tests reported for the estimates in Table 6 correspond to the null hypothesis that the ratio equals one, meaning no statistically significant effect.

In Model 3.1, the significant hazard ratio corresponding to percent Hispanic suggests that a CA investigation and cleanup is 2.2% (=0.978-1) less likely to be complete in a given year if the proportion of the population that is Hispanic is one percentage point greater. This effect becomes more significant and slightly greater as we control for additional neighborhood and facility characteristics, with our most thorough specifications (Models 3.6 and 3.7) suggesting a 4.3% decrease (=0.957-1) in the probability of CA completion. The more thorough models in Table 6 also suggest that a one-percentage point increase in the proportion of the population that is Nonwhite is associated with a 2.3% to 2.6% decrease in the probability of CA completion in a given year. Together these results suggest possible inequities; the CA investigation and cleanup activities take longer to complete in neighborhoods that have greater populations of Nonwhite and Hispanic residents.

There is little evidence of potential inequities in terms of income and poverty rates in Table 6, but we do find evidence that CA investigation and cleanup activities occur more quickly in more densely populated areas, perhaps reflecting regulators' priority to protect human health, especially in areas where a greater number of people could potentially be exposed. This is confirmed by the estimated hazard ratios corresponding to *risk* in Models 3.6 and 3.7, which suggest that sites prioritized for cleanup due to greater risks to the public and environment are remediated much faster. Increasing the 1 to 3 risk rating by one level suggests a roughly 167% increase in the likelihood that a CA will be completed in a given year. Conditional on risk prioritization, we find little evidence of systematic differences in the duration of cleanup across these sites.

V.D. Probit of more permanent cleanup approaches (Q4).

Using the sample of 77 completed CAs, we estimate two sets of Probit models of the implementation of more permanent cleanup solutions. The first set is of the dependent variable denoting "remedy construction", which involves active treatment/neutralization and/or removal of hazardous chemicals. The second set is of whether remedy construction and/or engineering and physical controls were put in place to limit human exposure and migration of contaminants. The coefficient estimates are presented Tables A.1 and A.2 in the Appendix. In short, across all models and both dependent variables, we find no evidence that neighborhood and facility characteristics are significantly associated with the type of cleanup approaches that are implemented. It is important to note that this result could be partly driven by our small sample of just 77 completed CAs.

IV. CONCLUSION

An estimated 12% of the US population (about 35 million people) live within one mile of a RCRA Corrective Action (CA) site (EPA 2013). Exposure to the toxic chemicals used at these facilities can lead to increased risks of cancer, birth defects, organ damage, and other adverse health effects (EPA 2013). Each of the nearly 130,000 RCRA sites located across the US has the potential to cause real, long-term damage to local populations, if chemicals are mishandled. Focusing on the largest, and often potentially most hazardous types of RCRA sites – large quantity generators (LQGs) and treatment, storage, and disposal facilities (TSDFs) – we examine whether the potential for exposure is disproportionately experienced by different subgroups of the population based on racial, ethnic, income, and other dimensions.

Our study contributes to the environmental justice literature on hazardous chemicals and industrial facilities in several respects. We provide an updated assessment and go beyond just the siting of hazardous sites. We examine (i) whether RCRA-regulated facilities tend to be located in neighborhoods with a higher percentage of Nonwhite, Hispanic, or lower income individuals, (ii) whether chemical releases and subsequent CAs are more likely to occur in such neighborhoods, (iii) if the duration of investigation and cleanup activities are systematically longer in different types of communities, and (iv) whether the implementation of less permanent cleanup approaches is associated with neighborhoods consisting of higher shares of Nonwhite, Hispanic, and/or lower income populations. Much of the literature has focused on abandoned, often non-operational Superfund sites. In contrast, sites regulated under RCRA can continue to be active industrial facilities.

We find evidence of disproportionate impacts across racial, ethnic, and income dimensions, but these findings vary across the different layers of the RCRA program. There are small, yet statistically significant, positive relationships between higher Nonwhite and Hispanic populations, and the likelihood of a RCRA site being present. Conditional on the presence of a RCRA site, however, we find that the probability of a CA investigation and cleanup is actually less likely at sites in communities with a greater proportion of minority populations. It could be that releases are less likely to occur in these communities, but this result could also partly reflect that releases that do occur are less likely to be detected and reported. Further research is needed to disentangle these two effects.

We find mixed evidence as to whether CAs are more likely at facilities in lower income communities. We find no significant association between the percent of the population with an income below the poverty line and the occurrence of a CA, but do find that a release and subsequent cleanup is more likely at facilities in communities with lower median income levels. For example, compared to a facility in the average neighborhood, a site in a community with a $20,000 lower median income is 0.11 percentage points more likely to undergo a CA due to contamination issues. This may seem small, but it represents a 26.9% increase compared to the baseline average risk of 0.41%.

Among facilities where a CA does occur, we find that the investigation and cleanup activities take significantly longer when located in communities where greater shares of the population are Nonwhite or Hispanic. The probability of a CA investigation and cleanup being completed in a given year decreases by 2.2 to 4.3 percentage points for each one percentage point increase in the proportion of the local population that is Nonwhite or Hispanic. It could be that these facilities pose more complicated and severe pollution issues, requiring more thorough (and thus lengthier) cleanup procedures, but these findings are robust even after controlling for characteristics of the facility and our coarse measure of contamination severity. An alternative explanation is that certain communities are being neglected or do not have the resources to organize and push regulators for quicker recoveries. Such speculative explanations cannot be teased out from the coarse data used in our broad-brush analysis, but more locally focused research and community engagement could shed light on these issues.

Lastly, we find no robust, significant associations between local socioeconomic characteristics and the permanence of the cleanup activities undertaken. The sample for this part of our analysis is small, consisting of just 77 RCRA sites where a CA was complete, so caution is warranted when interpreting this result. That said, these null findings suggest that no disproportionate impacts are occurring with respect to the types and permanence of cleanup methods.

There are a few important caveats to keep in mind when interpreting our results. These shortcomings also highlight important directions for future research. Although our analysis is comprehensive, it provides only a broad-brush, coarse look at the distributional implications of RCRA. Our estimates reflect the average associations across the contiguous US. A null average effect does not necessarily imply that there are not inequities systematically occurring at the regional or even individual community levels in some instances. Due to our reliance on spatially and temporally coarse Census data, our analysis could also be missing important dynamic and local, within-tract impacts. Although we strive to examine several different types of socioeconomic characteristics that partly define different subpopulations, there may be important dimensions that we did not consider, such as linguistic isolation, immigration status, age, etc. Finally, we emphasize that the causality of our estimated relationships is ambiguous. We see the identification of potential disproportionate impacts across aspects of the RCRA program as an important first step, especially at this broad nationwide level. But if the policy goal is to minimize potential disproportionate impacts, then further research is needed to identify the causal mechanisms driving these inequities.

Overall, we find that the EJ implications surrounding RCRA and the investigation and cleanup activities through the Corrective Action program vary across the different aspects of the siting and cleanup process. This highlights the need for multi-layered analyses when trying to identify and fully understand potential inequities associated with broad-scale environmental programs. Such perspective is timely given renewed calls to solidify the role of distributional analyses and equity considerations in federal regulatory development (Biden 2021).

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TABLES AND FIGURES

Figure 1. Large Quantity Generators (LQGs) and Treatment, Storage, and Disposal Facilities (TSDFs) in Contiguous US.

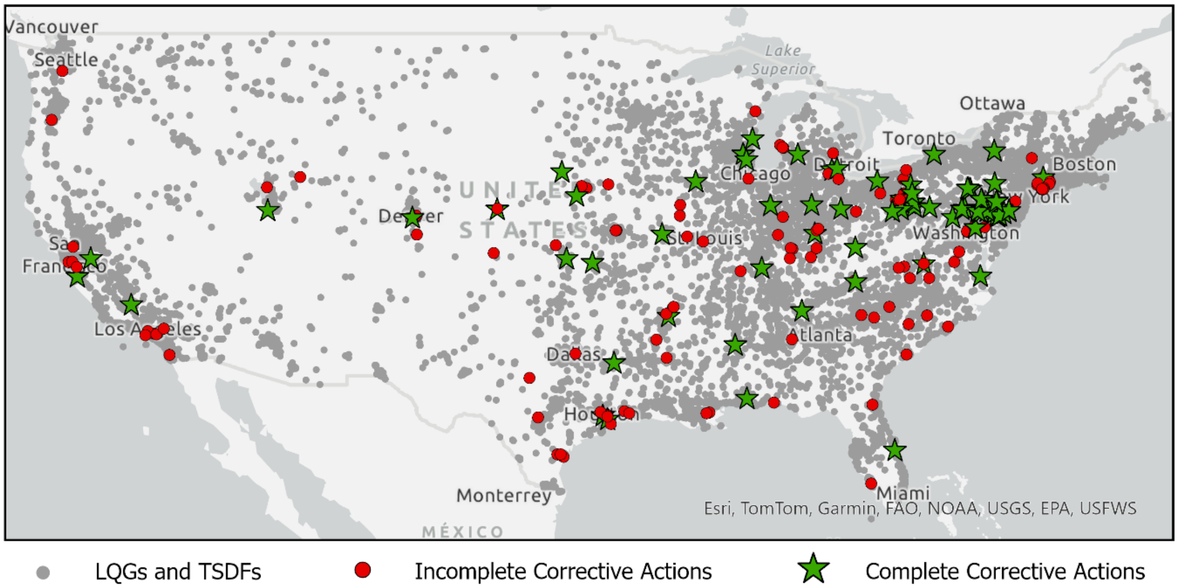

Table 1. Descriptive statistics of all year 2000 census tracts.

Variable	Mean	Std. dev.	Min	Max
RCRA site	0.3053	0.4605	0	1
# of RCRA sites	0.52	1.01	0	7
% Nonwhite	23.59	26.63	0	100
% Hispanic	11.22	18.59	0	100
% Below poverty	13.29	11.54	0	100
Median income ($1000 USD)	71.788	33.876	0	326
Population density (1000s/sqmi)	4.343	7.231	0.002	59.997

Note: Descriptive statistics for 63,083 census tracts in the contiguous U.S. from the 2000 decadal census.

Table 2. Descriptive statistics of RCRA facilities.

Variable	Mean	Std. dev.	Min	Max
CA Site	0.005	0.069	0	1
% Nonwhite	28.66	26.00	0	100
% Hispanic	16.92	22.32	0	100
% Below poverty	14.08	12.15	0	100
Median income ($1000s USD)	74.07	34.49	0	326
Population density (1000s/sqmi)	8.512	20.134	0.000	238.627
Large Quantity Generator (LQG)	0.97	0.16	0	1
Small Quantity Generator	0.05	0.22	0	1
Recycler	0.01	0.12	0	1
Treatment, Storage, Disposal Facility (TSDF)	0.04	0.20	0	1
Offsite Waste	0.007	0.085	0	1
Agriculture Ind.	0.013	0.112	0	1
Mining Ind.	0.011	0.104	0	1
Utility Ind.	0.133	0.340	0	1
Construction Ind.	0.046	0.209	0	1
Manufacturing Ind.	0.337	0.473	0	1
Trade and Transportation Ind.	0.345	0.475	0	1
Service Ind.	0.245	0.430	0	1
Waste Management Ind.	0.043	0.204	0	1
Industry Missing	0.036	0.186	0	1

Note: Descriptive statistics for the 41,361 RCRA sites in the contiguous United States that are designated as a LQG or TSDF.

Table 3. Additional descriptive statistics of Corrective Actions (CAs).

Variable	Obs	Mean	Std. dev.	Min	Max
Incomplete CAs					
CA Duration (years)	119	14.42	4.23	0.88	19.44
Completed CAs					
CA Duration (years)	77	7.07	5.08	0.04	17.32
Remedy Construction	77	0.88	0.32	0	1
Physical/engineering controls	77	0.25	0.43	0	1
Institutional controls	77	0.57	0.50	0	1
Remedy construction and/or physical/engineering controls	77	0.90	0.31	0	1
Institutional controls only	77	0.10	0.31	0	1

Note: Descriptive statistics for the 199 Corrective Actions that had a start date in or after the year 2000. This includes both complete and incomplete (censored) CAs (77 and .119 CAs, respectively).

Table 4. Average marginal effects: Probit model of probability of a RCRA site in census tract.

	(1.1)	(1.2)	(1.3)	(1.4)	(1.5)
% Nonwhite	0.000285***	0.000517***	0.000637***	0.000344***	0.000457***
	(0.000070)	(0.000073)	(0.000084)	(0.000078)	(0.000088)
% Hispanic	0.001206***	0.001297***	0.001341***	0.001128***	0.001163***
	(0.000099)	(0.000099)	(0.000100)	(0.000103)	(0.000104)
Median income ($1000 USD)		0.000596***		0.000579***	
		(0.000056)		(0.000056)	
% Below poverty			-0.001530***		-0.001508***
			(0.000204)		(0.000204)
Population density (1000s/sqmi)				0.001796***	0.001894***
				(0.000283)	(0.000283)
Observations	63,083	63,083	63,083	63,083	63,083
Log-likelihood	-38712.802	-38658.369	-38682.754	-38637.324	-38659.351

Notes: Binary dependent variable denoting whether a RCRA site is in census tract (=1) or not (=0). Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 5. Average marginal effects: Probit model of probability of a Corrective Action (CA).

	(2.1)	(2.2)	(2.3)	(2.4)	(2.5)	(2.6)	(2.7)
% Nonwhite	-0.000042**	-0.000061***	-0.000045**	-0.000022	-0.000010	-0.000021	-0.000006
	(0.000019)	(0.000019)	(0.000020)	(0.000019)	(0.000020)	(0.000017)	(0.000019)
% Hispanic	-0.000083***	-0.000086***	-0.000084***	-0.000052**	-0.000052**	-0.000045**	-0.000044*
	(0.000031)	(0.000029)	(0.000031)	(0.000025)	(0.000026)	(0.000022)	(0.000023)
Median Income ($1000 USD)		-0.000056***		-0.000049***		-0.000035***	
		(0.000013)		(0.000012)		(0.000011)	
% Below Poverty			0.000012		0.000024		-0.000010
			(0.000034)		(0.000033)		(0.000033)
Population Density (1000s/sqmi)				-0.000887***	-0.000939***	-0.000628***	-0.000646***
				(0.000186)	(0.000194)	(0.000171)	(0.000177)
LQG						0.001335	0.001179
						(0.001298)	(0.001302)
TSDF						0.012203***	0.012216***
						(0.001361)	(0.001358)
Offsite Waste						0.002743	0.002901
						(0.001791)	(0.001789)
Agriculture Ind.						-0.003554	-0.003308
						(0.003137)	(0.003141)
Mining Ind.						-0.001023	-0.000825

						(0.002711)	(0.002720)
Utility Ind.						-0.002231	-0.002375
						(0.001714)	(0.001714)
Construction Ind.						-0.002158	-0.002039
						(0.001661)	(0.001668)
Trade and Transportation Ind.						-0.003895***	-0.004025***
						(0.000846)	(0.000848)
Service Ind.						-0.001894**	-0.002046**
						(0.000819)	(0.000821)
Waste Management Ind.						0.003761***	0.003872***
						(0.001039)	(0.001038)
Industry Missing						-0.004334**	-0.004287**
						(0.001905)	(0.001904)
Observations	41,361	41,361	41,361	41,361	41,361	41,361	41,361
Log Likelihood	-1241.139	-1229.177	-1241.081	-1196.910	-1205.906	-1039.101	-1043.972

Notes: Binary dependent variable denoting whether a RCRA site has had a CA (=1) or not (=0). Robust standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 6. Hazard ratios: Proportional hazard model of Corrective Action duration.

	(3.1)	(3.2)	(3.3)	(3.4)	(3.5)	(3.6)	(3.7)
% Nonwhite	0.993002	0.992281	0.987756*	0.988026	0.985554*	0.977176***	0.973962***
	(0.006268)	(0.006104)	(0.006231)	(0.007695)	(0.007350)	(0.008594)	(0.008253)
% Hispanic	0.978057**	0.978052**	0.978200**	0.970894**	0.972009**	0.956719***	0.957006***
	(0.010741)	(0.010587)	(0.009947)	(0.011784)	(0.010975)	(0.016329)	(0.014762)
Median Income ($1000 USD)		0.997664		0.997543		0.997035	
		(0.005042)		(0.005002)		(0.004923)	
% Below Poverty			1.021280**		1.015254		1.019690
			(0.010542)		(0.010864)		(0.012501)
Population Density (1000s/sqmi)				1.163902*	1.143736	1.236149**	1.213871**
				(0.093532)	(0.096926)	(0.113048)	(0.113421)
Large Quantity Generator						1.048888	0.936188
						(0.489751)	(0.435418)
TSDF						0.491825	0.463718*
						(0.220639)	(0.207367)
Offsite Waste						2.251719	2.285972
						(1.176223)	(1.183674)
Risk						2.674618***	2.661281***
						(0.517368)	(0.519486)
Risk Miss						9.427973***	9.992352***

						(5.204926)	(5.505037)
Agriculture Ind.						3.480856	3.495334
						(5.059924)	(5.139636)
Mining Ind.						0.000000***	0.000000***
						(0.000000)	(0.000000)
Utility Ind.						1.497616	1.473723
						(0.887439)	(0.861405)
Construction Ind.						1.505640	1.536954
						(1.146235)	(1.110627)
Trade and Transportation Ind.						1.081971	1.143241
						(0.388662)	(0.410169)
Service Ind.						0.990105	0.950677
						(0.361207)	(0.344990)
Waste Management Ind.						1.813130*	1.821287*
						(0.637535)	(0.637192)
Industry Missing						11.918981***	11.800940***
						(5.320164)	(5.344547)
Observations							
Log likelihood	196	196	196	196	196	196	196

Notes: Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. The p-values here correspond to the null hypothesis that the presented hazard ratio estimates are equal to one (see section IV.C for details).

APPENDIX

Table A1. Average marginal effects: Probit model of more permanent cleanup technique – "Construction remedy".

	(4.1A)	(4.2A)	(4.3A)	(4.4A)	(4.5A)	(4.6A)	(4.7A)
% Nonwhite	-0.001222	-0.000708	-0.002195	-0.000446	-0.001596	0.000463	-0.001194
	(0.001520)	(0.001709)	(0.002024)	(0.001637)	(0.002211)	(0.001831)	(0.002260)
% Hispanic	0.002047	0.002263	0.002513	0.000539	0.000884	-0.000636	-0.000368
	(0.004100)	(0.004130)	(0.004219)	(0.004704)	(0.005286)	(0.005838)	(0.006190)
Median Income ($1000 USD)		0.000951		0.001206		0.001472	
		(0.001261)		(0.001284)		(0.001151)	
% Below Poverty			0.002736		0.001326		0.002381
			(0.003511)		(0.004479)		(0.004451)
Population Density (1000s/sqmi)				0.030720	0.026457	0.042759	0.036680
				(0.028463)	(0.033628)	(0.036798)	(0.041616)
LQG						-0.189789	-0.190522
						(0.146665)	(0.150390)
TDSF						-0.080384	-0.096616
						(0.109850)	(0.113379)
Offsite Waste						0.023273	0.031943
						(0.112217)	(0.115912)
Risk						-0.024529	-0.020349
						(0.061918)	(0.060527)
Risk Missing						-0.078812	-0.035057
						(0.194275)	(0.193009)
Observation	77	77	77	77	77	77	77
Log Likelihood	-27.429	-27.255	-27.246	-26.605	-26.851	-25.454	-25.772

Notes: Binary dependent variable denoting whether a CA site has been remedied using construction (=1) or not (=0). Robust standard errors in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.

Table A2. Average marginal effects: Probit model of more permanent cleanup technique – “Construction remedy" and/or engineering and physical controls.

	(4.1B)	(4.2B)	(4.3B)	(4.4B)	(4.5B)	(4.6B)	(4.7B)
% Nonwhite	-0.001270	-0.001114	-0.003091	-0.000877	-0.015503*	-0.000277	-0.002651
	(0.001419)	(0.001584)	(0.001904)	(0.001519)	(0.009417)	(0.001685)	(0.001923)
% Hispanic	0.001204	0.001274	0.002007	-0.000187	0.021365	-0.001273	-0.000421
	(0.003691)	(0.003678)	(0.003924)	(0.004276)	(0.024692)	(0.005556)	(0.005888)
Median Income ($1000 USD)		0.000285		0.000513		0.000616	
		(0.001068)		(0.001099)		(0.000908)	
% Below Poverty			0.005298		0.027804		0.005779
			(0.003644)		(0.018360)		(0.004062)
Population Density (1000s/sqmi)				0.025861	-0.047824	0.033149	0.024043
				(0.027169)	(0.103956)	(0.034684)	(0.039321)
Large Quantity Generator						-0.150912	-0.165616
						(0.139599)	(0.141323)
TDSF						-0.102683	-0.123009
						(0.106102)	(0.105499)
Offsite Waste						0.019178	0.025422
						(0.107239)	(0.107361)
Risk						0.015919	0.022758
						(0.055110)	(0.050542)
Risk Missing						0.017149	0.077956
						(0.174487)	(0.164279)
Observation	77	77	77	77	77	77	77
Log Likelihood	-25.272	-25.254	-24.629	-24.725	-24.413	-23.655	-23.108

Notes: Binary dependent variable denotes whether a CA site has been remedied using remedy construction and/or engineering and physical controls (=1) or not (=0). The latter (=0) corresponds to cases where only institutional controls are put in place. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.