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Abstract: This study evaluates the effect of EPA's Superfund cleanup program on children's lead exposure. We linked two decades of blood lead level (BLL) measurements from children in six states with data on Superfund sites and other lead risk factors. We used quasi-experimental methods to identify the causal effect of proximity to Superfund cleanups on rates of elevated BLL. We estimated a difference-in-difference model comparing the change in elevated BLL of children closer to versus farther from lead-contaminated sites before, during, and after cleanup. We also estimated a triple difference model including children near hazardous sites with minimal to no lead contamination as a comparison group. We used spatial fixed effects and matching to minimize potential bias from unobserved differences between the treatment and comparison groups. Results indicate that Superfund cleanups lowered the risk of elevated BLL for children living within 2 kilometers of lead-contaminated sites 8 to 18 percent.

Key words: Blood lead levels, child health, lead exposure, Superfund, contaminated land

JEL classification: I14, I18, Q51, Q53

Superfund Cleanups and Children's Lead Exposure[1]

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Blood lead levels in the United States have significantly declined over the last 40 years due to the phaseout of lead in gasoline, residential paint, food cans, plumbing, and pesticides. Yet, there is no known safe level of lead exposure, and hundreds of thousands of children are still affected by legacy contamination (CDCa). Lead is a neurotoxicant with well-established detrimental effects on children's cognitive function and behavior. It also damages children's and adults' neurological, cardiovascular, kidney, developmental, and reproductive functions (U.S. EPA 2013). Lead remains an ongoing multi-media children's health problem, with continued exposure from deteriorated paint in older homes; water systems with leaded pipes; cosmetics, toys, and other consumer products; and legacy soil contamination.

Lead also is one of the most prevalent contaminants at Superfund sites (ATSDR 2017a), affecting more than 700 sites across the nation. The federal Superfund program was established in 1980 to identify, fund, and oversee the cleanup of the most contaminated sites in the United States. The effects of the program nationally on childhood lead poisoning are unknown. Site-specific studies of changes in blood lead levels (BLL) resulting from Superfund remediation have focused on a handful of the most severe cases of lead contamination, particularly at mining and smelter sites (Murgueytio et al. 1996, 1998; von Lindern et al. 2003; Lanphear et al. 2003; U.S. EPA "Lead at Superfund Sites: Examples of Superfund Site Cleanups"). These studies showed that children's BLL dropped substantially during remediation efforts. For example, at the

[1] The data used in this study were acquired from the following institutions: Massachusetts Department of Public Health, Michigan Department of Health and Human Services, Missouri Department of Health and Senior Services, North Carolina Division of Public Health, Rhode Island Childhood Lead Poisoning Prevention Program, Wisconsin Division of Public Health, Zillow, Inc., EPA's Office of Land and Emergency Management, and the Agency for Toxic Substances and Disease Registry. The contents of this document, including analysis, interpretation, and conclusions, are solely the responsibility of the authors and do not represent the official views of these institutions or of the Environmental Protection Agency. We thank John Burchette, Michelle Burgess, Ann Carroll, Stiven Foster, Keith Fusinski, Kevin Koporec, Larry Zaragoza, and Ron Shadbegian for their comments on a draft version of the manuscript.
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Bunker Hill Mining & Metallurgical Complex Superfund site in Smelterville, Idaho, average BLL concentrations among children living in nearby communities fell from approximately 64 μg/dL to 2.7 μg/dL during 1974-2001. Such results may or may not be generalizable to the hundreds of other Superfund sites with varying exposure pathways and degrees of contamination. They also do not isolate the contribution of Superfund from other reductions in lead exposure sources (such as leaded gasoline) that may have occurred during the same time frame.

Over the last decade, a robust literature has developed that has used quasi-experimental statistical techniques to examine the effects of Superfund and other contaminated site cleanups on property values, showing that homes located near contaminated sites rise in value after cleanup (Zabel and Guignet 2012; Guignet 2013; Gamper-Rabindran and Timmins 2013; Guignet et al. 2016; Haninger et al. 2017; Timmins 2017). Studies examining the impacts of cleanups on cognitive performance and health outcomes are more limited. A study on infant health in five states found that Superfund cleanups reduced the incidence of congenital anomalies by roughly 20-25 percent among children living within 2 kilometers (km) of a contaminated site relative to those living 2-5 km from a contaminated site at birth (Currie et al. 2011). Research on Superfund sites in Florida showed significant positive effects on long-term cognitive and developmental outcomes after cleanup for children who lived within 2 miles (3.2 km) of a site at birth (Persico et al. 2016). Using data from Chile, researchers found that attending a school 1 km farther away from a lead-contaminated hazardous waste site significantly increased math and language scores for students living within 4 km of the site (Rau et al. 2015). We used statistical approaches similar to these studies to examine the effect of Superfund cleanups on children's BLL at sites spanning differing regions, lead contamination levels, and potential exposure pathways.

We developed a unique dataset that links two decades of BLL measurements from children in six states with data on the location and characteristics of Superfund cleanups and other risk factors for lead exposure. We estimated a difference-in-difference model that compares the change in the probability of elevated BLL for children located closer to versus farther from lead-contaminated Superfund sites before, during, and after cleanup. We defined "close" to a site as living within 2 km, and "farther" as living between 2-5 km.

We also estimated a triple difference model that includes children who live closer to and farther from Superfund sites that have minimal to no lead contamination as an additional comparison group. The intent is to help control for the fact that low-income or disadvantaged households are more likely to live near Superfund sites and are also more likely to be exposed to lead through other means, such as deteriorated lead paint in older housing. We used spatial fixed effects and matching to further minimize the potential for bias due to unobserved differences between the treatment and comparison groups. These approaches allow us to control for other sources of lead exposure and identify the how much of the reduction in children's BLLs near the sites were attributable to the Superfund program. Results indicate that Superfund cleanup lowered the risk of elevated BLL for children living within 2 km of a lead-contaminated site between 8 and 18 percent.

The Superfund Program

In the late 1970s, toxic waste dumps such as Love Canal and Valley of the Drums raised public concern over the risks to human health and the environment posed by contaminated sites. In response, Congress passed the Comprehensive Environmental Response, Compensation and Liability Act (CERCLA) in 1980. The law provided the U.S. Environmental Protection Agency (EPA) the authority to clean up contaminated sites and to compel parties responsible for the contamination to perform cleanups or reimburse the government for EPA-led cleanups. These sites include former manufacturing facilities, processing plants, landfills, and mining sites. The most common contaminants at these sites include lead, arsenic, and mercury. Contaminated media include sediments, soils, groundwater, and air. Under CERCLA, the most contaminated sites are assessed and then may be added to the National Priorities List (NPL)—a list of nation's most contaminated and complex hazardous waste sites. As of 2017, there were 1,475 sites on the NPL (U.S. EPA 2017).

There are four major milestones in the NPL cleanup process—proposal, listing, construction complete, and deletion. Once a hazardous waste site is identified, EPA conducts a preliminary assessment to understand the hazardous substances at the site and the severity of risks to human health and the environment. If there are excessive risks to public health due to site contamination, EPA may conduct a limited cleanup termed a time-critical removal action. EPA proposes that the site be added to the NPL if the assessment finds severe contamination and the site meets certain other criteria. EPA notifies the public by publishing the proposal in the Federal Register and providing information to local media outlets and the affected community.

After listing, a remedial investigation characterizes the extent of contamination, assesses all potential threats to human health and the environment, develops cleanup alternatives, and evaluates the performance and cost of those alternatives. It can take many years to develop and implement a permanent solution. These sites often require complex remedial actions, such as restoring contaminated groundwater or protecting wetlands. Construction complete is reached when the physical cleanup actions to address all immediate health threats and to bring all long-term threats under control are finished (US EPA 2018b), although final cleanup levels may not have been reached yet. A site or a portion of a site is deleted from the NPL if all cleanup goals have been met, long-term monitoring plans are in place, and no further cleanup is required to protect human health and the environment. If contamination is managed in place, the Superfund Program conducts five-years reviews to ensure the remedy remains protective. Deletion requires notification in the Federal Register and solicitation of comments from the public. As of 2017, 1,195 NPL sites had achieved construction complete, and 394 sites had been deleted from the NPL.

Data

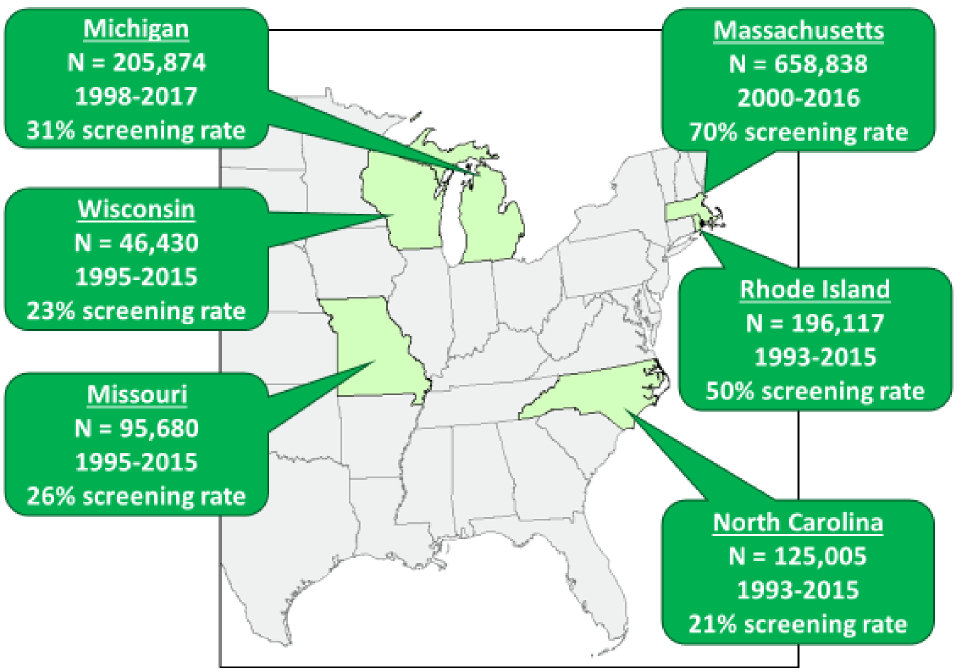
The primary data for the study are blood test results for all children age six months to five years old screened for lead from the mid-1990s to the mid-2010s in six states: Massachusetts, Michigan, Missouri, North Carolina, Rhode Island, and Wisconsin. The concentration of lead in blood is the metric most commonly used to assess lead exposure. Blood lead level (BLL), measured in micrograms of lead per deciliter of blood (μg/dL), is a useful outcome variable for this analysis in part because it is sensitive to recent lead exposure.[2]

[2] The half-life of lead in blood is roughly 30 days, and when exposure to lead drops, BLL typically falls to a new equilibrium within a few months. However, the relationship between lead exposure and blood lead is complicated by the fact that lead is also stored in bone and can be released from bone to blood over much longer time spans. The decline in BLL after a drop in exposure takes longer for highly exposed groups such as occupationally exposed workers (U.S. EPA 2013).

CDC recommends that states conduct widespread lead screening of children under age six. Federal law mandates testing of all children enrolled in Medicaid, though states vary in their screening policies, and not all states meet this goal (Safer Chemicals Healthy Families 2017). While state screening policies have varied over time, Massachusetts and Rhode Island currently require universal BLL testing, and the remainder of the states in our study focus on Medicaid recipients and other at-risk children. Figure 1 indicates that screening rates were higher in Massachusetts and Rhode Island than the other four states during the study period.

The state databases also included information about the child's sex, date of birth, home address, month and year of the blood lead test, and blood sample type.[3] Figure 1 reports the years of data obtained from each state.

Figure 1: Study area and time period



Children in the six states living within 5 km of at least one Superfund site that was added to the NPL or achieved construction complete during the study period comprise the sample for

[3] Our protocol for linking, managing, and analyzing these confidential data was approved by Institutional Review Boards in all six states. The Massachusetts Department of Public Health did not release home addresses to us but instead performed all data linkages requiring home address and then transferred partially de-identified data, including Census tract, to us. North Carolina did not release month of the blood lead test to us.

our analysis. Our focus on children located within 2 km relative to a control group 2 to 5 km from contaminated sites is consistent with past literature, which has found Superfund program impacts to be highly localized (Currie et al. 2011; Gamper-Rabindran and Timmins 2013; Timmins 2017). We used construction complete rather than deletion as the milestone to define "cleaned up," as this is the point when we expect that cleanup efforts have addressed all immediate and long-term health threats, and the time between construction complete and deletion may be very long.[4]

We constructed the key explanatory variables by determining the distance from each child's home address to each Superfund site boundary and identifying at what cleanup stage the child's blood lead test occurred.[5] The use of individual home addresses increases the precision of our distance measure compared to studies that used Census tract or zip code centroid to measure distance to environmental hazards (e.g., Persico et al. 2016; Zahran et al. 2017). Polygons representing approximate Superfund site boundaries were used for the location of the sites in the six study states, as well as sites in Illinois and Iowa that are located within 5 km of the study states.[6] We generated a 5 km buffer around each polygon and calculated the distance from each home address in the blood lead data that fell within the buffer to all sites located within 5 km. The distance to the site was recorded as zero when the child's address fell within Superfund site boundaries, which may occur at sites that include residential areas such as active military bases.

We used data from EPA's Superfund Enterprise Management System to identify cleanup milestone dates, whether lead was found as part of the remedial investigation, and whether lead was identified as a "contaminant of health concern" at each site (U.S. EPA 2017).[7] A

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[4] As of 2017, nationally only 29% of NPL sites had been deleted, whereas 89% had reached construction complete. Of the sites that have achieved construction complete but have not yet been deleted, on average those sites achieved construction complete approximately 15 years ago.

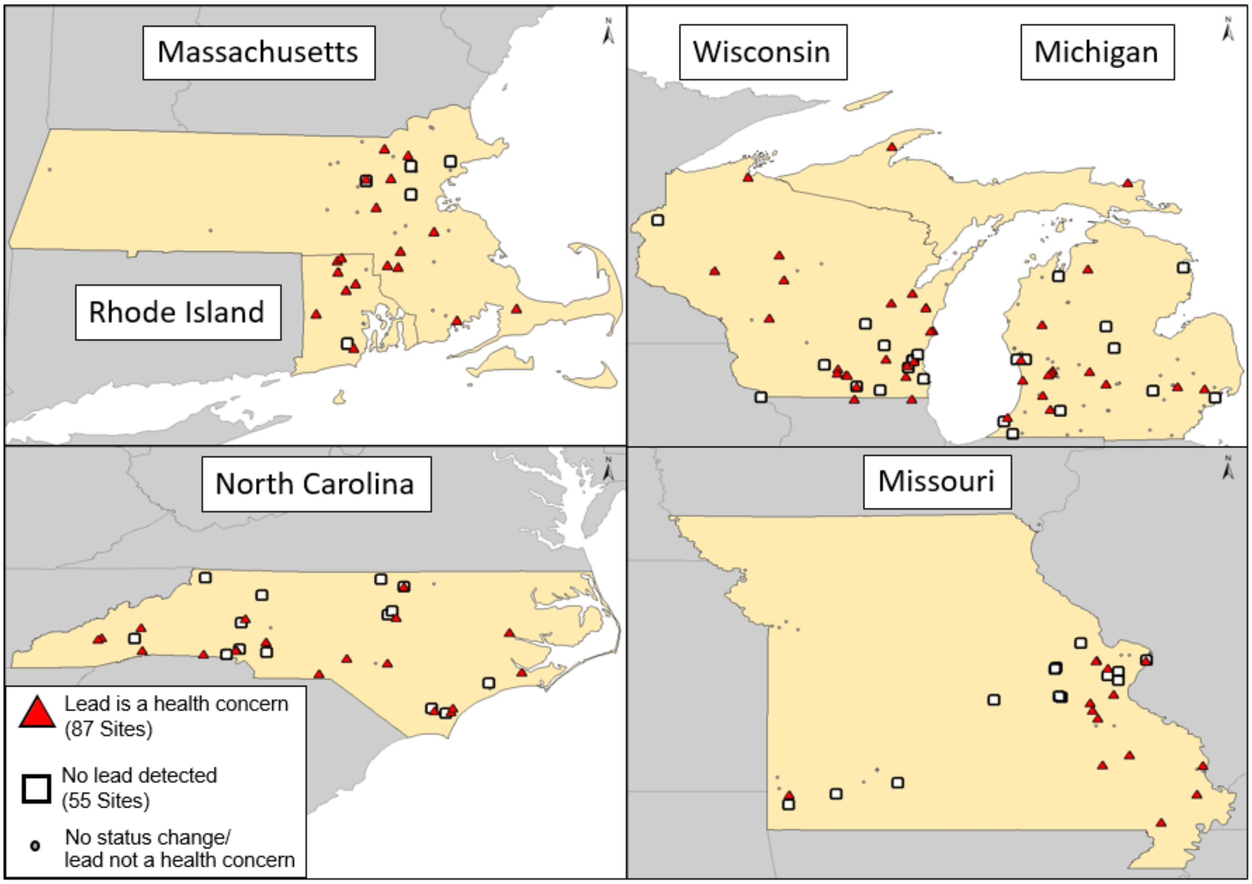
[5] We obtained distances between each child's home address and each Superfund site using ArcMap Geographical Information System software. We were unable to geocode 21% of home addresses across the Michigan, Missouri, North Carolina, Rhode Island, and Wisconsin lead screening databases. These addresses included incomplete or incorrect information or did not represent an accurate physical location (such as P.O. Boxes). These data were dropped from the analysis. The Massachusetts Department of Health geocoded all BLL data and determined distances between children's home addresses and Superfund sites in Massachusetts using a similar process. They were unable to geocode about 10% of Massachusetts addresses.

[6] Site boundary polygons were acquired from EPA's Office of Superfund Remediation and Technology Innovation (OSRTI). When site boundary polygons were not available from the existing OSRTI data, we used a combination of Agency for Toxic Substances and Disease Registry (ATSDR) Hazardous Waste Site Polygon Data and site-specific records containing attachments such as maps and satellite imagery from EPA's Superfund Enterprise Management System (ATSDR 2014; US EPA 2018).

[7] The Superfund Enterprise Management System is the official Superfund tracking and reporting system (replacing the Comprehensive Environmental Response, Compensation, and Liability System in 2014).

contaminant is identified as a “contaminant of health concern” when a baseline human health risk assessment shows that contaminant levels pose a potential risk to human health. A chemical does not represent a potential risk when adverse health effects are unlikely, and the probability of cancer due to site exposure is very small. Cleanup efforts are designed to manage human health and ecological risks at the site at protective levels (U.S. EPA 1989).

Figure 2: Superfund sites in study area where cleanup started or finished during study period



The analysis included 87 Superfund sites where lead was identified as a contaminant of concern and either were added to the NPL or reached construction complete during the study period (Figure 2). This represents approximately 11 percent of NPL sites nationwide where lead is a health concern. We also identified 55 sites that were added to the NPL or reached construction complete during the study period where lead was *not* found at levels that posed a health or ecological concern.[8] In the remainder of the paper, we refer to these as "non-lead" sites because the cleanup did not address lead, although there is a possibility that low levels of lead were present at these sites. The final dataset of all BLL measurements from children living within 5 km of at least one of these sites includes over 1.3 million observations (Table 1).

Table 1: Number of BLL observations by Superfund site proximity and contamination status

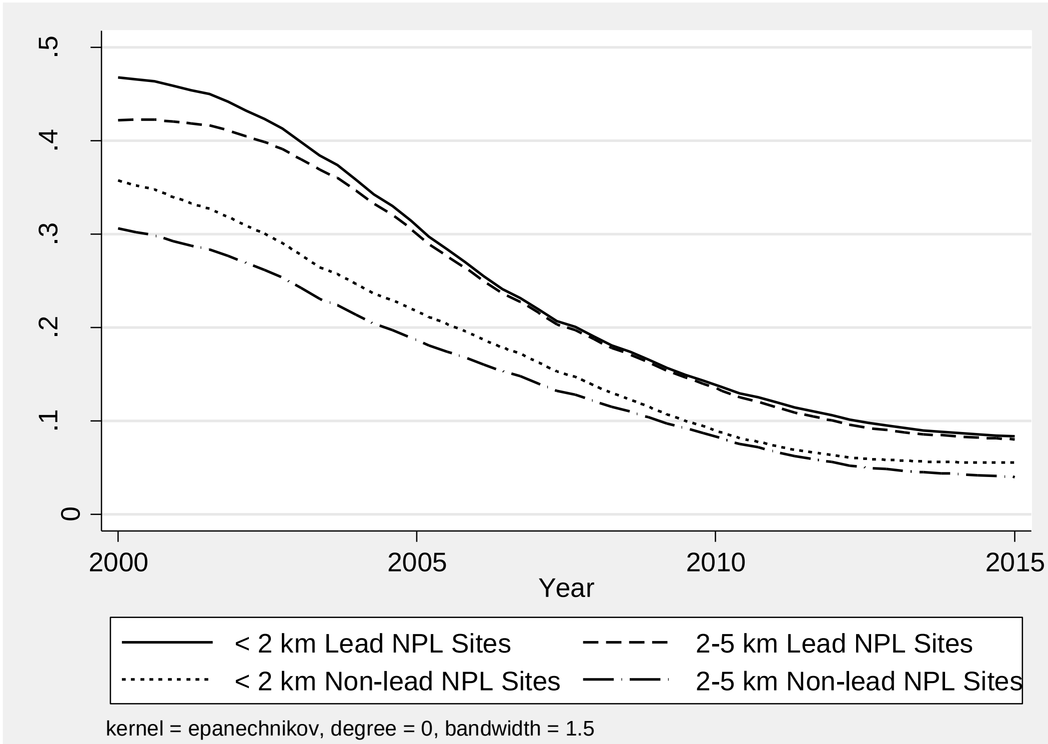
Superfund site contamination	Cleanup status	Proximity to sites ≤ 2 km	Proximity to sites 2-5 km	Total
Lead is a health concern	Before	39,645	74,028	113,673
	During	250,140	372,405	622,545
	After	147,729	363,474	511,203
Minimal to no lead contamination	Before	8,678	29,089	37,767
	During	17,844	67,528	85,372
	After	36,068	124,753	161,037
Total		467,658	893,684	1,361,342

*Note: Children may be located near multiple sites at different cleanup stages, so the sum of observations across cleanup status categories exceeds the total number of observations.

Figure 3 plots EBLL (defined as BLL above 3.3 μg/dL) in our sample during 2000-2015, the period for which we have data from all six states. It compares children in the treatment group (located within 2 km of a lead-contaminated Superfund site) to children farther from lead sites, close to non-lead sites, and farther from non-lead sites. The figure shows a similar dramatic decline in EBLL across all four groups. Unsurprisingly, EBLL rates were highest for children closest to lead sites. Children farther from lead sites had slightly lower EBLL rates earlier in the study period, though the two groups converge later. Children living within 5 km of non-lead sites have lower rates of EBLL than those living within 5 km of a lead site throughout the study period. Children living within 2km of non-lead sites had higher EBLL rates than children 205 km from non-lead sites.

[8] We excluded from our study 32 sites where lead was not classified as a contaminant of concern, but the Superfund Enterprise Management System indicated that lead was found and/or ATSDR data indicated that there was a completed exposure pathway for lead because we do not know whether cleanup reduced lead contamination at these sites. In addition, there were 89 sites in our study area that did not cross a Superfund milestone during the study period and so do not help identify the effect of the program (ATSDR 2017b).

Figure 3: EBLL over time among children in treatment and control groups



The home address at the time of the blood lead test was also used to link BLL observations to neighborhood characteristics and other geospatial data such as the location of other potential sources of lead exposure. While the most contaminated sites are generally under the Superfund program, lead is also a common contaminant at Resource Conservation and Recovery Act (RCRA) Corrective Action facilities. EPA develops guidance to assist RCRA Corrective Action facilities to conduct cleanups. We obtained data on the location of RCRA Corrective Action facilities' locations and whether lead was removed using RCRA Info, EPA's information system for cradle-to-grave waste tracking for RCRA hazardous waste handlers.

In contrast to other higher risk contaminated sites, a brownfield is a property for which a planned expansion, redevelopment, or reuse may be complicated by the presence or potential presence of a hazardous substance, pollutants, or contaminants. EPA's Brownfields Program has provided grants and technical assistance to communities, states, tribes, and other stakeholders to prevent, assess, safely clean up, and sustainably reuse brownfields. The presence of brownfields could serve as a proxy for an area of general decline and disinvestment with multiple community risk factors for lead exposure. We obtained data on the location and lead contamination status of federal Brownfields from the Assessment, Cleanup and Redevelopment Exchange System

(ACRES), a database for Brownfields grantees to submit data to EPA. Brownfield lead contamination status is based on information provided by EPA grantees and does not indicate the severity of contamination.[9]

For 35% of our sample, we obtained and linked individual property assessment data from Zillow, Inc. that included the age of the home.[10] Older housing is more likely to contain leaded paint and plumbing (Jacobs et al. 2002; Cornwell et al. 2016).[11] Exposure to lead in dust from deteriorated paint is currently the most common source of lead exposure for children in the U.S. (CDCb).

We obtained data on neighborhood characteristics at the tract level for each child in the dataset from the 1990, 2000, and 2010 decennial Censuses and the American Community Survey via the Geolytics Neighborhood Change Database, which accounted for the changes in Census tract boundaries over time by providing historical data in terms of 2010 boundaries. We also used Census data on the population of children age 0-4 along with the state blood lead data to estimate the BLL screening rate in each tract.[12] We used data on the concentration of lead in ambient air, also at the tract level, from EPA's National Air Toxics Assessment. We used data from the Department of Transportation[13] to construct a measure of traffic density in 1980 in the tract as a proxy for legacy contamination caused by leaded gasoline emissions, which was the

[9] Information on brownfield contamination status should be interpreted with caution. The U.S. EPA does not receive the results of site assessment or cleanup activities conducted by grantees or oversee their activities; oversight occurs under state law. Grantees provide no details on the number or distribution of sampling results or exceedances of risk threshold. Therefore, inferences about lead exposures at brownfield sites reported in ACRES are speculative.

[10] Data provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the authors and do not reflect the position of Zillow Group. When possible, we merged Zillow assessment data with BLL data based on an exact match of cleaned street address, city, and zip code. We then merged remaining unmatched BLL observations to Zillow assessment data using a spatial join in ArcMap, merging BLL addresses to the nearest Zillow property within 100 meters. Along with the other data sources, ZTRAX data were used to produce the results shown in Tables 2-5, A2-A6, Figure 3, and Figure A1.

[11] The sale of lead paint for residential use was banned in 1978, but it was used most frequently in homes built before 1940. Leaded water pipes and fixtures were banned for residential and public use in 1986 and were also more common in older housing.

[12] For Michigan, Missouri, North Carolina, Rhode Island, and Wisconsin, we summed the total number of successfully geocoded blood lead tests for each child age 0-4 in each Census tract over a multi-year period (typically 5-8 years) after eliminating repeat tests. We then divided this total by the estimated population of children age 0-4 in the Census tract for the corresponding time period. The Massachusetts Department of Health estimated the screening rates using a similar process.

[13] We use geospatial data on the lengths of different roadway types in each Census tract from the National Highway Planning Network, along with data on 1980 vehicle-miles traveled (VMT) per lane-mile by functional class from the Bureau of Transportation Statistics. We multiply road length by VMT per lane-mile for each roadway type and sum this product across roadway types within each Census tract to estimate 1980 traffic density.

largest source of lead exposure in the 20th century (U.S. EPA 2013). We incorporated data on average monthly temperatures by state from NOAA CIRES Climate Diagnostics Center, as warmer temperatures are associated with higher lead uptake in children (U.S. EPA 2013).

Table 2 presents summary statistics for the variables in our analysis. The first two columns compare means for the treatment group (observations within 2 km of lead-contaminated Superfund sites) and the control group (observations within 2-5 km of lead-contaminated sites and within 5 km of non-lead sites). In the next section, we discuss the matching procedure that we used in some of our analyses to restrict the sample to the common support in key control variables across the treatment and control groups. The remaining columns in Table 2 present means for the treatment and control groups from the matched sample, as well as L1 statistics measuring imbalance across the two groups for the full and matched samples.

Table 2: Summary statistics for treatment (within 2 km of a lead site) and control (within 2-5 km of a lead site or 0-5 km of a non-lead site) groups across full and matched samples

	Full sample			*Matched sample with weights*		
	≤ 2 km Pb Mean (SD)	2-5 km Pb or 0-5 km non-Pb Mean (SD)	L1*	≤ 2 km Pb Mean (SD)	2-5 km Pb or 0-5 km non-Pb Mean (SD)	L1
Individual level variables						
Blood lead ≥ 3.3 μg/dL (%)	0.27 (0.45)	0.25 (0.43)	0.02	0.24 (0.43)	0.23 (0.42)	<0.01
Blood lead ≥ 5 μg/dL (%)	0.18 (0.39)	0.17 (0.37)	<0.01	0.16 (0.37)	0.15 (0.36)	<0.01
Male (%)	0.51 (0.50)	0.51 (0.50)	<0.01	0.51 (0.50)	0.51 (0.50)	<0.01
Age (years)	2.04 (1.41)	1.97 (1.39)	0.02	1.97 (1.37)	1.92 (1.34)	0.02
Capillary blood sample (vs. venous sample) (%)	0.63 (0.48)	0.55 (0.50)	0.11	0.60 (0.49)	0.62 (0.49)	0.02
Sample year	2006.7 (5.75)	2006.4 (6.05)	0.04	2006.6 (5.90)	2006.6 (6.01)	0.03
Average monthly temperature at time of BLL test** (degrees)	48.53 (17.39)	47.56 (17.00)	0.14	48.61 (17.38)	47.63 (17.18)	0.08
Number of brownfields sites with grantee-reported lead contamination ≤ 2 km	2.08 (3.68)	2.28 (4.57)	0.26	1.50 (3.52)	1.46 (3.46)	0.08
RCRA site with lead ≤ 2 km (%)	0.23 (0.42)	0.13 (0.33)	0.12	0.18 (0.38)	0.15 (0.35)	0.05

Property built pre-1940*** (%)	0.35 (0.48)	0.39 (0.49)	0.08	0.30 (0.46)	0.29 (0.45)	0.03
Property built 1940-1959*** (%)	0.16 (0.36)	0.16 (0.37)	<0.01	0.15 (0.40)	0.16 (0.37)	0.02
Property built 1960-1978*** (%)	0.21 (0.41)	0.18 (0.38)	0.05	0.23 (0.42)	0.23 (0.42)	<0.01
Census tract variables						
Housing stock built pre-1940 (%)	0.31 (0.26)	0.30 (0.25)	0.18	0.22 (0.21)	0.24 (0.21)	0.13
Housing stock built 1940-1959 (%)	0.20 (0.11)	0.20 (0.12)	0.18	0.20 (0.12)	0.21 (0.11)	0.14
Housing stock built 1960-1979 (%)	0.23 (0.13)	0.24 (0.14)	0.16	0.27 (0.12)	0.26 (0.12)	0.13
Population receiving public assistance (%)	0.08 (0.08)	0.06 (0.07)	0.19	0.06 (0.07)	0.05 (0.06)	0.10
Population African American (%)	0.12 (0.20)	0.14 (0.19)	0.20	0.13 (0.21)	0.12 (0.18)	0.11
Population Hispanic (%)	0.10 (0.13)	0.10 (0.14)	0.23	0.08 (0.12)	0.09 (0.15)	0.10
Housing stock rental occupied (%)	0.42 (0.23)	0.43 (0.23)	0.21	0.35 (0.21)	0.35 (0.20)	0.15
Adults less than high school education (%)	0.14 (0.07)	0.11 (0.08)	0.30	0.12 (0.07)	0.11 (0.07)	0.15
BLL screening rate (%)	0.45 (0.28)	0.46 (0.25)	0.33	0.39 (0.25)	0.40 (0.24)	0.16
Lead air concentration (μg/m^3)	0.002 (0.02)	0.001 (0.003)	0.08	0.002 (0.008)	0.001 (0.002)	0.07
1980 traffic density (miles/ m^2)	0.002 (0.016)	0.003 (0.024)	0.11	0.002 (0.013)	0.003 (0.027)	0.06
Observations	405,068	956,274		215,014	382,955	

Observations are weighted by the inverse of the number of blood samples per child.
*The L1 statistic is a measure of imbalance across the entire distribution of a variable between the treatment and control groups. An L1 of 0 indicates that histograms of the variable among the treatment and control groups overlap perfectly, while an L1 of 1 indicates that the histograms do not overlap at all.
**Variable only available for 91% of sample.
***Source: ZTRAX; Variable only available for 35% of sample.

Econometric Approach

We relied on a difference-in-difference (DiD) quasi-experimental approach to identify the effect of Superfund cleanups on children's lead exposure. Quasi-experiments attempt to mimic the design of a randomized controlled trial by comparing a "treatment" group that receives a particular intervention (cleanup of a lead-contaminated Superfund site) with a "control" or comparison group that does not receive the intervention but is otherwise similar to the treatment group. This approach helps to isolate the impact of the treatment on the outcome of interest (children's BLL).

Identifying a valid control group when analyzing the effects of environmental programs in real-world settings can be challenging. As the environmental justice literature has shown, exposure to environmental hazards is rarely random; low-income and minority communities are disproportionately affected. This situation holds true in many communities containing Superfund sites (Ringquist 2005). Several studies have addressed this challenge by examining neighborhoods slightly farther away from contaminated sites as a control group for neighborhoods closer or adjacent to these sites (Currie et al. 2011; Gamper-Rabindran and Timmins 2013; Guignet 2013; Zabel and Guignet 2012; Guignet et al. 2016).

In our first model, we used this same approach, comparing the change in the probability of EBLL for children located closer to versus farther from lead-contaminated Superfund sites before, during, and after cleanup. The DiD sample is comprised of lead test results from children who lived within 5 km of a lead-contaminated Superfund site that either started or ended cleanup during the study period. (Sites that did not change cleanup status during the study period do not help identify the program's impact.) We estimated an equation explaining the probability that an individual child's BLL was elevated as a function of several measurable characteristics related to the child and the child's neighborhood at the time of measurement. The following equation describes this relationship, where $EBLL_{ijst}$ is a dichotomous variable indicating whether child *i* in neighborhood *j* in state *s* at time *t* had an elevated BLL:

$$\begin{aligned} EBLL_{ijst} &= \beta_0 + \beta_1 PBduring_{it} + \beta_2 PBafter_{it} + \beta_3 closePBbefore_{it} + \beta_4 closePBduring_{it} + \\ &\beta_5 closePBafter_{it} + \boldsymbol{\beta_6 X_{it}} + \boldsymbol{\beta_7 Z_{jt}} + \boldsymbol{\gamma_{st} state_s} * \boldsymbol{Y_t} + \boldsymbol{\alpha_j FE_j} + \varepsilon_{ijt} \end{aligned} \tag{1}$$

$PBduring_{ijt}$ and $PBafter_{ijt}$ are indicators that were set equal to one if the child lived within 5 km of a lead-contaminated site during or after cleanup, respectively, at the time of the blood lead test.[14] The omitted category captures children living within 5 km of a site before cleanup started. The indicators $closePBbefore_{ijt}$, $closePBduring_{ijt}$, and $closePBafter_{ijt}$ were set equal to one if the child

[14] We use the notation "PB" to indicate lead-contaminated sites following the chemical symbol for lead (Pb).

lived within 2 km of a lead-contaminated site before, during, or after cleanup at the time of the lead test.[15] The before, during, and after cleanup variables are not mutually exclusive if a child lived near multiple sites at different stages of cleanup. We also conducted sensitivity analysis regarding the use of 2 km to define "close" by examining other distance buffers.

The vector $\boldsymbol{X}_{it}$ contains child-specific control variables, including sex, age at the time of the blood lead test, state average monthly temperature at the time of the test, blood sample type (capillary or venous), and an indicator for whether the lead test was affected by a 2017 Food and Drug Administration alert.[16] Boys tend to have higher BLL than girls, and BLL varies systematically during early childhood due to changes in exposure and absorption, typically peaking around age two when children are most likely to exhibit hand-to-mouth behavior (National Toxicology Program 2012). Childhood BLL also shows a seasonal pattern, rising in the summer due to increased outdoor soil lead exposure (U.S. EPA 2013).

We included proxies for a few other potential sources of lead exposure measured at the individual level in $\boldsymbol{X}_{it}$. These include a dummy variable for presence of a RCRA Corrective Action site with lead and a variable measuring the number of properties with grantee-reported lead contamination receiving federal Brownfields grants within 2 km of the child's address. It is important to control for proximity to these sites if they tend to be located near lead-contaminated Superfund sites due to past industrial development. We included dummy variables indicating that the child lived in older housing constructed before the ban on leaded paint (before 1940, 1940-1959, and 1960-1978) generated using the ZTRAX individual property assessment data, when available.

Neighborhood characteristics, defined at the level of the Census tract, were included in $\boldsymbol{Z}_{jt}$. Socioeconomic characteristics that may help predict EBLL include the percent of the population receiving welfare assistance, percent African American population, percent Hispanic population, percent adult population with less than a high school education, and percent housing

[15] Twenty-nine percent of the data are BLL measurements from children who lived within 5 km of more than one Superfund site. Our results are robust to the exclusion of these observations.
[16] Capillary ("finger prick") samples are easier to collect, but they are more susceptible to contamination during collection (U.S. EPA 2013; Parsons, Reilly, and Esernio-Jenssen 1997). However, in 2017, the Food and Drug Administration issued a warning that blood lead tests performed on venous samples with a Magellan Diagnostics Inc. LeadCare Testing System yielded false negatives (FDA 2017 https://www.fda.gov/medicaldevices/safety/alertsandnotices/ucm558733.htm). One half of one percent of our sample is affected by this alert.

stock that is renter-occupied. We also included percent of the housing stock constructed before 1940, during 1940-1959, and during 1960-1979 to help control for lead exposure from dust and water in the home since we were unable to obtain individual housing age data for our full sample. Other variables include concentration of lead in ambient air, the blood lead screening rate, and 1980 traffic density. We also included an interaction between 1980 traffic density and years since 1980 to account for the potential decline in importance over time of this source of legacy contamination. Recent literature has shown similar characteristics to be predictive of children's blood lead levels measured by state surveillance data (Zahran et al. 2017; Schultz et al. 2017; Aizer and Currie 2017). We included these control variables to help mitigate the potential for omitted variable bias that would result if the location of lead-contaminated Superfund sites and timing of cleanup are correlated with other determinants of lead exposure.

We included two alternative sets of spatial fixed effects to control for time invariant neighborhood characteristics that affected lead exposure. The first set of fixed effects represents the nearest Superfund site or site group. For 71% of the dataset, this vector captures the nearest single Superfund site. The remaining 29% of the dataset represents children living within 5 km of two or more Superfund sites. We grouped such sites together when constructing the fixed effects because children living near co-located sites may have shared other common neighborhood characteristics affecting lead exposure. Our alternative approach was to define the fixed effects at the level of the Census tract, which is a much finer spatial resolution than Superfund sites. While Census tract characteristics discussed above mostly vary cross-sectionally, they also vary over time (except for 1980 traffic density) and so are still identified in the Census tract fixed effects model. In the Appendix, we discuss results from a model that used individual address-level fixed effects. This model controls for all time-invariant property characteristics (such as the presence of leaded paint or plumbing) but has much less power to detect the effects of Superfund cleanup.

Finally, all models included state by year fixed effects. As already noted, lead exposure trended steadily downward in the U.S. during the study period. The state by year fixed effects capture flexible trends that can vary geographically.

The coefficients to be estimated are β, γ, and α, and ε_{ijt} is a normally distributed error term. The change from before to after cleanup for those living close to the site (i.e., the first difference) is given by $\beta_2 + \beta_5 - \beta_3$, while the change from before to after cleanup for those living farther away is represented by β_2. The treatment effect—the impact of cleaning up a lead-contaminated site on EBLL for those living nearest the site, after netting out the trend experienced by the control group—is given by $\beta_5 - \beta_3$.

As already noted, we attempted to isolate the effect of Superfund site proximity and cleanup status from other determinants of lead exposure in the DiD model through an extensive set of control variables, as well as a treatment group that is likely to experience common trends in lead exposure sources as the control group, except for proximity to the Superfund site. However, it is still possible that there are unobserved factors that drive lead exposure patterns near Superfund sites due to their location in neighborhoods that are often economically disadvantaged—and that may experience gentrification or sorting as cleanup occurs (Currie 2011)—that are not adequately captured in this model.

Therefore, we extended the DiD analysis to include BLL measurements from children who lived within 5 km of Superfund sites where lead was *not* listed by EPA as a contaminant (though it may have been present at low levels). This technique is called difference-in-difference-in-differences, or triple difference (Wooldridge 2007). The triple difference model we estimated is:

$$\begin{aligned}EBLL_{ijst} &= \beta_0 + \beta_1 during_{it} + \beta_2 after_{it} + \beta_3 PBbefore + \beta_4 PBduring_{it} + \beta_5 PBafter_{it} + \\ &\beta_6 closebefore_{it} + \beta_7 closeduring_{it} + \beta_8 closeafter_{it} + \beta_9 closePBbefore_{it} + \beta_{10} closePBduring_{it} + \\ &\beta_{11} closePBafter_{it} + \boldsymbol{\beta_6 X_{it}} + \boldsymbol{\beta_7 Z_{jt}} + \boldsymbol{\gamma_{st} state_s} * \boldsymbol{Y_t} + \boldsymbol{\alpha_j FE_j} + \varepsilon_{ijt}\end{aligned} \tag{2}$$

The model included the indicators $during_{it}$ and $after_{it}$ to denote living near any Superfund site (with or without lead contamination) while cleanup is occurring and once it is complete, respectively. It also included indicators for living within 2 km of any Superfund site before, during or after cleanup ($closebefore_{it}$, $closeduring_{it}$, and $closeafter_{it}$, respectively). The triple difference estimate of the effect of cleaning up lead-contaminated sites on the probability of elevated BLL is given by $\beta_{11} - \beta_9$. In addition, $\beta_8 - \beta_6$ gives the change in the probability of elevated BLL for children living near non-lead Superfund sites. This effect will be non-zero if changing neighborhood demographics, redevelopment patterns, or other factors associated with Superfund cleanups systematically affect children's BLL at sites with minimal to no lead contamination.

We estimated equations (1) and (2) using a linear probability model due to the large number of fixed effects. We weighted the regressions by the inverse of the number of blood lead tests per child so that the estimates give equal weight to each child in the sample, rather than giving more weight to children with repeat tests.[17] We clustered standard errors by Superfund site group to account for heteroskadasticity across communities.

We relied on covariate matching as an additional approach to mitigate the potential for omitted variable bias. We used coarsened exact matching (CEM) to focus the analysis on BLL measurements from children who were similar in terms of key characteristics that are likely to be correlated with both lead exposure and proximity to Superfund sites. CEM provides a non-parametric approach to control for these characteristics by limiting the analysis to observations with a common support across the treatment and control groups.

Using CEM, the researcher "coarsens" continuous covariates into discrete bins. We matched on three Census characteristics—percent of housing stock built prior to 1940, percent of the population receiving welfare assistance, and percent African American. Housing age, poverty, and race are important predictors of children's BLL and are have been used to target at-risk communities for BLL screening (Roberts and English 2016; Schultz et al. 2017; Safer Chemicals Health Families 2017). We also matched on the number of Brownfields sites with grantee-reported land contamination within 2 km, the year of the BLL test, and the closest Superfund site.[18]

[17] The mean number of BLL tests per child in the dataset is 2.6. Repeat universal testing was more frequent in Rhode Island and Massachusetts than in in Michigan, Missouri, North Carolina, and Wisconsin. Children with BLL above the CDC level for public health intervention (10 μg/dL until 2012, 5 μg/dL after 2012) were more likely to have repeat tests.

[18] Coarsening involves a tradeoff between sample size and balance (King et al. 2015). We coarsened each Census variable using 15 equally spaced cutpoints. Cutpoints for these variables were determined automatically by the CEM algorithm, which we ran separately for each state. We coarsened the Brownfields variable using three to four cutpoints and the sample year variable using four to nine cutpoints, with more cutpoints used in states with larger datasets. We selected the cutpoints for the Brownfields and sample year variables to achieve a similar number of observations in each bin. For the DiD model, we used an exact match (no coarsening) for the closest Superfund site due to the discrete nature of this variable. For the triple difference model, we implemented a two-step matching procedure to ensure similar characteristics across children at lead and non-lead sites within each state in addition to similar characteristics across children close to and farther from each individual Superfund site. First, we used the procedure described above to match on housing age, welfare, African American, Brownfields, and sample year

The procedure allows us to compare observations that are similar along all of these dimensions simultaneously. For example, if the matched sample includes a BLL result taken during 2002-2003 from a child who lived in a Census tract with a lot of pre-1940 housing and welfare recipients and few African Americans, near no Brownfields, and within 2 km of a lead-contaminated Superfund site in Massachusetts, it must also include a BLL result from a child with these same characteristics but located 2 to 5 km from the same Superfund site.

We implemented the matching procedure using the CEM command in Stata, allowing many-to-one matching (Blackwell et al. 2010; Iacus et al. 2012). CEM assigns each observation to a stratum defined by a unique value of each of the coarsened covariates simultaneously. It drops all observations that fall into strata that do not contain observations from both the treatment and control groups. It then generates weights that balance the number of observations in each stratum across the treatment and control groups. Observations without a match are assigned a weight of zero. We ran the matched regressions using these weights.

The right half of Table 2 shows summary statistics for the treatment and control groups using the matched sample. The matching procedure pruned 56% of observations. Means of most covariates are closer across the treatment and control groups using the matched sample compared to the full sample. In the full sample, L1 statistics range from < 0.01 to 0.33, indicating moderate imbalance in some covariates. After matching, the L1 statistics declined substantially for most variables (not just those used in the matching algorithm), with a maximum imbalance of 0.16.[19] In addition, the multivariate L1 statistic representing joint imbalance across the four environmental and socioeconomic covariates used for matching (pre-1940 housing, welfare recipients, African American population, and Brownfields) fell from 0.84 to 0.45.[20]

Measurement error is another potential concern that could bias the estimates of interest. Most laboratories report the accuracy of their blood lead tests to be ±2 ug/dL, which is large considering that the current population mean is below 1 ug/dL (Caldwell et al. 2017). Because our dependent variable is binary, measurement error can lead to inconsistent estimates (as well as

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within each state but did not match on the closest Superfund site. After dropping all observations without a match in the first step, we re-ran the same matching algorithm, this time including the closest Superfund site as an exact match variable.

[19] L1 statistics provide a measure of imbalance across the entire distribution of a variable between the treatment and control groups (Blackwell et al. 2010). An L1 of 0 indicates that histograms of the variable among the treatment and control groups overlap perfectly, while an L1 of 1 indicates that the histograms do not overlap at all.

[20] Multivariate imbalance is lower in the DiD sample (limited to observations located within 5 km of a lead-contaminated Superfund site), falling from 0.81 to 0.38 after matching.

reduced precision). Measurement error in a binary dependent variable is negatively correlated with the error term, so it typically leads to attenuation, biasing the coefficient estimates towards the null (Hausman et al. 1998; Meyer and Mittag 2017).

We also expect error in our measure of exposure to lead from Superfund sites. Measurement error in an independent variable also biases the coefficient estimate of that variable towards the null (and biases coefficient estimates of colinear variables, though the direction of bias depends on the sign of the correlation with the mismeasured variable; Hausman 2001). We defined our treatment and control groups using buffers that extend an equal amount in all directions from the boundaries of each Superfund site, even though there is likely to be heterogeneity in the spatial extent of exposure across sites. Due to data limitations, the Superfund exposure variables in our study also fail to account for variation across sites in the type of contaminated media or the severity of lead concentration, though we limited our analysis of lead sites to those where EPA determined that lead was a contaminant of human health concern. In addition, the dates we used to distinguish the periods before, during, and after cleanup may not correspond exactly to remediation efforts at the site. Cleanup actions can occur even before sites are added to the NPL, especially if severe contamination warrants an emergency response. Finally, there may be error in the geocoding of home addresses that we use to measure distance to Superfund sites.[21] We do not take any formal measures to address attenuation bias in our analysis, but it is an important caveat to keep in mind when interpreting our results.

Selection bias could also affect our results if either blood lead screening or residence at an address that could not be geocoded are correlated with exposure to lead-contaminated Superfund sites. Our screening rate variable captures both effects. As already noted, Massachusetts and Rhode Island are the only states in our study area that currently require universal BLL screening, and rates still fall short of 100% in these states. Guidelines in Michigan, Missouri, North Carolina, and Wisconsin require screening for all children receiving Medicaid and recommend screening for other at-risk children (Safer Chemicals Healthy Families 2017). Thus, screening was neither comprehensive nor random, but rather was directed towards children most likely to have elevated BLL, such as those living in poverty and in older housing.

[21] Because our dataset excluded children over age five and most children were tested at age one or two, we do not expect the location of schools to drive lead exposure in our sample.

To address the potential for bias due to nonrandom screening and/or geocoding success, we included the estimated Census tract screening rate as a control variable in the EBLL regressions. Our matching procedure also helps to mitigate this issue, since we matched on the same types of variables that are used to target at-risk households and neighborhoods. The L1 statistic for screening rate confirms that matching reduced imbalance in this variable by more than fifty percent. Finally, we found that screening rate is uncorrelated with location within 2 km of a lead-contaminated Superfund site after conditioning on the other individual and Census tract control variables included in equations (1) and (2) (coefficient = -0.0008, p = 0.92).

Results

Table 3 presents the key coefficients estimates from the difference-in-difference model. Estimates in columns (1) and (3) use Superfund site fixed effects, and estimates in (2) and (4) use Census tract fixed effects. Columns (1) and (2) include the full sample of children living within 5 km of a lead-contaminated Superfund site, while columns (3) and (4) use the pruned sample and weights derived from coarsened exact matching. All four variants of the model yield similar results: They show that, prior to the start of cleanup, children living within 2 km of a lead-contaminated Superfund site had significantly higher rates of EBLL than children living 2-5 km away, by 3 to 4 percentage points. During cleanup, the difference between the two groups fell and was no longer statistically significant. After cleanup, rates of EBLL among children closest to the site were slightly lower than those in the control group, though this effect is only statistically significant in column (1). Subtracting the "before cleanup" coefficient from the "after cleanup" coefficient to derive the net treatment effect shows that EBLL declined by 3.4 to 5.1 percentage points relative to the control group.

Appendix Table A.3 presents the same set of model estimates using a higher value of 5 μg/dL as the cutoff for EBLL. The results are very similar to those using a 3.3 μg/dL cutoff, yielding a net 3.6 to 4.2 percentage point drop in EBLL in the treatment group as a result of cleanup.

Table 3: Difference-in-difference estimates of the effect of Superfund cleanup on elevated blood lead level (≥ 3.3 μg/dL)

	(1)	(2)	(3)	(4)
Fixed effects	Superfund site	Census tract	Superfund site	Census tract
Matching	No	No	Yes	Yes
Close Pb before	**0.037** (0.013)**	**0.044*** (0.011)**	**0.036*** (0.013)**	**0.030* (0.016)**
Close Pb during	**0.007 (0.005)**	**0.009 (0.007)**	**0.003 (0.006)**	**-0.001 (0.009)**
Close Pb after	**-0.014** (0.005)**	**-0.003 (0.006)**	**-0.005 (0.008)**	**-0.004 (0.010)**
R2	0.29	0.30	0.27	0.28
N	1,046,392	1,046,392	494,473	494,473
# of groups	68	994	62	683

All standard errors are clustered at the Superfund site group level. *** p<0.01, ** p<0.05, * p<0.1
Observations are weighted by the inverse of the number of blood samples per child.

Coefficient estimates for the full set of individual and neighborhood control variables highlight other drivers of children's lead exposure. In fact, many other risk factors have a larger effect on EBLL than proximity to a lead-contaminated Superfund site. Appendix Table A.2 presents these estimates for the Superfund site fixed effects model using the unmatched sample, corresponding to column (1) in Table 3. Results are consistent with past literature predicting children's lead exposure patterns (Miranda, Anthopolos, and Hastings 2011; Schwartz et al. 2017; Zahran et al. 2017; Wheeler et al. 2019). Rates of EBLL were significantly higher among boys and children tested at 2 to 3 years old, during warmer months, and using capillary blood samples. Housing age was a critical determinant of lead exposure. Children living in pre-1940 housing were 10 percent more likely to have EBLL than those living in post-1978 housing. Housing built during 1940-1978 posed a smaller but still statistically significant risk. Children living in housing where the year built is missing from assessment records were also at higher risk, which makes sense if these properties tend to be older. Similarly, children living in a Census tract where all housing was built before 1940 were 17% more likely to have EBLL, though the percent of 1940-1979 housing is not statistically significant relative to the percent of housing built after 1979.

The Census tract screening rate is also highly predictive of EBLL, confirming that screening efforts targeted at-risk children. Children in Census tracts with a higher concentration of welfare recipients, African Americans, rental housing, and less educated adults, and a lower concentration of Hispanics were at significantly higher risk, even though the coefficients of some of these variables may be attenuated by inclusion of the screening rate variable since these characteristics were used for targeting. Census tracts with more traffic density in 1980 also had higher rates of EBLL, though the effect declined in importance over time since the phase out of leaded gasoline, consistent with Aizer and Currie's (2017) results. Proximity to Brownfields sites with grantee-reported lead contamination is another statistically significant risk factor. Ambient air lead concentration and location near a RCRA Corrective Action site with lead are not significantly predictive of EBLL. While not presented, the spatial fixed effects are highly significant, as are state by year fixed effects. All states showed a downward trend in EBLL over time, with EBLL dropping by 35 percentage points on average from 2000-2015 after controlling for all other covariates.

Table 4 presents results from the triple difference model. The four sets of estimates again correspond to differences in fixed effects and the use of matching. We contrast the rates of EBLL for children living near a site with little to no lead contamination (in regular text) with those for children near a lead-contaminated site (emphasized in bold text), relative to children farther away from each type of site, respectively. The results show that children living near non-lead sites had significantly higher rates of EBLL than children living farther from these sites, suggesting that risk near Superfund sites may not have been entirely due to contaminants from the site itself. Rather, other unobserved risk factors for lead exposure may have been co-located with contaminated sites. Once the triple difference model nets out this effect, children within 2 km of lead-contaminated sites before cleanup did not have significantly higher rates of EBLL.

However, EBLL rates diverged between the two groups after cleanup was complete: The risk for children located near lead-contaminated sites declined significantly more than for those near non-lead sites. This result suggests that Superfund program interventions did result in reduced lead exposure, even if the site itself it was not entirely responsible for elevated risk prior to cleanup. The net effect is a drop in EBLL of 2.0 to 4.9 percentage points for those close to lead sites, depending on the model. The results using an EBLL cutoff value of 5 μg/dL, shown in Table A.4, are similar.

Table 4: Triple difference estimates of the effect of Superfund cleanup on elevated blood lead level (≥ 3.3 μg/dL)

	(1)	(2)	(3)	(4)
Fixed effects	Superfund site	Census tract	Superfund site	Census tract
Matching	No	No	Yes	Yes
Close before	0.020 (0.013)	0.036** (0.018)	0.037** (0.016)	0.032* (0.017)
Close during	0.004 (0.010)	0.002 (0.009)	-0.004 (0.006)	-0.002 (0.006)
Close after	0.021*** (0.003)	0.012** (0.005)	0.024*** (0.006)	0.024*** (0.008)
Close Pb before	**0.015 (0.019)**	**0.021 (0.021)**	**-0.009 (0.020)**	**-0.006 (0.02)**
Close Pb during	**0.004 (0.010)**	**0.006 (0.011)**	**0.010 (0.009)**	**0.003 (0.012)**
Close Pb after	**-0.034*** (0.006)**	**-0.016** (0.007)**	**-0.029*** (0.007)**	**-0.027*** (0.008)**
R2	0.28	0.29	0.27	0.28
N	1,327,943	1,327,943	581,412	581,412
# of groups	98	1355	92	886

All standard errors are clustered at the Superfund site group level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Observations are weighted by the inverse of the number of blood samples per child.

The triple difference estimates of the net benefits of cleanup are slightly lower but generally similar to the estimates from the DiD model. The biggest difference between the two sets of estimates is the timing of the effect. The DiD model estimates suggest that EBLL fell relative to the control group during cleanup. The triple difference model instead finds that EBLL rates did not fall significantly relative to the control group until after cleanup.

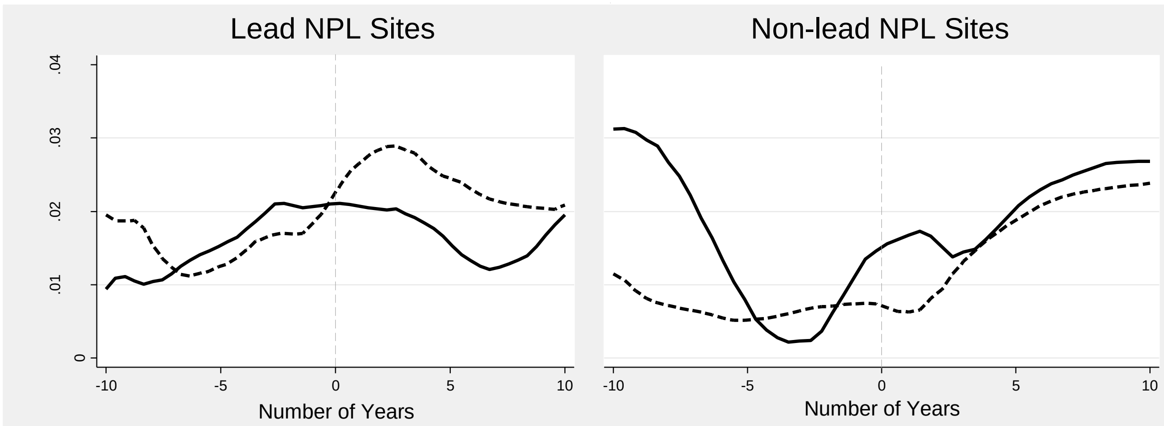
It is not clear which set of estimates is preferable, since each model has advantages. The DiD model directly compares children living close to and slightly farther from the same lead-contaminated sites who are also likely to share other common exposure sources. The triple difference estimates help control for systematic drivers of EBLL across Superfund sites broadly, since they are based on comparisons to children living near non-lead sites located in other communities, which may have other differences in lead exposure. However, at least some of these sites have had low levels of lead present. Using the entire range of estimates from the DiD and triple difference models and given an average rate of EBLL of 23.7% among children in the treatment group after cleanup, the results imply that EBLL among children in the treatment group fell by 8 to 18 percent as a result of Superfund cleanup.

We present the results graphically to gain insights about the timing of the drop in EBLL resulting from cleanup. Figure 4 plots the mean residuals of a series of EBLL regressions binned by time since the cleanup milestones. The regressions were estimated separately for children near lead-contaminated sites and for children near non-lead sites and included all control variables in X_{it} and Z_{it}, as well as Superfund site fixed effects, but excluded the Superfund site exposure variables. Number of years was calculated as the difference between the blood lead test year and the cleanup milestone year. Panel A shows the listing milestone, while Panel B presents construction complete. We considered these milestones separately because most sites in our sample crossed just one of these milestones during our study period.

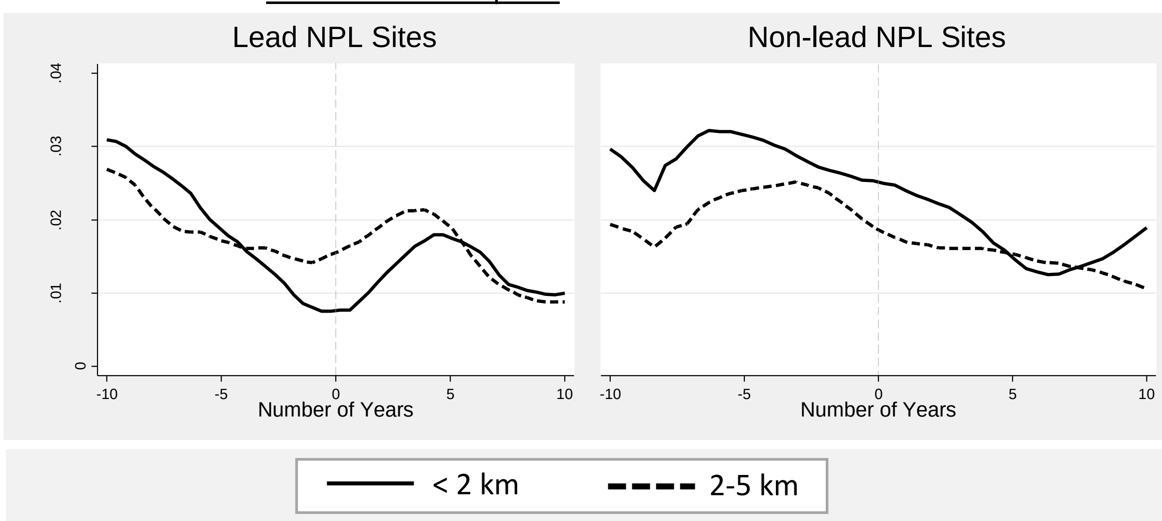
Panel A confirms that EBLL rates among children within 2 km of lead-contaminated sites fell relative to those of children 2-5 km away when sites were added to the NPL, but the same pattern did not hold at sites with minimal to no lead contamination. It also illustrates that there were common trends between children closest to and farther from lead-contaminated sites in all unobserved factors affecting EBLL, particularly in the years leading up to the listing of sites on the NPL. Panel B shows that EBLL among children within 2 km of lead-contaminated sites was also lower relative to children 2-5 km away after construction complete. The drop occurred a few years before the construction complete milestone was reached, which makes sense because lead would have been removed or contained to limit exposure during cleanup. There was no notable change in relative EBLL between children located closer to and farther from non-lead Superfund sites when construction complete was reached (though EBLL rates among the two groups temporarily converged 5-7 years after construction complete).

Figure 4. Probability of EBLL at lead-contaminated and non-lead Superfund sites before and after “listing” and “construction complete” cleanup milestones

A. Before and after <u>listing</u>



B. Before and after <u>construction complete</u>



Note: After regressing the probability of EBLL on characteristics related to the child, the child’s neighborhood, state*year dummies, and Superfund site fixed effects, we plotted mean residuals binned by the time from NPL milestones and smoothed using lpoly (kernel=epanechnikov, degree=0, bandwidth=1.5). Number of years was calculated as the difference between the blood lead test year and the relevant cleanup milestone year (listing in Panel A and construction complete in Panel B). The solid line represents observations within 2 km of a site. The dashed line represents those within 2-5 km of a site. The left shows results for lead sites, and the right for non-lead sites. Observations were weighted by the inverse of the number of blood samples per child.

In the primary analysis, we used 2 km as the cutoff for defining “close” to a Superfund site. This definition is somewhat arbitrary, since we do not expect a discrete change in exposure at any given distance from the site boundaries, especially when estimating an average effect across multiple sites. Research on Superfund in Florida found increases in children’s school performance up to 2 miles (3.2 km) away from contaminated sites after cleanup (Persico et al.

2016). We investigated the robustness of the results by examining 1 km and 3 km as alternative cutoffs for defining the treatment and control groups using the DiD model. Table 5 presents these results. As expected, the net effect of cleanup is larger using a 1 km cutoff for the treatment group compared to a 2 km cutoff; the probability of EBLL fell by 3.7 to 6.7 percentage points. When defining 3 km as the treatment group cutoff, the effect is smaller, and the two estimates from the matched sample (shown in columns (7) and (8)) suggest that there was no improvement in EBLL resulting from cleanup. These results confirm that 2 km is a reasonable cutoff point to identify those most affected by Superfund cleanups.

Table 5: Difference-in-difference estimates of the effect of Superfund cleanup on elevated blood lead level (≥ 3.3 μg/dL) using alternative distance cutoffs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
"Close" cutoff	1 km				3km			
Fixed effects	Superfund site	Census tract	Superfund site	Census tract	Superfund site	Census tract	Superfund site	Census tract
Matching	No	No	Yes	Yes	No	No	Yes	Yes
Close Pb before	0.040*** (0.007)	0.046*** (0.013)	0.031*** (0.011)	0.053*** (0.011)	0.016 (0.015)	0.013 (0.014)	0.008 (0.015)	-0.001 (0.015)
Close Pb during	0.011** (0.005)	0.007 (0.006)	0.021* (0.011)	0.025* (0.013)	-0.001 (0.007)	-0.002 (0.008)	0.004 (0.008)	0.006 (0.009)
Close Pb after	-0.026*** (0.009)	-0.021*** (0.005)	-0.006 (0.009)	-0.010 (0.010)	-0.013** (0.005)	-0.006 (0.005)	0.010** (0.004)	0.010* (0.006)
R2	0.29	0.30	0.26	0.27	0.29	0.30	0.27	0.28
N	1,046,392	1,046,392	313,651	313,651	1,046,392	1,046,392	548,506	548,506
# of groups	68	994	60	533	68	994	65	732

All standard errors are clustered at the Superfund site group level. *** p<0.01, ** p<0.05, * p<0.1
Observations are weighted by the inverse of the number of blood samples per child.

We also conducted a sensitivity analysis estimating the DiD and triple difference models using property fixed effects, shown in Appendix Tables A.5 and A.6, respectively.[22] These models compare BLL results from children living at the same address at different points in time. The coefficients of interest are only identified at properties where children (usually not the same

[22] The net effect in these models is given by the coefficient on the "after cleanup" variable alone, since before cleanup is the omitted category.

child) were tested for lead before and during, or during and after, cleanup. Thus, the subsample used to estimate these models overrepresents children living in multifamily housing, properties that change occupancy more frequently, and households with siblings spaced far apart, and it may not be representative of all children living near Superfunds sites. These models have much less power to precisely estimate effects, since they used only 31% of the sample, and there are only six children per address in this subsample (falling to five children in the matched sample). The results are qualitatively similar to those from the primary models, though the drop in EBLL from cleanup is not always statistically significant.

Estimating National Superfund Benefits

We apply our regression results to quantify partial benefits of the estimated decrease in EBLL from Superfund cleanups nationally. Our approach focuses on one outcome, children's cognitive function, that EPA has quantified and monetized in past regulations (e.g., U.S. EPA 2018a). There are many other negative child and adult health outcomes associated with lead exposure (U.S. EPA 2013) that are not quantified in this analysis. We calculated the increase in the net present value of lifetime earnings accruing to one cohort of children living within 2 km of Superfund sites where lead was a contaminant of concern and where construction is complete.

For this exercise, we focus on the Census tract fixed effects triple difference CEM model estimate (column (4) in Table 4), since this estimate represents our most comprehensive attempt to address potential omitted variable bias. This estimate corresponds to an 8.1% drop in the rate of EBLL relative to a baseline without site cleanup.

To estimate the link between lead exposure and cognitive function, we relied on a reanalysis of international pooled data linking BLL and IQ (Crump et al. 2013).[23] In order to apply this estimate, we converted our estimated change in EBLL *rate* to a change in mean BLL using nationally representative historic data from the National Health and Nutrition Examination Survey (NHANES).[24] We then estimated the gain in lifetime earnings per child associated with

[23] Crump estimated the relationship between BLL and IQ as: $IQ = -3.315*ln(BLL+1)$.

[24] We used NHANES data on children age 1-5 from 1988-2016 to regress geometric mean (GM) BLL on the natural log of percent of BLL above 3.3 μg/dL. We estimated that $GM\ BLL = -0.054 + 0.753*ln(EBLL)$ (N = 11, R^2 = 0.88).

the predicted change in IQ using an approach developed by Salkever et al. (1995) and updated by U.S. EPA (2018a).[25] Assuming that the average child living within 2 km of a lead-contaminated Superfund site during 2015-2016 had a BLL equal to the national average level of 0.76 μg/dL, we estimated that the child's BLL would have been 0.063 μg/dL higher and his or her IQ would have been 0.12 points lower if cleanup had not occurred.

There are 581 Superfund sites nationwide where lead was classified as a contaminant of concern and that had reached construction complete as of September 31, 2017. We estimated that there were 382,061 children age 0-4 living within 2 km of these sites using data from the 2011-2015 American Community Survey.[26] Dividing the number of children by five to represent a single year cohort, we estimated a benefit to these children of $173 million, assuming a 3% discount rate. The lifetime earnings benefit is only experienced once by each child, but because a new cohort of children is affected each year, this value can serve as a rough proxy for the partial annual benefits from cleanup. The 581 NPL sites nationally include a similar distribution of site types (manufacturing, waste management, mining, etc.) as the 87 lead-contaminated sites included in our analysis. Nevertheless, we acknowledge the uncertainty inherent in applying estimates based on data from six states to other states with potentially different NPL site characteristics and other lead exposure sources.

We also estimate the range of benefits using all eight econometric models (Figure A1). The estimated benefits across these models range from $165 million to $389 million, assuming a 3% discount rate. These estimates are conservative because they do not account for the decline in EBLL during cleanup found in the DiD models. There are more than 380,000 additional children living near sites with lead as a contaminant of concern where cleanup is in progress, but construction is not yet complete. About 90% of the drop in EBLL occurred during cleanup according to the DiD estimates, so accounting for benefits to these children would almost double the partial benefit estimates from Superfund cleanup.

To provide context, we compare these partial benefit estimates to annual Superfund expenditures at these sites. From 1980 to 2017, EPA expenditures at these 581 sites totaled $9.62

[25] Salkever (1995) estimated that 1-point increase in IQ is associated with a 2.38% gain in lifetime earnings on average across males and females. U.S. EPA (2018a) estimated that this gain is equivalent to $19,359 at a 3% discount rate for a child age 3 in 2016.

[26] Child counts surrounding these sets of Superfund sites were calculated using Census block group population centroids within 2 km of site boundaries.

billion, yielding an average annual expenditure of $253 million (authors' calculations using data from EPA OSRTI).[27] While estimated annual EPA expenditures fall within the range of the estimated annual benefits, we have only quantified one benefit category. Other health benefits from reduced lead exposure include improved neurobehavioral, cardiovascular, renal, and immunological health in adults and children. Furthermore, cleanup at many of these sites also addressed other contaminants such as arsenic, mercury, or polychlorinated biphenyls. Ideally, we would have identified the portion of cleanup costs allocated to lead versus other contaminants but were unable to do so due to data constraints.

Discussion

Our results provide strong evidence that Superfund cleanups led to reductions in children's blood lead levels near a broad sample of lead-contaminated sites, complementing previous site-specific studies (Murgueytio et al. 1996, 1998; von Lindern et al. 2003; Lanphear et al. 2003; U.S. EPA "Examples of Superfund Site Cleanups"). A limitation of our approach is that it does not identify which types of interventions were responsible for these benefits. EPA supplements engineering approaches that remove or stabilize contaminants with community outreach and health education, particularly at sites with lead-contaminated residential areas (U.S. EPA 2003). At such sites, EPA works with local public health agencies to educate communities about the risks of children's lead exposure and to identify lead hazards, including sources like deteriorated paint and plumbing in the home (U.S. EPA 2003). Therefore, the remediation process has the potential to spur reductions in lead exposure from multiple sources. Our estimates of reduced blood lead levels represent the combined effect of all interventions related to the Superfund program.

[27] The EPA expenditure total does not include funds spent by potentially responsible parties (PRPs) at sites where the PRP conducts the cleanup. The agency has limited cost data on these sites because PRPs are not generally required to maintain or disclose their cleanup costs to the EPA, and they typically consider such cost information to be confidential. EPA expenditures from 1980-2017 were adjusted for inflation using the ENR Construction Cost Index (CCI) (ENR 2018). All sites did not have expenditure in all 38 years, however, the average total annual expenditure at these 581 sites was calculated by dividing the total expenditure at all sites from 1980-2017 by 581 sites, and then dividing by 38 years. An annual average based on the number of years of actual expenditures at each specific site could not be calculated because expenditure data from 1980-1989 were only available as a total for the 10-year period. To adjust expenditure data from 1980-1989, we used the average annual CCI over the 10-year period.

Another caveat is that the results represent an average effect across Superfund sites in six states. We focused on Massachusetts, Michigan, Missouri, North Carolina, Rhode Island and Wisconsin in part due to the availability of blood lead data extending back decades. States with longer-running blood lead screening and data collection programs may differ in terms of lead exposure patterns from those with less robust screening.[28] We also lack sufficient data to assess whether these six states differ systematically from other states in terms of NPL site lead concentrations or exposure pathways, although we found that the site types in our study area are broadly similar to the types of lead sites targeted by Superfund nationally in terms of previous use.

In addition, soil lead contamination—the most common form of contamination at lead sites—is subject to different cleanup standards across states. Levels of lead in soil in non-urban areas of the US generally range from below 10 parts per million (ppm) to 95 ppm (U.S. EPA 2013). Federal Superfund program guidance from our study period suggested a preliminary remediation goal (PRG) of 400 ppm and recommended using the Integrated Exposure Uptake Biokinetic (IEUBK) Model for Lead in Children for setting site-specific risk-based PRGs (U.S. EPA 1998). Michigan, North Carolina, and Wisconsin use 400 ppm as a recommended cleanup level, while Missouri, Massachusetts, and Rhode Island use more stringent levels, varying from 150 to 260 ppm. We could not evaluate heterogeneity in soil lead reduction since we lacked data on soil lead concentration prior to cleanup and on site-specific cleanup levels. In addition, as already noted, blood lead screening varied across states, though we found no evidence that screening varied systematically with proximity to Superfund sites after controlling for neighborhood sociodemographic characteristics.

If impacts of cleanup on elevated BLL extended to 5 km or beyond, then our results underestimate the benefits of cleanup. While we tested alternative approaches to defining the treatment group and found no evidence of effects beyond 2 km relative to children living within 5 km of Superfund sites, we did not examine the change in elevated BLL rates for children living beyond 5 km. We also underestimate benefits in the triple difference model if our comparison group included sites with low levels of lead where lead contamination fell as an incidental benefit of cleanup—a possibility that we cannot rule out due to data constraints.

[28] In recent years, blood lead levels have been lower in the South and West than the Northeast and Midwest after controlling for race, poverty, and housing age (Roberts and English 2016).

Finally, our identification strategy is designed to isolate the causal effect of Superfund program interventions at lead-contaminated sites, but we cannot eliminate the potential for bias due to unobserved differences between the treatment and control groups. There is always the possibility that other lead policies or sociodemographic trends were responsible for differing rates of decline in elevated blood lead levels. However, the fact that lead levels fell more sharply near lead-contaminated sites than sites with minimal to no lead suggests that the results are not solely attributable to gentrification or other systematic trends in neighborhoods experiencing cleanup. Our results also may underestimate the effect of Superfund cleanups given the potential for attenuation bias, since our analysis likely measures both EBLL and exposure to Superfund sites with error, and the EBLL outcome variable is binary.

Conclusions

We assembled a unique dataset pairing over one million blood lead measurements with data on the location and cleanup status of Superfund sites and other lead risk factors in six states to study the impacts of the Superfund program on children's lead exposure. We showed that Superfund cleanups at lead-contaminated sites had a measurable impact on children's blood lead levels. Cleanups yielded a 2 to 5 percentage point drop in the probability of elevated BLL for children living with 2 km of these sites, which is equivalent to a decline of 8 to 18 percent compared to what rates would have been without cleanup. This result is robust to different definitions the control group (children farther from lead-contaminated sites or those close to non-lead sites), the spatial scale of fixed effects (Superfund site or Census tract), the cutoff for elevated blood lead level, and matching on observable characteristics that are strongly predictive of lead exposure.

Our estimates suggest that partial annual benefits, measured by increased lifetime earnings for young children living within 2 km of remediated sites, range from $165 million to $ $389 million (assuming a 3% discount rate). This is by no means a comprehensive estimate of the benefits of the Superfund program, or even a complete estimate of the benefits from reduced lead exposure at Superfund sites, since lead has numerous adverse health effects on children and adults (U.S. EPA 2013). While this study finds that proximity to a Superfund site was not as large a contributor to elevated BLL as other risk factors like older housing and poverty, it underscores the importance of addressing legacy contamination to continue the progress made in reducing children's lead exposure in recent decades.

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Appendix

Table A1: Number of observations by state and Superfund exposure status

Superfund site contamination	Cleanup status	Massachusetts	Michigan	Missouri	North Carolina	Rhode Island	Wisconsin
Lead is a health concern	Before	33,152	0	28,467	2,350	48,839	865
	During	316,539	52,288	45,257	38,565	130,371	39,525
	After	201,389	174,328	10,680	60,030	32,159	32,530
No lead contamination	Before	26,108	0	1,017	10,024	0	618
	During	62,641	1,553	7,661	9,441	1,573	2,505
	After	132,159	11,491	5,773	8,042	470	3,096
Total		658,838	205,874	95,680	125,005	203,202	72,743

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Table A2: Difference-in-difference estimates of the determinants of elevated blood lead level (≥ 3.3 μg/dL), full set of estimated coefficients (corresponding to Table 3, column (1))

Fixed effects	Superfund site
Matching	No
During cleanup	-0.007
	(0.009)
After cleanup	0.027***
	(0.009)
2 km Pb before cleanup	0.037***
	(0.013)
2 km Pb during cleanup	0.007
	(0.005)
2 km Pb after cleanup	-0.014**
	(0.005)
Male	0.018***
	(0.001)
Sex unknown	0.007
	(0.011)
Less than 1 year old	-0.074***
	(0.011)
1 year old	-0.003
	(0.008)
2 year old	0.040***
	(0.009)
3 year old	0.024***
	(0.008)
4 year old	0.014**
	(0.006)
Capillary blood sample	0.061***
	(0.013)
Blood sample type unknown	-0.057
	(0.042)
Test affected by FDA LeadCare alert	0.084***
	(0.017)
Average state temperature in month of blood lead test	0.001***
	(0.000)
Lived within 2 km of lead-contaminated RCRA Corrective Action site	0.003
	(0.007)
Number of Brownfields with grantee-reported lead contamination within 2 km	0.003***
	(0.001)
Property not matched to assessment data	-0.035***
	(0.011)
Property year built missing	0.068***
	(0.012)
Property built before 1940	0.103***
	(0.011)
Property built 1940-1959	0.025**
	(0.009)

Property built 1960-1978*	0.020***
	(0.003)
Census tract blood lead screening rate	0.227***
	(0.043)
Census tract air lead concentration	0.075
	(0.163)
Census tract % population African American	0.063**
	(0.029)
Census tract % population Hispanic	-0.068**
	(0.034)
Census tract % population less than high school education	0.146**
	(0.071)
Census tract % receiving public assistance	0.244**
	(0.095)
Census tract % rental housing	0.024*
	(0.013)
Census tract % housing stock built before 1940	0.165***
	(0.016)
Census tract % housing stock built 1940-1959	0.002
	(0.015)
Census tract % housing stock built 1960-1979	0.019
	(0.018)
Census tract 1980 vehicle miles traveled density	4.735**
	(2.235)
Census tract 1980 vehicle miles traveled density x years since 1980	-0.253**
	(0.124)
Constant	0.224***
	(0.026)
State x year fixed effects	Included
N	1,046,392
R2	0.290

All standard errors are clustered at the NPL cluster level. *** p<0.01, ** p<0.05, * p<0.1
Observations are weighted by the inverse of the number of blood samples per child.
Omitted categories are before cleanup 2-5 km from lead-contaminated site, female, age 5, venous blood sample, and property built after 1978.

Table A3: Difference-in-difference estimates of the effect of Superfund cleanup on elevated blood lead levels (≥ 5 µg/dL cutoff)

	(1)	(2)	(3)	(4)
Fixed effects	Superfund site	Census tract	Superfund site	Census tract
Matching	No	No	Yes	Yes
2 km Pb before cleanup	**0.029* (0.015)**	**0.038** (0.014)**	**0.034** (0.013)**	**0.030** (0.013)**
2 km Pb during cleanup	**0.007 (0.005)**	**0.009* (0.005)**	**0.005 (0.007)**	**0.003 (0.010)**
2 km Pb after cleanup	**-0.013*** (0.004)**	**-0.002 (0.004)**	**-0.006 (0.006)**	**-0.006 (0.008)**
R2	0.24	0.25	0.21	0.22
N	1,077,382	1,077,382	509,643	509,643
# of groups	68	995	62	684

All standard errors are clustered at the Superfund site group level. *** p<0.01, ** p<0.05, * p<0.1
Observations are weighted by the inverse of the number of blood samples per child.

Table A4: Triple difference estimates of the effect of Superfund cleanup on elevated blood lead level (≥ 5 µg/dL cutoff)

	(1)	(2)	(3)	(4)
Fixed effects	Superfund site	Census tract	Superfund site	Census tract
Matching	No	No	Yes	Yes
2 km before cleanup	0.024 (0.016)	0.038** (0.019)	0.027** (0.012)	0.019* (0.011)
2 km during cleanup	-0.001 (0.015)	-0.007 (0.013)	-0.016 (0.014)	-0.015 (0.014)
2 km after cleanup	0.022*** (0.003)	0.013*** (0.005)	0.023*** (0.005)	0.023*** (0.006)
2 km Pb before cleanup	**0.001 (0.024)**	**0.005 (0.024)**	**-0.001 (0.017)**	**0.008 (0.019)**
2 km Pb during cleanup	**0.010 (0.015)**	**0.015 (0.013)**	**0.022 (0.015)**	**0.018 (0.016)**
2 km Pb after cleanup	**-0.033*** (0.005)**	**-0.015** (0.007)**	**-0.029*** (0.007)**	**-0.029*** (0.007)**
R2	0.24	0.25	0.21	0.22
N	1,361,341	1,361,341	597,969	597,969
# of groups	98	1358	92	889

All standard errors are clustered at the Superfund site group level. *** p<0.01, ** p<0.05, * p<0.1
Observations are weighted by the inverse of the number of blood samples per child.

Table A5: Difference-in-difference estimates of the effect of Superfund cleanup on elevated blood lead levels using address fixed effects

	(1)	(2)	(3)	(4)
EBLL cutoff	3.3 µg/dL	3.3 µg/dL	5 µg/dL	5 µg/dL
Matching	No	Yes	No	Yes
2 km Pb during cleanup	**-0.032* (0.018)**	**-0.050** (0.019)**	**-0.025 (0.028)**	**-0.049*** (0.016)**
2 km Pb after cleanup	**-0.037* (0.021)**	**-0.072*** (0.027)**	**-0.030 (0.026)**	**-0.076*** (0.025)**
R2	0.53	0.54	0.50	0.50
N	323,581	137,311	339,456	146,356
# of groups	50,568	28,389	50,898	28,755

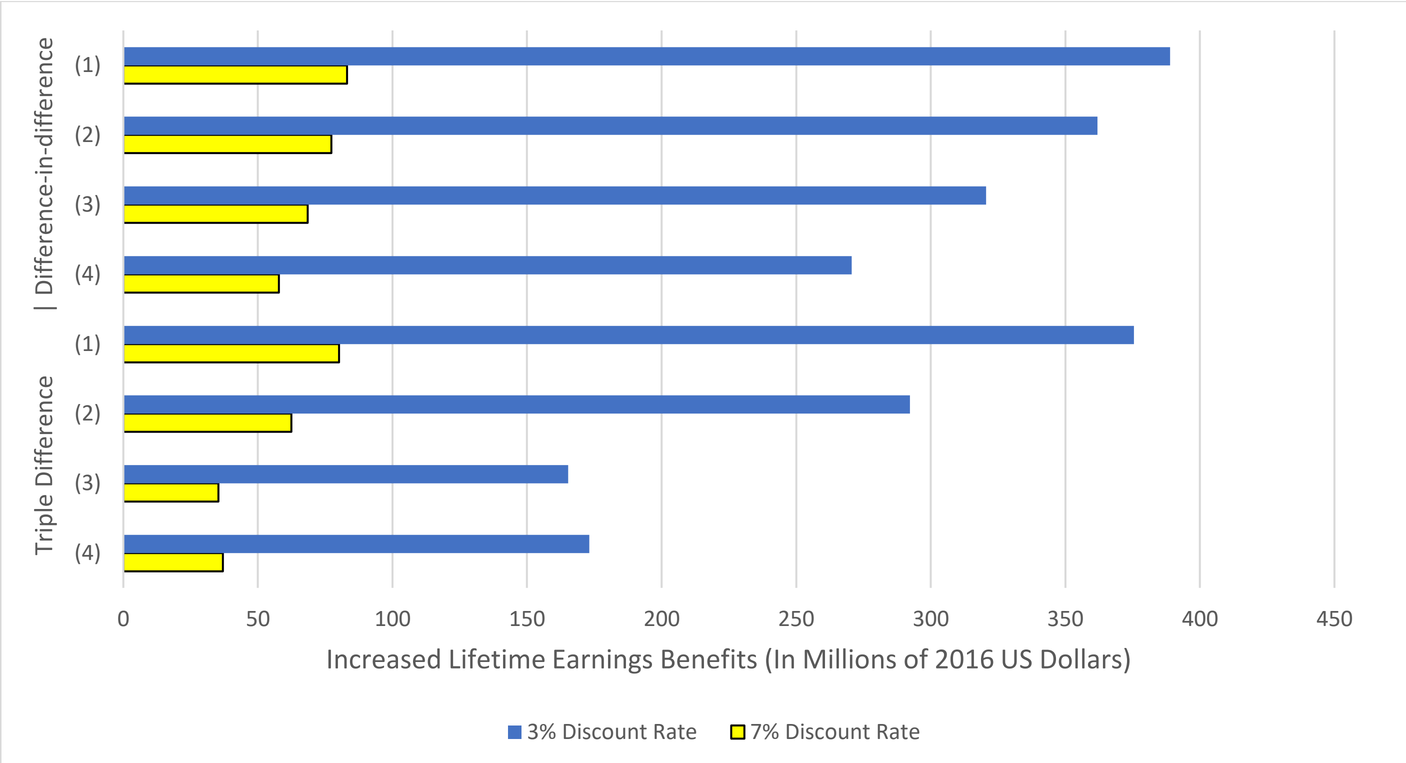
All standard errors are clustered at the Superfund site group level. *** p<0.01, ** p<0.05, * p<0.1
Observations are weighted by the inverse of the number of blood samples per child.

Table A6: Triple difference estimates of the effect of Superfund cleanup on elevated blood lead levels using address fixed effects

	(1)	(2)	(3)	(4)
EBLL cutoff	3.3 µg/dL	3.3 µg/dL	5 µg/dL	5 µg/dL
Matching	No	Yes	No	Yes
2 km during cleanup	-0.029 (0.022)	-0.038 (0.026)	-0.020 (0.025)	-0.027 (0.019)
2 km cleanup complete	-0.027 (0.025)	-0.019 (0.039)	-0.007 (0.025)	-0.004 (0.020)
2 km Pb during cleanup	**-0.001 (0.030)**	**-0.010 (0.033)**	**-0.004 (0.039)**	**-0.020 (0.026)**
2 km Pb after cleanup	**-0.007 (0.032)**	**-0.046 (0.055)**	**-0.022 (0.037)**	**-0.066* (0.036)**
R2	0.51	0.54	0.49	0.51
N	407,899	162,929	424,336	172,228
# of groups	64,809	34,519	65,183	34,903

All standard errors are clustered at the Superfund site group level. *** p<0.01, ** p<0.05, * p<0.1
Observations are weighted by the inverse of the number of blood samples per child.

Figure A1: Partial benefits from cleanup of lead-contaminated Superfund sites: Full ranges of estimates



Note: The Difference-in-difference estimates correspond to Table 3, columns (1)-(4). The triple difference estimates correspond to Table 4, columns (1)-(4).