Hazed and confused: Prenatal pollutant exposure and CEO risk-taking☆

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Abstract

Over the past several decades, a growing literature has documented the adverse health effects of pollution at the individual level. In this paper, we document the detrimental impact of prenatal exposures to pollution on CEOs. Specifically, we draw on the extensive medical literature documenting the adverse cognitive and behavioral outcomes caused by developmental toxicants released by Superfund sites in the U.S., which were plausibly unknown when the CEOs were in utero. We find that CEOs with greater prenatal exposure to Superfund sites take more risks, but the risks do not pay off, adversely affecting the firms' performances and the CEOs' careers. Our results demonstrate the role that prenatal exposure to pollution plays in affecting CEO risk-taking and point to a large indirect effect of pollution on society beyond the immediate health effects.

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"*From its origins as a manufacturer of silicon chips and semiconductors, Santa Clara County is riddled with 23 toxic Superfund sites, more than any county in the country. This was news to Ms. Armstrong, who lives a mile from one of the sites … "Most people I talked to in the community seemed unaware of their presence," she said. "Often, even the notion of Superfund sites is foreign to many people. We are used to taking for granted the safety of the environment we inhabit.*""

Evelyn Nieves, "The Superfund Sites of Silicon Valley", *The New York Times*, March 26, 2018

Mitchell Montgomery said he knew there was something curious about his new home when he moved in last year … in Niagara Falls. When he brushed his teeth, for instance, he sometimes noticed a peculiar smell coming through the drain. It seemed like his 8-year-old son's asthma was getting worse, and his pregnant girlfriend was having occasional nosebleeds and headaches. And a couple of months ago, when he replaced a sump pump in the basement, it was covered in a thick tar-like substance… But none of these things struck him as too suspicious until he realized what was underneath the large, empty swath of grass, sealed off by a tall chain-link fence, just two blocks from his front door. It was Love Canal, the scene of one of the nation's worst toxic-waste catastrophes and now — 45 years later — the site for a new, and sometimes unknowing, generation of homesteaders.

Jesse McKinley, "His Home Sits Alongside America's First Superfund Site. No One Told Him", *The New York Times*, June 12, 2023

1. Introduction

Over the past several decades, the detrimental impact of pollution has been the subject of intense scrutiny. However, most papers examining the impact of pollution have focused on health outcomes for the individuals affected, such as deleterious effects on physical health, cognition, hospitalizations, or deaths (see, e.g., Schlenker and Walker (2016)). A growing literature in economics examines the causal effect of pollution on real economic consequences, including individual productivity (Graff Zivin and Neidell (2012); Lichter, Pestel, and Sommer (2017)), school performance (Graff Zivin et al. (2020); Persico, Figlio, and Roth (2020)), risk-taking (Yokota et al. (2016)), and crime and unethical behavior (Burkhardt et al. (2019); Herrnstadt et al. (2021)). In this paper, we build on this literature to examine the real long-term consequences of prenatal exposure to developmental pollutants on chief executive officers' (CEOs') risk judgments. Examining this issue is important because CEOs typically have high socioeconomic status and make consequential real decisions that affect large numbers of stakeholders in the firm and society.

Selection is a major methodological concern in this analysis. It is plausible that parental risk preferences affect the willingness of individuals to be exposed to pollution. The evidence shows that Americans move reasonably frequently.[1] Hence, it could be argued that the families that choose to settle in polluted areas have different risk perceptions than families that don't – and these risk preferences are transmitted from parents to their offspring (Dohmen et al. (2012)). While a growing body of literature has shown that CEO management styles explain a significant portion of the variation in firm corporate policies (e.g., Bertrand and Schoar (2003); Bamber, Jiang, and Wang (2010); Graham, Li, and Qiu (2012)), the evidence that links this heterogeneity in CEO management styles to variations in the CEO's life and career experiences[2] is subject to this selection concern. For example, Bernile, Bhagwat, and Rau (2017) document a non-monotonic relation between the intensity of the CEOs' early-life exposure to fatal natural disasters and corporate risk-taking and argue that such exposure to disasters shapes the CEOs' preferences for risk-taking. However, it is plausible that although the children do not decide to live in a disaster-prone area, the decision to move to the area may reflect parental risk preferences., which might better explain the CEO risk attitudes than disaster experience. Natural disasters like massive wildfires and tornadoes occur in specific U.S. states, and the existence of these disaster-prone regions is common knowledge to Americans. Thus, it is reasonable to assume that CEOs' parents take the regular occurrence of natural disasters into consideration when choosing where to bring up their children.

In this paper, we address the selection issue by examining the effect of a clearly exogenous event that likely directly affected CEO risk preferences during the prenatal phase *without* simultaneously being affected by the risk preferences of the parent. Specifically, we examine the effect on the subsequent risk-taking behavior of a CEO who was born in a heavily polluted area, an area later designated as a Superfund site (among the most hazardous toxic waste sites in the U.S.), without either the CEO or her parents making a deliberate choice to live in the polluted area.

Prior to the publication of "Silent Spring," by Rachel Carson in 1962, there was not much information about the use of chemical pesticides (e.g., DDT, which was banned in 1972) and the harm they cause to animals, humans, and the environment. "Silent Spring" was the beginning of

[1] See for example https://www.jchs.harvard.edu/blog/who-is-moving-and-why-seven-questions-about-residential-mobility. Based on the numbers in this article, around 40 million×14% = 5.6 million Americans typically move across states and around 12.4 million (40 million × 31%) Americans move away from their counties every year. The mobility rates were double this rate in the 1940s when a significant proportion of current CEOs were born.

[2] Examples of papers documenting this linkage include e.g., Malmendier and Tate (2005), Malmendier and Nagel (2011), Malmendier, Tate, and Yan (2011), Benmelech and Frydman (2015), Dittmar and Duchin (2016), Bernile, Bhagwat, and Rau (2017), and Schoar and Zuo (2017).

the U.S. environmental movement.[3] In 1970, President Nixon signed the National Environmental Policy Act (NEPA), the first major federal environmental statute, and officially formed the EPA. Despite the subsequent passing of environmental acts such as the Resource Conservation and Recovery Act (RCRA) of 1976 and the Toxic Substances Control Act (TSCA) of 1976, the general public was unaware of the most egregious sites until the Cuyahoga River fire in 1969, the Love Canal disaster in 1978, and the leaking of chemical wastes in the "Valley of the Drums" in 1979.[4] Partly to address the problems of these toxic waste dumps, on June 13, 1979, President Carter proposed CERCLA to Congress to fund the cleanups of the sites. CERCLA was passed in 1980.[5]

In this paper, we focus on inadvertent prenatal exposure to hazardous Superfund toxicants to examine the impact on CEOs' ability to gauge risks. Our research design offers two unique advantages. First, all except two CEOs in our sample were born when these industrial chemicals were not identified as carcinogens or developmental toxicants. Second, before 1980, most individuals did not know that they lived near the neighborhoods that, over time, would be designated as Superfund sites. Based on the scarce information about neurotoxicity at that time, it is unlikely that the CEO's parents would know about this potentially dangerous exposure. Hence, it is implausible that our sample of Superfund CEOs is disproportionately represented by CEOs with risk-taking genotypes, i.e., risk-taking proclivities inherited from their parents. Our research design enables us to rule out this type of selection bias and an omitted variable bias such as intrinsic risk-taking preferences as potential confounders that affect both the CEOs' risk-taking behaviors and their prenatal pollution exposure.

How does prenatal exposure to Superfund sites affect cognitive and behavioral development? During early fetal development, the blood-brain barrier, which protects the brain from toxicants, is immature (Zheng et al. (2003); Grandjean and Landrigan (2006); Needham et al. (2011); Grandjean and Landrigan (2014); Lanphear (2015)). Therefore, the developing brain and several developmental processes are highly vulnerable to toxicants during fetal development.[6] Superfund

[3] See "Milestones in EPA and environmental history" available at the EPA website.

[4] The Cuyahoga River was listed as the Krejci Dump Superfund site, the Love Canal was listed as the Love Canal Superfund site, and Valley of the Drums was listed as the A.L. Taylor (Valley of Drums) Superfund site. Both the Love Canal and the A.L. Taylor (Valley of Drums) sites were listed on the Superfund program on September 8, 1983.

[5] The Superfund Program deals only with the nation's most hazardous waste sites. A number of other major environmental laws—such as the RCRA, the Clean Water Act (CWA), the Clean Air Act (CAA), TSCA, and the Safe Drinking Water Act (SDWA)—were enacted to deal with other types of pollution.

[6] According to the medical literature (Berkowitz, Price-Green, Bove, and Kaye (2006); Currie, Greenstone, and Moretti (2011)), among infants who survive to adulthood, outcomes related to prenatal developmental toxicant

contaminants, whether released through the air, ground, or water, have been documented to have severe adverse effects on children's neurodevelopment, psychophysical, and cognitive dimensions. These effects include impaired inhibitory control, somatic symptom disorders, increased risk for attention-deficit/ hyperactivity disorder (ADHD) (e.g., Guxens et al. (2018); Ke et al. (2021)), and a reduction in serotonin levels (Yokota et al. (2016)). Low serotonin levels have been associated with increased aggression and impulsivity. In addition, prenatal exposure to Superfund sites produces long-term consequences. The fetal origins hypothesis (Barker (1990); Almond and Currie (2011)) argues that while no apparent impact might exist during the pollution exposure period, effects on socioeconomic and health outcomes such as wages, human capital accumulation, and criminal behaviors can remain latent for many years. Margolis et al. (2016) show that prenatal exposure to pollutants produces long-lasting effects on deficits in self-regulatory capacities and that these deficits result in high-risk adolescent behaviors. Almond, Edlund, and Palme (2009) and Black et al. (2019) examine prenatal radiation exposure to the 1986 Chernobyl incident in Sweden and nuclear weapon testing events in Norway, showing significantly lower adult cognitive ability and earnings. For example, relative to individuals in the least radioactive fallout quintile in months 3 and 4, those in the most radioactive fallout quintile experienced a 2% decrease in earnings at age 35. Persico, Figlio, and Roth (2020) show that prenatal exposure to Superfund sites is associated with substantially lower elementary school test scores and higher behavioral incidents. Aizer and Currie (2019) show that boys born in close proximity to high-traffic roads with high lead exposure are associated with higher rates of juvenile detention and incarceration. For boys, a 1 unit increase in blood lead levels increased the probability of juvenile detention/incarceration by 57%.

Accordingly, we conjecture that Superfund CEOs' prenatal exposure to toxic chemicals impairs their risk judgments. We focus on three major dimensions of corporate consequences: the risk-taking corporate policies, firm performance, and Superfund CEOs' careers. The results are strikingly consistent across all three dimensions – Superfund CEOs tend to take more risks that do not appear to pay off, adversely affecting the firm performance, and leading the CEOs to be fired after shorter tenures at their firms.

More specifically, the greater the CEO's prenatal exposure to Superfund sites, the riskier the firms' financial policies – the firms tend to hold less cash, have higher leverage, and return less

exposure include growth retardation, functional impairment, or damage to neurodevelopment, psychophysical, and cognitive development.

cash to shareholders through share repurchases. Superfund CEOs are more likely to overutilize debt relative to available tax benefits. The debt issued by these firms tends to be excessive and more aggressive – the firms have lower credit ratings, higher bankruptcy scores, and higher estimated default probabilities. The cost of the debt is higher – the firms have higher bank loan all-in-spreads, and bond issue spreads. Shareholders also appear to be subject to more risks. Firms managed by Superfund CEOs have greater stock return volatilities, greater idiosyncratic stock return volatilities, are more likely to have negatively skewed firm-specific returns, larger ratios of firm-specific volatilities in down to up weeks and are more likely to have crash weeks. They earn smaller abnormal returns after M&A announcements and are more likely to make unrelated acquisitions. Turning to performance, firms managed by Superfund CEOs also perform worse as measured by unadjusted and industry-adjusted ROA, Tobin's Q, and stock returns. Finally, Superfund exposure also appears to hurt the CEOs' careers. The forced turnover rate for these CEOs is significantly higher, and their tenures are significantly shorter. All the models include a host of industry, firm, and CEO control variables that are likely to affect debt and equity risk, performance, and CEO turnover. There are no statistically significant differences between the industries in which the Superfund and non-Superfund CEOs manage firms, suggesting that the explanation does not lie in Superfund CEOs simply gravitating to riskier industries.

The literature (O'Neill et al. (2003)) documents a negative association between pollution exposure and socioeconomic status which suggests that our results may potentially be driven by poverty. Alternatively, it is possible to argue that the real effects on the economy are minor since poor people have negligible economic impacts on society. We note that in all our models, we control for firm (or industry), year, CEO's birth year, county of birth, and firm's headquarters state fixed effects. We control for macroeconomic conditions when the CEOs are born, including CEO birth county poverty, employment status, and earnings per capita. Hence, our results are unlikely to be driven by the negative association between local socioeconomic status and pollution exposure. Beyond this, our data show that though Superfund sites are spread nationwide across the U.S., they are concentrated in wealthy states in the United States (e.g., New Jersey, Pennsylvania, New York, California, Michigan, and Florida). Finally, the medical literature documents that pollution has deleterious effects on wealthy families as well. For instance, Forastiere et al. (2007) document that people with higher socioeconomic status are more likely to live in areas with higher traffic density and air pollutant concentrations.[7]

We also conduct a number of additional tests to exclude other channels that may drive our results. First, we focus on CEO prenatal exposure exclusively to developmental toxicants, as the developing brain is vulnerable to toxicants during fetal development. Our results remain largely similar when we consider only developmental toxicants. In contrast, our results become weaker when considering only Superfund sites that never released *any* developmental toxicants. Second, we examine the effect of CEOs' *postnatal* exposure to Superfund sites, that is, whether our result is driven by continuous *postnatal* exposure to Superfund pollution during the child's development. Controlling for prenatal exposure, postnatal exposure has similar but weaker effects. Our findings of potentially greater adverse consequences of prenatal Superfund exposure are consistent with Ronchetti et al. (2006) and Hu et al. (2006).

Another potential explanation for our results is that the CEO manages a local firm that is still in close proximity to the Superfund site and hence is currently exposed to pollution from the site. Alternatively, the firm might be a current polluter. Controlling for indicator variables for whether the firm is a current polluter and whether the firm's headquarters or facilities are exposed to pollution, the CEO Superfund exposure variable remains consistently significant across the three corporate consequences. Our results are also not driven by cultural effects (Lei, Petmezas, Rau, and Yang (2023)). Eliminating home CEOs − CEOs born, went to high school, and then manage firms in the same area − does not change our results.

Yet another issue is that it is unclear how much of this difference in CEO behavior is attributable to the Superfund exposure effect alone rather than being driven by a lifetime of engaging in different risk-taking behaviors. While we cannot definitively answer this question, we find that Superfund CEOs are significantly less likely to be outside CEOs. Instead, they appear to be promoted internally, suggesting that Superfund CEOs are significantly more likely to take the top position without being seen to be solely accountable for the overall risks of the company.

Our results are robust to a battery of robustness tests. First, we match every Superfund CEO to a non-Superfund CEO born in the nearest neighboring county, in the same year (if feasible, or in the same decade, if not), and in the same Fama-French (1997) 48-industry. Second, we match

[7] Similarly, Tyrrell et al. (2013) find that wealthy families, due to their greater consumption of fish and shellfish, have higher burdens of environmental toxicants (such as mercury, arsenic, thallium, and perfluorononanoic acid).

the firms managed by Superfund CEOs to the firms in the same FF48 industry with headquarters located in the nearest neighboring counties to the treated firm managed by non-Superfund CEOs who are born in the same year (if feasible) or in the same decade (if not). In both cases, our results are largely unchanged. Third, we contrast the firm-year observations for the three years before and the three years after the sudden death of a Superfund CEO. The difference-in-differences (DID) analysis shows that the effect of the Superfund CEO on firm policies largely reverses over the next three years. Fourth, we run two falsification tests where we replace each CEO's birthplace with a randomly assigned county. The first falsification test uses all U.S. counties (not limited to counties that contain the CEOs' birthplaces in our sample). The probability of being assigned as the CEO's pseudo birthplace is weighted by the relative population size of the county. In the second falsification test, we replace the CEO's birthplace with a randomly chosen county from the 10 nearest counties. In both cases, our results mostly lose significance. Overall, our results are strikingly robust – CEOs with prenatal pollutant exposure tend to adopt riskier corporate policies that do not appear to pay off, negatively affecting their careers.

Our paper contributes to the vast literature on environmental pollution in economics. For example, Heyes, Neidell, and Saberian (2016) show that air pollution causes Manhattan-based traders to lower the return of the S&P 500 on the same day via health and behavior channels. Huang, Xu, and Yu (2020) find that air pollution worsens investors' trade performance. Li, Massa, Zhang, and Zhang (2021) argue that individual investors suffering from air pollution-induced depressed moods may trigger the disposition effects. Relative to other pollutants, only a small number of economic papers focus on Superfund sites. These papers discuss the impact of Superfund sites on the financial market (Harper and Admans (1996)), the housing market (Gayer, Hamilton, and Viscusi (2000); Greenstone and Gallagher (2008); Mastromonaco (2014); Kim, Schieffer, and Mark (2020); Gamper-Rabindran, Mastromonaco, and Timmins (2023)), potential CERCLA enforcement discretion (Akey and Appel (2021)), health (Klemick, Mason, and Sullivan (2020); Currie, Greenstone, and Moretti (2011)), and long-term human capital consequences (Currie (2011); Persico, Figlio, and Roth (2020)). We add to this literature by showing that prenatal exposure to Superfund sites affects CEOs' decision-making, particularly risk-taking.

Our paper is also consistent with the growing literature on the fetal origins hypothesis (Barker (1990)) that argues that while no apparent impact might exist during the pollution exposure period, pollution consequences can remain latent for many years. Almond and Currie (2011) argue that the delayed impacts of fetal conditions are persistent and can show up in non-health outcomes. Specifically, the delayed effect of prenatal pollution exposure may show up many years later in lower educational attainment and wages as adults. Our paper also points to the real long-term consequences of pollution exposure. Our paper is consistent with Currie (2011) and Persico, Figlio, and Roth (2020). Aizer and Currie (2019) examine only children born between 1990 and 2004 in Rhode Island. Persico, Figlio, and Roth (2020) examine only the Florida Superfund sites and those conceived before, during, and after the Superfund cleanup (children born between 1994 and 2002). Here, there continues to be a selection effect since parents should be aware of potential prenatal exposure to Florida Superfund sites. Sanders (2012), Aizer and Currie (2019), and Persico, Figlio, and Roth (2020) use high school test scores, high school dropout, school disciplinary problems, and juvenile detention and incarceration to show that prenatal exposure to Superfund and other pollution has long-term effects on cognitive and behavioral outcomes. In contrast to Sanders (2012), Aizer and Currie (2019), and Persico, Figlio, and Roth (2020), our results are noteworthy in the sense that (1) our sample is composed of individuals who have *ex-post* high socioeconomic status in the U. S., (2) we mitigate the self-selection effect by focusing on the pollutants accumulation period when people did not know the existence of the Superfund sites, (3) our observations contain much longer horizons (CEOs born between 1912 and 1985) and are widely spread in their geographical scale, and (4) the cognitive trials for CEOs are much more complicated (Durán and Aguado (2022)) than high-school education and juvenile detention and incarceration outcomes.

The rest of the paper is organized as follows. Section 2 reviews the federal Superfund program and literature and develops our hypotheses. Section 3 presents our data sources, variable construction, and descriptive statistics. Section 4 presents our primary analyses. Section 5 presents robustness tests and examinations of alternative potential explanations. Section 6 concludes.

2. The federal Superfund program and literature review

2.1. A brief overview of the federal Superfund program[8]

Superfund sites are typically the most hazardous contaminated sites in the U.S., including manufacturing facilities, processing plants, landfills, and mining sites. EPA documents show that most of them were actively polluted for decades over the twentieth century. Under CERCLA, the

[8] The history of the Superfund program is available at: https://www.epa.gov/history/epa-history-superfund.

EPA developed a nationwide program to react to emergency responses, collect information and analyze, identify, and determine liability for responsible parties for their releases of contaminants, and perform site cleanup. The CERCLA also established a trust fund (the "Superfund") to finance these activities. In 1982, the EPA implemented the Hazardous Ranking System (HRS) as a numerical measure to assess each reported site's potential threat to human health and the environment. In practice, sites with an HRS score of at least 28.5 are eligible for placement to the National Priorities List (NPL). Sites unsuitable for NPL are on the No Further Remedial Action Planned (NFRAP) status, and their cleanup is the responsibility of states, tribes, and other federal government agencies.

Superfund sites can be classified as proposed NPL, NPL, and deleted NPL according to their current cleanup status. Cleaning up Superfund sites is a complex, multi-phase process. When the EPA proposes adding a site to the NPL, it issues a public notice about its intention in the Federal Register. After a preliminary investigation, if the site continues to meet the listing requirements, it is formally listed on the NPL. The first stage of the cleanup process, remedial investigation/feasibility study (RI/FS), serves as the mechanism for collecting data to determine the nature and extent of contamination at the site, conduct treatability testing, and evaluate alternative remedial actions. At this stage, the EPA is required to solicit public opinion on the various proposed cleanup options. After the RI/FS stage, a Record of Decision (ROD) is issued, which describes remedy decisions for cleanup. The second stage of the cleanup process, remedial design/remedial action (RD/RA), includes preparing for and commencing the various remedial specifications described in the ROD. This phase normally takes years for the remedial actions to be implemented. The first milestone in the cleanup process is when a site is labeled as "construction completion." It indicates that all physical construction required for the site's cleanup has been completed, and the immediate (long-term) threats to public health or the environment have been addressed (under control).[9] The post-construction completion (PCC) phase may involve several activities necessary for achieving the ultimate cleanup goal of returning hazardous waste sites to safe and productive use. When no further response is required, the site reaches the second milestone in the cleanup process, the date the site is deleted from the NPL.

[9] Construction completion does not mean that all threats have been neutralized and the final cleanup levels have been achieved. For example, though a groundwater treatment system has been constructed, it may need to operate for a prolonged period to remove all contaminants. It is possible for the source of the contamination to have been completely removed. Still, the surrounding media may remain toxic and thus not ready for being returned to general use.

2.2. *The fetal origins hypothesis: The effect of in-utero exposure to hazardous waste sites and air pollution on cognitive, physical, and mental health outcomes*

The fetal origins hypothesis (Barker (1990)) argues that no apparent impact may exist during pollution exposure, and that consequences can remain latent for many years. Almond and Currie (2011) argue that the delayed effects of fetal conditions are persistent and can show up in non-health outcomes. For example, the delayed impact of prenatal pollution exposure may show up many years later in lower educational attainment and wages as adults. Relevant to our study, Superfund sites release endocrine-disrupting chemicals (EDCs). The neurotoxicity of these chemicals is the source of several behavioral and neurological disorders during adolescence, such as learning impairment, memory impairment, anxiety, delinquent behaviors, aggressiveness, and ADHD (Shoaff, Calafat, Schantz, and Korrick (2019); Samon et al. (2023)). Tachachartvanich et al. (2018) show that Trichloroethylene (TCE), an endocrine-disrupting chemical, is found at more than 60% of proposed Superfund sites. Fetal development is a critical period of susceptibility, as the developing brain is vulnerable to EDCs and other contaminants.[10] Raja, Subhashree, and Kantayya (2022) provide a comprehensive summary of medical findings that *in-utero* exposure to EDCs can cause permanent alteration to neurobehavioural functions, leading to behavioral disorders in adult life. Persico, Figlio, and Roth (2020) document the long-run negative impacts of prenatal exposure to Florida Superfund sites on cognitive and behavioral outcomes.[11] Studies show that prenatal exposure to contaminants released from the New Bedford Harbor Superfund site (listed on NPL in 1983) weakens childhood and adulthood memory and increases risk-taking behavior and hyperactivity in adolescents (Orenstein et al. (2014); Oppenheimer et al. (2022); Vieira et al. (2021)). Ke et al. (2021) provide a literature review of epigenetic studies and show that prenatal exposure to heavy metal developmental toxicants (such as arsenic, lead, cadmium, antimony, and methylmercury, ranked as top1, top 2, top 7, top 236, and top 118, respectively, among the 275 Superfund chemicals in the ATSDR 2022 Substance Priority List) contribute to the risk of ADHD behavior problems in children.

[10] See for example the Endocrine Society's position statement at https://www.endocrine.org/advocacy/position-statements/endocrine-disrupting-chemicals.

[11] Although genes influence cognitive disabilities such as learning disabilities, intellectual disability, ADHD, or autism, there is evidence that the development of cognitive disabilities is strongly influenced by the environment (Escudero-Lourdes (2016); Bellinger, O'Leary, Rainis, and Gibb (2016)). There is also increasing evidence that the developing brain is highly vulnerable to toxic chemical exposure (Grandjean and Landrigan (2006); Grandjean and Landrigan (2014); Lanphear (2015)).

Herrnstadt et al. (2021) offer several channels through which pollution causes increased aggression, impulsivity, and ADHD. The first channel is that pollutants cause neuro-inflammation (a dopaminergic effect). A second channel is that pollution directly affects brain chemistry by lowering serotonin levels, which, in turn, is associated with increased aggression and impulsivity (Murphy et al. (2013); Yokota et al. (2016)). Perera et al. (2014) and Myhre et al. (2018) show that prenatal exposure to air pollution is associated with a significantly increased risk of ADHD behavior problems in children.

The extant literature suggests that ADHD, impulsivity, hyperactivity, and aggression are associated with increased engagement in risk-taking behaviors. Satterfield et al. (2007) conduct a 30-year follow-up survey and show that children with ADHD are at increased risk for adult criminality. Margolis et al. (2016) conduct a cohort-based study of children born in New York City and show that prenatal exposure to pollutants produces long-lasting effects on impairment in self-regulatory capacities and that these deficits result in high-risk adolescent behaviors. The perceived overestimated benefit from risk-taking plays a significant role in explaining the association between ADHD and increased engagement in risk-taking behaviors (Shoham et al. (2016); Shoham et al. (2021)).

3. Sample construction, variable definitions, and descriptive statistics

3.1. Superfund sites

We begin with a list of 1,803 Superfund sites collected from the EPA's websites as of December 31, 2018.[12] Figure 1 shows that the number of Superfund sites is spread throughout the 50 states and the District of Columbia and is concentrated in highly populous states like New Jersey, Pennsylvania, New York, California, Michigan, and Florida.[13] For example, Silicon Valley, home to over 2,000 tech companies and headquarters of more than 30 Fortune 1000 corporations, is located in California's Santa Clara County, which has 23 active Superfund sites, more than any other county in the United States.

Our list of 1,803 Superfund sites consists of 53 proposed sites but never added to the NPL, 1,338 sites currently listed, and 412 sites deleted from NPL. Regardless of their current cleanup

[12] The latest list of Superfund sites is available here: https://www.epa.gov/superfund/superfund-national-priorities-list-npl.
[13] Figure 1 does not show Superfund sites in the five U.S. territories (Puerto Rico, American Samoa, Commonwealth of Northern Marianas, Virgin Islands, and Guam) and the Federated States of Micronesia.

status, we use all three types of Superfund sites for our study. This is because our research design relies on whether CEOs were exposed to the hazardous pollutants released from these sites in the prenatal stage. For each Superfund site, EPA hosts a website homepage.[14] From each website homepage, we collect the following information for each Superfund site: site name, map and links for site location, site EPA ID, site HRS score, size of each site, site background information, full list of contaminants, archived key documents such as Record of Decisions, and archived administrative records. More importantly, we identify each Superfund site's pollution accumulation period (accumulation of contaminants period) based on its background information, the archived key documents, and archived administrative records. The pollution accumulation periods allow us to identify whether or not CEOs were exposed *in utero* to the Superfund sites.

Table 1 presents summary statistics on the Superfund sites through 2018. The summary statistics are similar to those reported by Greenstone and Gallagher (2008). For all 1,803 Superfund sites, 1,463 (81%) were proposed in the 1980s and 1990s, 203 (11%) were proposed in the 2000s, and 137 (8%) were proposed in 2010-2018. There are 23 sites with missing HRS scores, and one with an HRS score less than the requisite score of 28.5.[15] The mean (median) HRS score on the NPL listing date is 43.85 (43.70). Due to some large sites (such as the military bases, mining sites, etc.), the mean Superfund site size (at 6,852 acres) is substantially larger than the median site size (at 38 acres).

Table 1 also documents the lengthy nature of the Superfund cleanup process.[16] The median years from the NPL proposal date until the remedial action started date (when a site achieved the construction completion milestone, and when a site was deleted from the NPL) are around 7.83 (12.36, and 13.69, respectively) years. It takes over two decades (median 24.13 years) before the site can be reused and redeveloped. The three non-mutually exclusive contaminated environmental

14 For example, the website homepage for the A.L. Taylor (Valley of Drums) site in Brooks, KY on the EPA website is at: https://cumulis.epa.gov/supercpad/cursites/csitinfo.cfm?id=0402072.

15 These sites are proposed by the states as their top-priority site and are limited to one per state. According to CERCLA, sites that do not attain the requisite score of 28.5 or do not apply the HRS can be added to the NPL as proposed by the state as its top-priority site and are limited to one per state.

16 397 sites have their remedial action started dates marked as "not yet achieved," which means that the remedial action has not started yet at this particular site. 598 sites have their construction completion status marked as "not yet achieved." 1,391 sites have their deletion status marked as "not yet achieved." 932 sites have their ready for reuse and redevelopment status marked as "not yet achieved."

media at Superfund sites are air, water, and ground.[17] For example, due to gravity or rainfall, liquid contaminants can flow through the soil to the groundwater. Table 1 reveals that toxicants released into the air (4.88%) are uncommon at Superfund sites, while 82.03% and 87.97% report toxicants released into the ground and water, respectively.

Our study on the effect of prenatal Superfund exposure at the national level uses the county-level geographic scale. Our county-level Superfund exposure approach is the same as Kirpich and Leary (2017), Amin, Nelson, and McDougall (2018), Davis, McDermott, McCarter, and Ortaglia (2019), and Hubal et al. (2022). To show the negative impact on infant health, we collect infant mortality and low birthweight rates data from U.S. County-Level Natality and Mortality Data, 1915-2007 (Bailey et al. (2016)). Panel A of Table 2 presents the percentage of Superfund infants (i.e., infants born in a county with at least one Superfund site during the pollution accumulation periods) among all infants and the counterpart for CEOs. Superfund CEOs form a lower proportion of all CEOs relative to the proportion of Superfund infants. One explanation is that Superfund infants are less likely to become CEOs than other infants. An alternative explanation is that CEO families' relatively higher socioeconomic status makes them less likely to give birth to Superfund infants. We control for the latter possibility by using CEOs' year-of-birth and county-of-birth fixed effects, and the birth county's demographic characteristics in all our models. Panel B and C compare the infant mortality rates and low birthweight rates between counties with Superfund sites during the pollutant-accumulation periods and (1) all counties, (2) counties with Superfund sites during periods before or after the pollutant-accumulation periods, or (3) counties without Superfund sites. The key takeaway from these two panels is that the most negative impact on infant health for the Superfund sites was during the pollutant-generating periods.

3.2. CEO characteristics

3.2.1. CEOs' early life biography: Birthplace, high school, and higher education

We begin with the S&P 1500 firms on Execucomp from 1992 to 2018. Our initial set of CEOs consists of 7,890 unique CEOs. We start with CEO birthplace data obtained from Bernile, Bhagwat, and Rau (2017), and Lei, Petmezas, Rau, and Yang (2023). For CEOs without the above birthplace records, we manually collect their birthplace and birth year from textual, visual, and audio sources,

[17] Ground media consist of debris, landfills, landfill gas, leachate, soil, sediment, sludge waste disposed in underground injection wells, surface impoundments, or spills and leaks released to land. Water media consist of groundwater, surface water, fish tissue, liquid waste, or non-aqueous phase liquids (NAPL).

including Bloomberg People Profiles, Forbes, Conference Board CEO's biography, Legacy.com (from their obituaries),[18] Marquis Who's Who, Standard and Poor's Register of Directors and Executives, the U.S. Executive Compensation database on Lexis-Nexis, NNDB.com, the Business Week Corporate Elite issues, The Wall Street Journal, Wikipedia, other media coverage, or in the last instance, via Google search. We are able to collect birthplace information for 3,511 CEOs. Of these, 501 are non-American-born CEOs, 9 have only partial birthplace information, and 3,001 CEOs born in the United States have complete birthplace records at the county level. For American-born CEOs with complete birthplace records, matching the locations of the Superfund sites and their pollution accumulation periods with CEOs' birthplaces and birth years, we identify 734 unique Superfund CEOs and 2,267 non-Superfund CEOs. The ratio of Superfund CEOs to our initial CEO sample (CEOs of birthplace information, and American-born CEOs) is around 9% (20.9%, and 24.5%, respectively).[19] We restrict our research to American-born CEOs with complete birthplace records since we cannot confirm whether non-American-born CEOs were exposed to pollution at birth.

Our key explanatory variable, "*CEO #Superfund exposure*," measures the number of sites (later designated as Superfund sites) that were actively polluting the CEO's birth county during her birth year. For example, General Motors CEO, Mary T. Barra, was born in 1961. Her birth county, Oakland County, Michigan, has 5 Superfund sites, and 3 of the 5 sites were polluting before 1961. Therefore, Mary T. Barra is identified as a "*Superfund CEO,*" and her "*CEO #Superfund exposure*" is 3. As of today, none of the 3 sites have been deleted from the NPL. In addition, we use the indicator variable "*Developmental toxic chemical* (0,1)", which is described later, to identify whether the contaminants the CEO was exposed to during her prenatal period were classified as developmentally toxic. Detailed descriptions of the construction of the variables in this study can be found in the Appendix.

To measure CEOs' exposure to Superfund pollution while they were growing up, we first collect their high school records via birthplace data sources, LinkedIn, yearbooks, alumni association websites, and official high school websites, as in Duchin, Simutin, and Sosyura (2021).

[18] For the deceased CEOs, in addition to legacy.com, we use findagrave.com, courierpress.com, and dignitymemorial.com.

[19] Interestingly, our ratio of Superfund CEOs is comparable to that of dyslexic entrepreneurs (https://chiefexecutive.net/quarter-ceos-dyslexic-says-ciscos-john-chambers/). Logan (2009) reports that the ratio of dyslexic entrepreneurs in the U.S. (U.K.) is around 35% (20%).

To prevent misidentification with people with the same name, we double-check using CEOs' work experiences, ages, or birthplaces. Among 3,003 American-born CEOs with complete birthplace records at the county level, we obtain 1,397 CEOs' high schools county FIPs codes and identify 733 CEOs who were born and went to high school in the same county. We then collect CEOs' higher education records from BoardEx and supplement BoardEx data with data sources discussed above. For those with missing high school records, we assume that they were born and grew up in the same county if they attended a university in the same state. Making this assumption allows us to further identify 1,511 CEOs' university state FIPs codes. Of these, 679 CEOs were born and went to a university in the same state. In sum, the data show 1,412 (47%) CEOs who were born and likely stayed in the same area while growing up.[20]

3.2.2. Other CEO characteristics

To address concerns that other CEO characteristics may drive our findings, we include a host of CEO characteristics: Ln(CEO age), Ln (1+CEO tenure), CEO duality (0,1), founder CEO (0,1), outside CEO (an indicator variable for whether or not the individual joined the firm and became CEO in no more than two years), CEO employment contract (0,1) (an indicator variable for whether or not CEO has an explicit employment contract), CEO ownership, and ln(1+Delta) (the natural logarithm of one plus the change in the risk-neutral (Black-Scholes) value of a CEO's stock and option portfolio in response to a 1% change in the price of the underlying stock). Data on CEO characteristics are obtained from Execucomp, BoardEx, Equilar Consultants, Risk Metrics, and Compustat. Missing data on CEO characteristics are collected from SEC filings when available.

3.3. Firm characteristics

To illustrate the characteristics of our sample, we provide two sets of comparisons in Table 3. Panel A compares our sample with firms in Compustat and Execucomp. Intuitively, given that our sample was drawn from Execucomp, our sample firms should be more like Execucomp firms than Compustat firms. Also, our sample comprises the S&P 1500 firms, among the largest firms in Compustat. Panel A shows that, on average, our sample firms are more similar to those in Execucomp than Compustat. The last column suggests that our sample firms are still significantly

[20] Of our 501 non-American-born CEOs, 167 moved to the U.S. for their high school and higher education.

larger than typical Execucomp firms. One explanation is that larger firms' CEOs attract more media coverage, and thus their birthplace records are more accessible.

Panel B compares our sample of Superfund CEOs and non-Superfund CEOs. We have 734 unique Superfund CEOs and 2,267 non-Superfund CEOs. Strikingly, Superfund CEOs are typically hired by larger firms than non-Superfund CEOs. There is preliminary evidence that firms managed by Superfund CEOs perform worse in terms of ROA. They also bear higher equity risk (higher total and firm-specific stock return risk). They appear to have riskier investment policies (lower capital expenditures, and higher R&D) and riskier financial policies (lower credit ratings and higher probability of default). In addition, these firms are less likely to pay dividends. The bottom of Panel B shows that, on average, Superfund CEOs were born in counties with lower poverty status, higher employment rates, and higher earnings per capita, suggesting that lower local socioeconomic status does not drive our results for Superfund CEOs. Using a two-sample Kolmogorov-Smirnov test, we find no significant differences between the Fama–French (1997) 48 industry distributions for our Superfund and non-Superfund CEO and CEO-firm samples (results not tabulated),[21] suggesting that the results are not due to Superfund CEOs managing firms in riskier industries than non-Superfund CEOs.

4. Empirical results: Baseline tests

As discussed above, prenatal exposure to Superfund sites has long-term consequences on neurodevelopment, psychophysical, and cognitive dimensions in adulthood. In particular, Superfund chemicals may increase aggression, impulsivity, and risk-taking behaviors (e.g., Ke et al. (2021)). Accordingly, we hypothesize that, all else constant, CEOs' prenatal Superfund exposure is associated with an increased aggressive tendency in their managerial decisions.

The dependent variables in our baseline models in Equation (1) are the risk-taking policies, financial performance, and CEOs' career outcomes of firm *i* in year *t*. We regress these variables on whether the firm *i* is managed by a Superfund (or non-Superfund) CEO *j* and a vector of control variables *k* measured in year *t*-1. To account for unobservable firm heterogeneity in the dependent

[21] In our CEO sample, the top ten Fama–French (1997) 48 industry for Superfund CEOs are business services (13.1%), retail (11.5%), electronic equipment (6.8%), communication (6.4%), petroleum and natural gas (6.O%), pharmaceutical products (5.1%), computers (4.8%), transportation (4.8%), automobiles and trucks (4.3%), and chemicals (3.9%). The top ten industries for non-Superfund CEOs are business services (10.6%), retail (8.4%), petroleum and natural gas (5.8%), electronic equipment (5.3%), communication (5.0%), computers (4.8%), chemicals (4.2%), transportation (4.0%), pharmaceutical products (3.9%), and machinery (3.8%).

variables and for possible time-trends, all baseline models contain firm, firm's state of headquarters (HQ), and year fixed effects. In addition, a potential concern is that nonrandom migration across counties might change the composition of newborns in each county over time. To account for unobservable heterogeneity in the dependent variables across counties in the composition of newborns and for possible CEO age and cohort effects, the baseline models also contain CEO birth year and birth country fixed effects. All standard errors account for CEO-firm and year (two-way) clustering. The baseline model estimated is:

Dependent variable$_{i,j,t}$ = $\beta_0 + \beta_1 \times$ Ln(1+ CEO #Superfund exposure$_{i,j,t}$)

+ $\Sigma_k \beta_k \times$ Controls $_{i,j,k,t\text{-}1}$+Σ firm$_i$, HQ$_i$, year$_t$, CEO birth year$_j$, and CEO birth county$_j$ fixed effects + $\varepsilon_{i,t}$. (1)

The main coefficient of interest in Equation (1) is β_1, the coefficient for our key explanatory variable, *Ln*(1+ *CEO #Superfund exposure*).

4.1. CEOs' prenatal exposure to Superfund sites and risk-taking

4.1.1. CEOs' prenatal exposure to Superfund sites and firms' financial policies

We begin our analysis by testing whether Superfund CEOs tend to make more aggressive financial decisions, measured by the cash-to-asset ratio, leverage ratio, and the natural log of one plus the amount of cash returned to the shareholders in the form of share repurchases. We examine share repurchases instead of dividends because the former are largely discretionary while the latter are sticky. Table 4 presents the results. In all specifications, we include lagged CEO and firm characteristics similar to those in Bates, Kahle, and Stulz (2009), Custódio and Metzger (2014), and Bernile, Bhagwat, and Rau (2017). Consistent with our hypotheses, Table 4 shows that *Ln*(1+ *CEO #Superfund exposure*) is positively associated with leverage and negatively associated with the firm's cash holdings and the natural log of one plus dollar amounts of repurchases. Economically, *ceteris paribus*, relative to firms managed by non-Superfund CEOs, firms managed by a CEO born in a county with one polluting Superfund site hold 1.32% (= −0.0191×Ln(2)-Ln(1)) less cash-to-asset ratio, buy back 42% (=exp(−0.7948×Ln(2)−Ln(1))−1) smaller dollar amounts, and have 3.13% (=0.0451× Ln(2)−Ln(1)) greater leverage ratio. The estimated effects of prenatal exposure to one Superfund site are comparable to those of a medium fatality experience documented by Bernile, Bhagwat, and Rau (2017) that CEOs with medium fatality experience have 1% lower cash holdings and a 3% higher leverage ratio. Our effects of prenatal exposure to one Superfund site are also comparable to CEOs with private pilot licenses (proxy for risky behavior) documented by Cain and McKeon (2016). Our mean sample firm has a leverage of 21.2%, implying that Superfund CEOs are associated with 14.8% (3.13%/21.2%) higher firm leverage, at the mean. Cain and McKeon (2016) report that pilot CEOs are associated with 11.4% higher firm leverage, at the median. The results for the control variables are also comparable to those from the prior studies referenced here.

Is the debt accrued by the Superfund CEOs beneficial for the firm? To answer this question, we compute the kink defined by Graham (2000) and Malmendier, Tate, and Yan (2011) as the ratio of the hypothetical level of interest at which the expected marginal tax-shield benefits of debt start to fall (numerator) to the actual amount of interest paid (denominator). If the kink is greater than one, then a firm could increase its interest expense and earn full benefits on these incremental tax deductions − such a firm would be using debt conservatively. If kink is less than one, the firm would earn reduced tax benefits at the actual interest expenses, suggesting that the firm has excessive debt relative to available tax benefits.

Table 5 presents the results using the kink as the dependent variable and includes lagged CEO and firm characteristics similar to those in prior studies. As the kink is left censored at 0 and right censored at 8, Table 5 uses a Tobit model (column 1). However, a general drawback of the Tobit model with fixed effects is the well-known incidental parameters bias in the coefficient estimates (Greene (2004)). Therefore, Table 5 also reports coefficients from an OLS model (column 2). Not surprisingly, the coefficients on the *Ln*(1+ *CEO #Superfund exposure*) in the two kink regressions are significantly negative at the one percent level, suggesting that the debt issued by firms managed by Superfund CEOs tends to be excessive. Economically, *ceteris paribus*, relative to firms managed by non-Superfund CEOs, firms managed by a CEO born in a county with one polluting Superfund site have kink reductions of 0.82 (−1.1758×Ln(2)−Ln(1)), representing a 16% decrease in kink from its sample mean at 5.002. This Superfund CEO effect on kink is similar in magnitude but opposite to the Depression Baby CEO effect in Malmendier, Tate, and Yan (2011). Again, the impact is likely to be amplified if the CEO was exposed to multiple polluting Superfund sites *in utero*.

4.1.2. CEOs' prenatal exposure to Superfund sites, credit risk, and cost of borrowing

From a creditor's perspective, if the debt issued by the Superfund CEOs is excessive (or exhausts their firms' debt capacities), it should negatively affect the credit risk and the cost of borrowing of their firms. Table 6 reports how firm credit ratings and the default risk vary with CEO Superfund exposure.

We obtain credit ratings from Compustat Standard & Poor's (S&P) Rating database, with a 0 corresponding to a rating of D and a 24 corresponding to a rating of AAA. Since the S&P Rating database was discontinued after February 2017, we fill the missing data and data after February 2017 using Mergent Fixed Income Securities Database (FISD), which contains bond credit ratings from S&P, Moody's, Fitch, and Duff and Phelps. We convert credit ratings from other credit rating agencies to those of S&P.

Column 1 of Table 6 reports estimates from an Ordered Probit model. In line with our earlier results, firms managed by Superfund CEOs have significantly lower credit ratings. Column 2 focuses on the extreme credit risk of obtaining a junk rating (i.e., if S&P domestic long-term issuer credit ratings or converted credit ratings from other agencies are lower than BBB−). We find no significant relationship between firms managed by Superfund CEOs and the probability of junk-rated companies. In the last two columns, we show that firms managed by Superfund CEOs have higher bankruptcy scores based on Zmijewski (1984) and higher estimated default probabilities based on KMV-Merton's (1974) model (Bharath and Shumway (2008)).

Next, Table 7 reports estimates of whether Superfund CEOs are associated with a higher cost of borrowing using three measures of the cost of borrowing as the dependent variables: (1) interest expenses scaled by total debt, (2) bank loan all-in spread defined as all-in-spread in basis points over LIBOR for new bank loans, and (3) bond issue spread defined as the yield-to-maturity for newly issued bonds minus the yield for U.S. Treasuries of equivalent maturity. We collect bank loan data from DealScan database and bond issue data from Mergent Fixed Income Securities Database (FISD). Following Ivashina (2009) and Drucker and Puri (2009), columns (2) and (3) control for a wide array of loans/bonds contract characteristics, and each observation corresponds to each loan/bond issue. The bank loan all-in-spread regression also includes lead lender fixed effects.[22] In addition, columns (2) and (3) explicitly control for firm leverage and credit ratings. Hence, the estimated impact of Superfund exposure on the cost of borrowing is incremental relative to the impact of firm leverage and credit rating. This is particularly important given that

[22] For the loan deals with multiple facilities, we use the loan characteristics of the largest tranche with the earliest active date. We use the variable LeadArrangerCredit in the DealScan database to identify if a lender is also a lead arranger. We include all loans with at least one lead arranger in our sample. For loans with multiple lead arrangers, we have one observation corresponding to each lead arranger.

our earlier results show a strong relationship among leverage ratio, credit risk, and CEOs' prenatal Superfund exposure.

Using Interest expense/Debt as the dependent variable, column (1) shows an insignificant Superfund CEO effect. This is perhaps because interest expenses for total debt may arise from interest owed on debt issued a long time prior, even before the current CEO takes her position. Therefore, we next focus on new bank loans or newly issued bonds in the current fiscal year. The advantage of this approach is the direct link between the cost of borrowing and the CEO leading the firm at the time of the loans/bonds issuance. Columns (2) and (3) show that Superfund CEOs are associated with higher bank loan all-in-spread and bond issue spread, respectively. Economically, *ceteris paribus*, compared to firms managed by non-Superfund CEOs, firms managed by a CEO born in a county with one polluting Superfund site pay an increased all-in bank loan spread (bond issue spread) of 11.65 (64.43) basis points. Again, the estimated effects of prenatal exposure to one Superfund site are comparable to, although weaker than, those of a medium fatality experience documented by Bernile, Bhagwat, and Rau (2017) that CEOs with medium fatality experience pay an increased all-in bank loan spread of 16.85 basis points.

Taken together, the evidence from Tables 4 to 7 is largely consistent with medical research linking prenatal exposure to Superfund pollution to aggressive decision-making. From a creditor perspective, we find that the effect of CEO prenatal exposure to pollution on financial policies is uniformly negative – Superfund CEOs take on excessive debt, beyond the points where the marginal benefits of tax shields turn negative. The aggressive financial policies ultimately lead to an increase in the firm's credit risk and cost of borrowing.

4.1.3. CEOs' prenatal exposure to Superfund sites and equity risk

From the shareholder's perspective, we examine whether aggressive managerial decisions result in higher equity risk, measured by the annualized total stock return volatilities ($\sigma_{Stock\ return}$), the annualized firm-specific (idiosyncratic) stock return volatilities ($\sigma_{\text{Specific return}}$), and three proxies for the stock's vulnerability to firm-specific extreme negative price movements. Column (1) of Table 8 shows that, ceteris paribus, compared to firms managed by non-Superfund CEOs, firms managed by a CEO born in a county with one polluting Superfund site are associated with 2.23% (0.0322×Ln(2)−Ln(1)) increases in $\sigma_{Stock\ return}$, representing a 5.7% increase in $\sigma_{Stock\ return}$ from its sample mean at 0.3902. Again, our Superfund CEOs effects are economically comparable to the previous studies. Cain and McKeon (2016) report that pilot CEOs are associated with, ranging from 2.20% to 3.5%, increases in $\sigma_{Stock\ \mathrm{return}}$. Column (2) shows that the same pattern holds but is weaker for $\sigma_{\mathrm{Specific\ return}}$, which is calculated from an expanded index model regression including contemporaneous, two leads, and two lags for the market and industry indexes (Hutton, Marcus, and Tehranian (2009); Kim, Li, and Zhang (2011); Xu, Xuan, and Zheng (2021)). The effect of Superfund CEOs on $\sigma_{\mathrm{Specific\ return}}$ is close to, although weaker than, that of CEOs with medium fatality experience in Bernile, Bhagwat, and Rau (2017).

Next, we test the robustness of our findings to alternative measures of idiosyncratic risk; we use three proxies for the stock's vulnerability to firm-specific extreme negative price movements: (1) Negative skewness in firm-specific returns, (2) the ratio of the firm-specific volatilities in the down to those in up weeks, and (3) the frequency of firm-specific crashes (defined as firm-specific weekly returns fall 3.09 standard deviations below the annual mean). In the three specifications, we include control variables similar to those in Hutton, Marcus, and Tehranian (2009), Kim, Li, and Zhang (2011), and Xu, Xuan, and Zheng (2021). Columns (3) to (5) show that the results using alternative measures of idiosyncratic risk are consistent with our main findings reported in column (2). The presence of a Superfund CEOs appears to result in a higher vulnerability of the firm's shares to extreme adverse stock price movements.

4.1.4. CEOs' prenatal exposure to Superfund sites and acquisition activity

Existing studies suggest that CEO hubris, an overly optimistic belief in takeover gains, drives unrelated (or diversifying) and/or unprofitable acquisitions (Roll (1986)). Moreover, the personality traits literature suggests that hubris is associated with higher levels of impulsivity and aggression (Carver, Sinclair, and Johnson (2010)). Corporate acquisitions are inherently riskier than internal growth due to the typically large commitment of resources and thus significant financial loss. Therefore, in our next set of tests, we examine whether Superfund CEOs are associated with unprofitable and/or unrelated acquisitions.

We obtain merger and acquisition (M&A) announcements that involve U.S. public acquiring firms between 1992 and 2018 available in the Securities Data Corporation's (SDC) U.S. Mergers and Acquisitions database. After excluding buybacks, share repurchases, self-tenders, and spinoffs, there are 13,719 M&A announcements for 6,630 acquirer-year observations. Each observation in Table 9 corresponds to each M&A announcement. To examine the M&A announcement effect for acquiring firm shareholders, we calculate the acquirer's cumulative abnormal returns (CAR) over day −1 to day +1 relative to the M&A announcement (day 0) based on the market model regressions of daily stock returns on the CRSP value-weighted market index and an estimation period from day −131 through day −31. We also calculate the CARs based on the Carhart (1997) four-factor model and apply standard event study methods. For acquirers managed by Superfund CEOs, the average market model CAR (-1, +1) is 0.088% with a t-value of 1.04, while for non-Superfund CEO acquirers, it is 0.2435% with a t-value of 4.89.

Columns (1) and (2) of Table 9 present the results of a cross-sectional analysis of the CAR(−1, +1). The acquirers' Superfund CEOs seem to negatively impact CAR(−1, +1), controlling for acquirers', acquirer CEOs', and M&A deal characteristics. Using a probit model, Column (3) shows that acquiring firms managed by the Superfund CEOs are more likely to announce unrelated acquisitions defined using the Fama-French (1997) 48 industry definition. As described earlier, a general drawback of the nonlinear (such as probit) model with fixed effects is the well-known incidental parameters bias in the coefficient estimates (Greene (2004)). Therefore, Table 9 also uses OLS with fixed effects regression (column 4). Again, our result on the acquisition activity is economically comparable to previous studies (e.g., Bernile, Bhagwat, and Rau (2017)).

4.2. CEOs' prenatal exposure to Superfund sites and firm performance

The literature documents that prenatal exposure to pollution has long-term effects on cognitive performance in adulthood (e.g., Raja, Subhashree, and Kantayya (2022); Oppenheimer et al. (2022)). In this subsection, we examine whether CEOs' prenatal exposure to Superfund sites adversely impacts firm performance measured by industry-adjusted ROA, Tobin's Q, and stock returns. In all specifications in Table 10, we control for lagged respective industry-adjusted performance (Wintoki, Linck, and Netter (2012)), possible restrictions of CEO mobility using a state-level noncompetition enforceability index (Garmaise (2011)), CEOs' local labor market opportunities (Jochem, Ladika, and Sautner (2018)), and product market competition using product market similarity based on TNIC classifications (text-based network industry classifications (Hoberg and Phillips (2016)).

We find that Superfund CEOs indeed adversely impact firm performance. *Ceteris paribus*, compared to firms managed by non-Superfund CEOs, firms managed by a CEO born in a county with one polluting Superfund site experience industry-adjusted ROA reductions of 0.42%, representing a 12% decrease in industry-adjusted ROA from its sample mean at 0.0343. In untabulated tests, we repeat the Table 10 regressions using unadjusted ROA, Tobin's Q, and stock return and our findings persist.

4.3. CEOs' prenatal exposure to Superfund sites and CEO careers

Given that CEOs' prenatal exposure to Superfund sites adversely impacts their important managerial decisions, we expect Superfund CEOs to face higher forced turnover risk and shorter CEO tenures. Indeed, columns (1) and (2) of Table 11 show that Superfund CEOs are more likely to have shorter tenures and higher forced CEO turnover risk, controlling for local labor market opportunities, restriction of CEO mobility, industry and firm abnormal (i.e., industry-adjusted) performance on a percentile basis within the annual cohort (Jenter and Kanaan (2015)), and industry and firm abnormal volatility (Peters and Wagner (2014)).

Next, we test the robustness of our forced turnover findings to alternative turnover events that may not be caused by poor firm performance or unethical behaviors. For example, CEOs could step down voluntarily, perhaps due to age. If some generic turnover events are not caused by poor firm performance, we may expect generic turnovers to be indistinguishable between Superfund and non-Superfund CEOs. Moreover, severance pay to departing CEOs is usually determined by *ex ante* CEO employment contracts rather than *ex post* firm performance (Rau and Xu (2013)). Columns (3) and (4) show that the coefficient estimates for Superfund CEOs are indistinguishable from zero, consistent with the conjecture that Superfund CEOs are unlikely to be dismissed without cause.

Taken together, we show that Superfund CEOs take more risks without corresponding payoffs, adversely affecting their careers. We also contrast our results with other studies on CEOs' early-life experience and personal risk-taking. Even using the most conservative case (i.e., only one Superfund site polluting the CEOs' birthplaces), our results are comparable to theirs in both economic and statistical magnitudes. In other words, the negative impact of exposure to more Superfund sites is likely to further aggravate important managerial decisions, firm performance, and CEOs' careers.

A natural question arises: why do boards hire these Superfund CEOs after all? Gopalan, Milbourn, and Song (2010) identify CEOs appointed from outside the firm as being more talented than inside CEOs, "since these executives overcome their relative lack of firm-specific knowledge to get hired anyway" (page 2075). In contrast, inside CEOs promoted from within the firm, benefit from firm-specific knowledge and relationships but lack opportunities to demonstrate managerial talent and accountability at the CEO level. We, therefore, investigate whether Superfund CEOs are more likely to be internal than external candidates. We find that they are. Table 12 presents probit regression results using outside CEO (an indicator variable that equals one if the individual joined the firm and became CEO in no more than two years and zero otherwise) as the dependent variable and includes departing CEO and firm characteristics similar to those in Dahya and McConnell (2005) and Marshall, McCann, and McColgan (2014). Table 12 shows that Superfund CEOs are significantly less likely to be outside CEOs, suggesting that Superfund CEOs are significantly more likely to take the top position without being tested outside the firm and without being seen to be solely accountable for the whole company.

5. Additional empirical analyses

In this section, we address other plausible explanations. We first focus solely on the exposure to the developmental toxicants released by Superfund sites, which we conjecture is the primary channel harming fetal neurodevelopment, psychophysical, and cognitive dimensions, as the fetal brain is highly vulnerable to chemical toxicity (e.g., Black et al. (2019)). Second, we examine if the CEOs' postnatal exposure to Superfund sites up to adolescence and CEOs' current exposure to pollution at work have incremental impacts beyond their prenatal exposure. Third, we perform a battery of robustness tests. Finally, we perform two matched-pair sample analyses, a difference-in-differences (DID) analysis using CEOs' sudden deaths, and two falsification tests to consolidate our main results.[23]

5.1. CEO prenatal exposure to only developmental toxicants released from Superfund sites

The fetal origins hypothesis argues that *in-utero* exposure to developmental toxicants has long-term consequences on adulthood's neurodevelopment, psychophysical, and cognitive dimensions. In addition, *in-utero* exposure to toxicants not classified as developmental toxicants could also induce chronic diseases in adulthood, including cancers (e.g., Young and Cai (2020)). Therefore, prenatal exposure to those not classified as developmental toxicants could be an alternative channel driving our results.

Each Superfund site website homepage's health and environment section contains the full list of Superfund chemicals released from each Superfund site. Specifically, the health and environment section provides the names of the contaminants with their contaminated media, the

[23] The results, reported in the tables in the Internet Appendix present kink regression results using an OLS (instead of a Tobit) specification and unrelated acquisitions (0,1) regression results using an OLS (instead of a Probit) specification.

chemical identifiers: the chemical abstracts service registry numbers (CASRN), and the Agency for Toxic Substances and Disease Registry (ATSDR) toxicological profiles. We identify developmental toxicants based on the assessed critical effect on human body systems in the EPA's Integrated Risk Information System (IRIS) [24] and developmental toxicity studies in laboratory animals.[25] To identify whether Superfund sites release any developmental toxicant, we match the contaminants' 10-digit CASRN for each Superfund site with their developmental toxicity risk assessment. As described in section 3.1, we identify each Superfund site's pollution accumulation period based on archived documents. Unfortunately, the archived documents do not break down the pollutant accumulation period into each toxicant accumulation period. Hence, we assume the full list of Superfund chemicals was accumulated and released simultaneously and run regressions at the CASRN chemical level.

Our primary explanatory variable is an indicator variable, *Developmental toxic chemical* (0,1), that equals one if the contaminants are developmental toxicants. We construct a CASRN-firm-year sample and repeat our analyses in section 4 by replacing "*Ln*(1+*CEO #Superfund exposure*)" with "*Developmental toxic chemical* (0,1)" and adding CASRN fixed effects. Across nearly all our regressions, reported in Table OA1, except for leverage and share repurchases, the coefficients on *Developmental toxic chemical* (0,1) are typically significant (except for kink) and have the same sign as our baseline results. In contrast, removing Superfund sites with *any* developmental toxic chemicals (i.e., including only Superfund sites with toxicants not classified as developmental toxicants) weakens the results considerably (results untabulated for brevity). Overall, these results confirm that prenatal exposure to developmental toxicants appears to be the primary channel that drives our results.

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[24] The list of chemicals in the IRIS database and its assessed critical effect on human body systems are available at https://iris.epa.gov/AtoZ/?list_type=alpha. The IRIS summary icon contains each chemical's IRIS chemical toxicity assessment summary.

[25] The EPA published guidelines for studying developmental toxicity in 1991 (USEPA (1991)). However, as the fields of toxicology and risk assessment continued to develop, early versions of the guidance document were later revised. Moreover, a number of chemicals were found to cause developmental toxicity in experimental animal studies. In most of these cases, the toxic effects of the chemical on human development have not been studied; hence there is no clear evidence of hazards in humans. Among 573 chemicals listed in the IRIS database, the IRIS toxicological review or supporting document is unavailable for 468 (82%=468/573) listed chemicals. Therefore, in addition to the IRIS, we also identify developmental toxicants based on developmental toxicity studies in laboratory animals.

5.2. Postnatal exposures to Superfund sites

5.2.1. Postnatal exposures to Superfund sites up to adolescence

A natural question is whether the CEOs' postnatal exposure to Superfund sites has effects similar to their prenatal Superfund exposure if the CEOs lived in the same neighborhoods from birth to adolescence. *A priori*, the literature on the fetal origins hypothesis and the vulnerability of the developing brain to toxicants suggest that the postnatal effects could be smaller. Hence, we next examine the impacts of CEOs' postnatal exposure to Superfund sites up to the age of adolescence. As described in Section 3.2., we collect CEOs' high school and higher education records to identify non-moving CEOs born and grew up in the same county. Focusing specifically on the non-moving Superfund CEOs sample, we first compute the length of the pollutant accumulation periods for each Superfund site in the CEO's county *after* the CEO's birth year. We then measure the natural log of the length of likely CEO postnatal exposure to Superfund sites up to adolescence, *Ln*(*length of CEO postnatal exposure*), as the minimum (maximum length of the pollutants accumulation periods for all nearby Superfund sites after the CEO's birth year, 15 (age of entry into senior high school)).

Using only the non-moving Superfund CEOs sample, we repeat all our regression models in Tables 4 to 11 with "*Ln*(*length of CEO postnatal exposure*)". The results reported in Table OA2 are largely similar but statistically weaker than the main results. In an unreported test, we focus on those CEOs *without* prenatal Superfund exposure but who moved to and grew up in a county with Superfund sites. The unreported results show that postnatal exposure again has weaker effects.

5.2.2 CEOs' current exposure to pollutants at work

The firm risk-taking activities could also arise from the firm being a current polluter. Risk-taking firms might, for example, take shortcuts in controlling the pollution they emit. We, therefore, next control for the current polluting activities of the firm. As mentioned in Section 2.1., the EPA identifies the potentially responsible parties (PRPs) who may be deemed liable as generators of contaminants at a Superfund site and determines their liability for cleanup responsibility at each Superfund site.[26] To mitigate the concern that the Superfund CEO is managing a firm named a PRP, we collect the identities of PRPs for Superfund sites from the Noticed Parties at Sites in

[26] Typically, the EPA uses "general notice letters" and "special notice letters" to communicate with PRPs regarding their identification as PRPs and potential cleanup liabilities. For more details about the EPA's use of notice letters, please refer to the EPA's website at: https://www.epa.gov/enforcement/superfund-notice-liability-letters.

SEMS (FOIA 11) from the EPA's Superfund Data and Reports. We also collect the complete list of firms with large amounts of toxic chemical emissions that are required to self-report their emissions to the Toxics Release Inventory (TRI) program on Form R,[27] with information such as Facility name, TRI facility ID, reporting year, TRI facility address, parent company, and contaminants. The identities of PRPs and TRI facilities' parent companies allow us to determine if a firm is a current polluter. We use the indicator variable, *Firm current polluter?* (0,1), to denote these firms.

Alternatively, the current exposure to pollution could lower the CEO's and workers' performance. It has been shown that even short-term exposure to hazardous waste sites reduces performance in highly skilled, cognitively demanding jobs. [28] A Superfund CEO could later be exposed to a Superfund site at work. This work exposure of the Superfund CEOs to pollutants might be the cause of the effects on risk-taking and firm performance that we document here. Yet another possibility is that the Superfund CEOs' desensitization towards pollution might alter their ESG policies. They may become more likely to pollute and increase potential environmental liabilities, perhaps resulting in worse firm performance. To mitigate this concern, we collect the longitude-latitude coordinates of firms' headquarters and facilities. Since the headquarters (HQ) address from Compustat only reports the firm's current principal executive office, not its historical HQ location, we draw on Bill McDonald's historical headquarters data,[29] and the header sections of the 10-K/Qs filed on SEC EDGAR. We collect key facility-level information, including facility

[27] After the passage of the Emergency Planning and Community Right-to-Know Act (EPCRA) in 1986, industrial facilities employing 10 or more full-time equivalent employees are required to self-report their emissions of specific hazardous pollutants to the TRI program using various forms. Among them, the detailed reporting form (Form R) is used by firms with large amounts of emissions.

[28] Even short-term exposure to hazardous waste sites and ambient air pollution reduces performance in highly skilled, cognitively demanding jobs. Archsmith, Heyes, and Saberian (2018) document that short-term exposure to ambient carbon monoxide (CO) and fine particulate matter (PM2.5) significantly reduces performances of major league baseball (MLB) umpires. Heyes, Rivers, and Schaufele (2019) show evidence that PM2.5 can reduce the speech quality of professional communicators (Canadian members of parliament). Zhang, Chen, and Zhang (2018) find that both cumulative and transitory exposure to air pollution impairs cognitive performance, and the damaging effect on brain becomes stronger as people age. As PM2.5 particles easily penetrate indoors, using indoor and climate-controlled settings, Chang, Graff Zivin, Gross, and Neidell (2019) document evidence showing that indoor air pollution limits productivity in high-skilled, cognitively demanding professions such as call center workers. Ebenstein, Lavy, and Roth (2016) show evidence that transitory exposure to PM2.5 during high-stakes examinations is associated with a significant decline in performance. Such poor exam outcomes have substantial negative long-term consequences on students' postsecondary educational attainment and adult earnings. Huang, Xu, and Yu (2020) show that individual stock investors' trading performance decreases monotonically with the severity of air pollution; the underperformance associated with air pollution might be explained by the high frequencies of investment biases such as disposition effect, the tendency to buy attention-grabbing stocks, and excessive trading.

[29] Available at https://sraf.nd.edu/data/augmented-10-x-header-data/.

name, address, geospatial information, and its parent company from EPA.[30], [31] Following Greenstone and Gallagher (2008) and Persico, Figlio, and Roth (2020), we construct our indicator variables, *HQ current pollution exposure* (0,1) and *Facility current pollution exposure* (0,1), to identify Superfund sites within the three-mile zone around a firm's HQ and its facilities, respectively. We focus on the three-mile radius circle around the company HQ (and facility) that is likely to pose an imminent and substantial threat to human health. Our results in Table OA3 show that *Ln*(1+*CEO #Superfund exposure*) remains statistically significant after controlling for CEOs' current exposure to pollution at work and their firms' polluting behavior.

One issue with Table OA3 is that, as shown in Table 1, the Superfund site pollution is mostly ground- or water-based. The literature also stresses the causal link between exposure to ambient air pollution and increased aggression, impulsivity, and a reduction in cognition or mental acuity (e.g., Archsmith, Heyes, and Saberian (2018); Herrnstadt et al. (2021)), suggesting that exposure to air pollution could be an alternative channel driving our results. For robustness, we replace the current Superfund exposure with the current air pollution exposure at both headquarters and facilities levels. We obtain the annual county-level air quality index (AQI) from the EPA website.[32] The higher the AQI value, the greater the level of air pollution. When AQI values are above 100, air quality is considered unhealthy. We use *Ln*(1+# *Days HQ AQI* > 100) and *Ln*(1+# *Days Facility AQI* > 100) to measure, respectively, the natural log of one plus the number of days in the focal year of unhealthy levels of air pollution at the company headquarters and its facilities. Results (untabulated) show that adding these variables to the baseline regressions in tables 4-11 does not alter the significance of *Ln*(1+*CEO #Superfund exposure*).

5.3. Other robustness tests

In this section, we report other robustness tests. Since the results are broadly similar to our main results in Tables 4 to 11, they are not tabulated. First, to eliminate the possibility that the firm

[30] We obtain the file NATIONAL_FACILITY_FILE.CSV of key facility-level information and NATIONAL_ORGANIZATION_FILE.CSV of facilities' parent company information from https://www.epa.gov/frs/epa-state-combined-csv-download-files.

[31] Following Autor, Dorn, Hanson, Pisano, and Shu (2020), we use a search-engine-based algorithm (i.e., Bing Web Search API under Microsoft Azure) to match parent company names appearing on EPA to Compustat firms based on at least three shared web search URLs for those observations where the parent name strings on EPA and Compustat firm records do not match exactly.

[32] The county level air quality index (AQI) data is available at https://www.epa.gov/outdoor-air-quality-data/about-air-data-reports.

policies under the Superfund CEO are a holdover from the departing CEO, we remove the first year after the CEO takes her position and find little change in the sign or significance of the results.

Second, one might argue that our results are driven by imbalanced data. 13% (400) of our CEOs and 14% of our CEO-firm-year observations come from three counties (New York County (top) and Kings County (top 3) in New York, and Cook County (top 2) in Illinois). Eliminating these CEOs does not qualitatively change our results. Some counties are much larger than others (e.g., San Bernardino County in California). Hence in a large county, as measured by total area or income disparity, there might be wide disparities within the county, so using county-level fixed effects might not be adequate. However, our results remain similar if we eliminate the top 3 counties by total area size or income disparities.

Third, we replace the natural log of one plus the number of Superfund exposure (*Ln(*1+CEO #Superfund exposure) by the natural log of one plus the average Hazard Ranking System (HRS) scores. We use zero HRS scores for firm-CEO observations without prenatal Superfund exposure. A potential advantage of using the HRS score is that it provides a continuous measure of Superfund exposure risks. However, the HRS score, though playing a key role in NPL listing decisions, has received significant criticism due to judgments about the relative degree of risk by migration, direct contact, and fire/explosion pathways, and was thus revised following the Superfund Amendments and Reauthorization Act of 1986 (Jennings, Mehta, and Mohan (1994)).[33] In addition, a site with a higher HRS score does not necessarily have a more significant impact on the CEOs than two sites with lower scores. Therefore, we use the HRS scores only for a robustness test. Our results are qualitatively similar.

Fourth, our results might be attributed to a cultural factor. Home CEOs (born, grew up, and then manage firms in the same area) may be culturally different from other CEOs. For example, due to personal attachment to their hometowns, home CEOs may choose to work in their hometowns, ignoring potential Superfund pollution effects. This attachment may also affect CEOs' managerial styles (e.g., Lei, Petmezas, Rau, and Yang (2023)). We define a home CEO if her birth county is also the county of the firm's headquarters. Eliminating these home CEOs does not qualitatively change our results. In an alternative definition, we classify a CEO as local if the CEO

[33] The revised HRS retains the water migration and air migration pathways, drops the direct contact and fire/explosion pathways, and adds a fourth pathway, soil exposure.

was born, attended high school in the same county (or college in the same state), and then serves as CEO in a firm headquartered in the same county. Again, eliminating these CEOs does not change our baseline regression results. Adding the home CEO dummy to our main regressions in tables 4 to 11 does not change the significance of the main Superfund exposure variable.

5.4. Matching sample analysis

Although we have already controlled for various fixed effects, there may still be potential omitted variables in our analysis. To validate our results, we construct two matching samples. Our first nearest CEO birthplace matching sample consists of CEO-firm-year pairs with Superfund CEOs matched with non-Superfund CEOs. Matched pairs satisfy the following criteria: (1) the matched CEOs were born in the same year (if feasible, or in the same decade, if not), and (2) they are in the same FF48 industry. For those satisfying the above requirements, we choose our control non-Superfund CEO as the CEO born in the nearest neighboring counties to the treated Superfund CEO. This matching process gives us CEO-firm-year pairs within the same industry, which are best proximate across CEOs' birthplaces and birth years. Table OA4 uses this nearest CEO birthplace matching sample and shows that most of our findings remain unchanged. Hence our results do not appear to be driven by potential omitted variables at the CEO birth county-year level.

Our second nearest firm headquarter matching sample is composed of matched CEO-firm-year pairs satisfying the following criteria: (1) the matched firms' CEOs were born in the same year (if feasible, or in the same decade, if not), and (2) they are in the same FF48 industry. For those satisfying the above requirements, we choose the control firm managed by a non-Superfund CEO with headquarters in the nearest neighboring counties to the treated firm managed by a Superfund CEO. This matching process gives us CEO-firm-year pairs within the same industry, which are best proximate across CEOs' birth years and their firms' HQs. Table OA5 uses this nearest firm headquarter matching sample and shows that our baseline findings remain largely unaltered in this matching sample. Hence, our conclusions do not appear to be affected by potential omitted variables at the firm's HQ-year level.

5.5. Difference-in-differences (DID) analysis on CEOs' sudden deaths

We next perform a DID analysis on CEOs' sudden deaths. If there is a causal relation between Superfund CEOs' prenatal exposure and their aggressive managerial decisions (and poor performance), we would expect their successors to reverse these decisions in the years following the sudden deaths of the Superfund CEOs. Following Salas (2010) and Fracassi (2017), CEOs' sudden death events are collected from major newspaper databases (ProQuest newspapers, Factiva, and Google News Archive) and articles published on the internet.[34] These exogenous events allow us to mitigate concerns that the policy dissimilarity took place because the CEO was replaced following poor performance.

To test our conjecture, sudden deaths of the Superfund CEOs form the treated group, while those of the non-Superfund CEOs form the control group. We record the deceased CEO's prenatal Superfund exposure as *Ln*(1+*deceased CEO #Superfund exposure*). We contrast the firm-year observations for the three years before (i.e., pre-treatment period) and three years after (post-treatment period) the CEO's death. We define our *Post CEO demise* (0,1) variable as one for the three years after the CEOs' deaths and zero otherwise. The main coefficient of interest is the coefficient for the DID interaction variable (*Post CEO demise* (0,1) × *Ln*(1+*deceased CEO #Superfund exposure*)). We report results from the DID analysis in Table OA6.[35] In almost every case, our results show that the signs of coefficient for the DID interaction variable reverse (except for *Ln*(1+CEO tenure)) from the previous baseline results, and it continues to be significant. The DID analysis shows that after the sudden death of Superfund CEOs, relative to the sudden death of non-Superfund CEOs, the new CEOs tend to adopt more dissimilar corporate policies.[36]

5.6. *Placebo tests with falsely assigned birthplaces*

In our last robustness test, we perform falsification tests assigning an incorrect birthplace to each CEO in our sample for two empirical bootstrap resampling distributions. To construct each empirical distribution, we replace the sample CEOs' birth counties (and county-level control variables) with pseudo-birth counties. In Table OA7 column (1), the pseudo-county is randomly chosen from all U.S. counties (not limited to the counties containing CEOs' birthplaces in our sample). This is done for each firm-CEO in the sample, forming a single pseudo sample on which we run each regression in the main tables. This process is repeated 1,000 times, forming an empirical pseudo-random CEO birthplace bootstrap resampling distribution. In Table OA7 column

[34] The cause of death of the CEO is indicated as a heart attack, stroke, plane crash, car, boating, or mountain accident, cancer within a year of diagnosis, and other similar unexpected death events.
[35] The test for CEOs' forced turnover is not feasible because the model did not converge.
[36] The results are mostly similar, albeit slightly weaker, if we examine the change from the two years before to two years after the CEO's demise. We cannot examine the change from one year before to one year after the CEO's demise since the number of observations is less than the number of explanatory variables, including CEO-firm, year, birth year, birth county, and state of HQ fixed effects.

(2), for each firm-CEO in the sample, the pseudo-county is randomly chosen from the 10 nearest counties to the CEO's birth county. Following the replacement, we again run each regression in the main tables. This process is repeated 100 times, forming an empirical pseudo-nearest CEO birthplace bootstrap resampling distribution. In both columns, we use *Ln*(1+ *Pseudo-random CEO #Superfund exposure*) to capture the effect of CEO's randomly assigned prenatal Superfund exposure for the bootstrap resampling distributions. In each column, we include the same control variables and fixed effects as the corresponding previous tables. We report the fraction of the total number of bootstrap regressions that report similar significant (p-value ≤0.05) coefficients on *Ln*(1+ *Pseudo-random CEO #Superfund exposure*) as our main tables.

Table OA7 shows that our CEO pseudo prenatal Superfund exposure variable is largely insignificant in most of our specifications. In column (1), out of 24 specifications, we obtain the same significant results in a random assignment more than 5% of the time only in 10 cases. In column (2), there are only 3 cases where the same results occur more than 5% of the time entirely by chance. In addition, there are only two cases (credit rating and forced CEO turnover), where the two randomization techniques coincide.

6. Conclusions

This paper studies the detrimental impact of CEOs' prenatal exposure to Superfund sites on three corporate consequences: the risk-taking policies of their firms, firm performance, and CEOs' careers. Superfund sites are the most hazardous contaminated waste sites in the U.S. We draw on the fetal origins hypothesis and the extensive medical literature arguing that *in-utero* environment has long-lasting consequences for adult health, human capital, and socioeconomic status and that prenatal exposure to Superfund sites has long-term implications on neurodevelopment, psychophysical, and cognitive dimensions in adulthood. Accordingly, we hypothesize that, all else constant, CEOs' prenatal Superfund exposure may be associated with more aggressive managerial decisions. Indeed, consistent across all three dimensions – Superfund CEOs tend to take more risks that do not appear to pay off, adversely affecting the firm performance, and leading the CEOs to be fired after shorter tenures at their firms.

Most of our sample CEOs were born in an era when industrial chemicals were not identified as developmental toxicants, nor did they know that they lived near the neighborhoods that, over time, would be designated as Superfund sites. Therefore, it is plausible that prenatal pollutant exposure would have been inadvertent without the CEO's parents deliberately choosing to live in the polluted area. Our research design mitigates the selection concern in the extant CEOs' risk-taking literature – that CEOs with risk-taking genotypes transmitted from parents affect both the CEOs' risk-taking behaviors and their prenatal pollution exposure.

Beins and Lester (2015) note a dramatic reduction in the number of Superfund sites cleanups per year; from an average of 87 sites cleanups completed by EPA per year for the years 1997 to 2000 to only 8 sites cleanups completed in year 2014. Our results imply that Superfund cleanup efforts to reduce environmental toxicants will not only offer long-term benefits to low-income families, but also offer long-term benefits to people with higher socioeconomic status such as corporate CEOs and large sections of shareholders and stakeholders.

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Appendix

Variable Name	Definition
Pollution exposure variables	
Superfund CEO	An indicator variable that takes the value of one if the CEO's birth county generated the U.S. worst hazardous contaminants during her birth year and zero otherwise. These sites are later designated as Superfund sites.
CEO #Superfund exposure	The number of sites later designated as Superfund sites in the CEO's birth county during her birth year.
Developmental toxic chemical (0,1)	An indicator variable that equals one if the contaminant is a developmental toxic substance and zero otherwise. Significant prenatal outcomes related to developmental toxicant exposure include poor infant birth outcomes. Among infants who survive to adulthood, outcomes related to developmental toxicant exposure include growth retardation, functional impairment, or damage to neurodevelopment, psychophysical, and cognitive development. Our toxicity classification is based on the human health risk assessment by the U.S. EPA's IRIS database and developmental toxicity studies in laboratory animals.
Ln(length of CEO postnatal exposure)	The natural log of the length of likely CEO postnatal exposure to Superfund sites up to adolescence is calculated as the minimum (maximum length of the pollutants accumulation periods for all nearby Superfund sites after the CEO's birth year, 15 (age of entry into senior high school)).
Firm current polluter? (0,1)	An indicator variable that equals one for the firm-year observations when firms are required to self-report their emissions to the Toxics Release Inventory (TRI) program on Form R, or the firm is one of the potentially responsible parties (PRPs) for the Superfund sites.
HQ current pollution exposure (0,1)	An indicator variable that equals one when there are Superfund sites within a three-mile radius circle around the firm's headquarters (HQ) and zero otherwise.
Facility current pollution exposure (0,1)	An indicator variable that equals one when there are Superfund sites within a three-mile radius circle around the firm's facilities and zero otherwise.
Post CEO demise (0,1)	An indicator variable that equals one in the three years after a CEO's sudden death, and zero in the three years before the demise of a CEO. CEOs' sudden deaths refer to heart attack, stroke, plane crash, car, boating, or mountain accident, cancer within a year of diagnosis, and other similar unexpected death events.
Deceased CEO #Superfund exposure	The number of later designated as Superfund sites in the deceased CEO's birth county during her birth year.
Pseudo-random CEO birthplace bootstrap resampling	To construct an empirical pseudo-random CEO birthplace bootstrap resampling distribution, we replace the sample CEOs' birth county (and county-level control variables) with a pseudo CEO birth county randomly chosen from all U.S. counties (not just limited to the same counties as CEOs' birthplaces in our sample). This is done for each firm-CEO in the sample, forming a single pseudo sample. This process is repeated 1,000 times, forming an empirical pseudo-random CEO birthplace bootstrap resampling distribution.
Pseudo-nearest CEO birthplace bootstrap resampling	To construct an empirical pseudo-nearest CEO birthplace bootstrap resampling distribution, we replace the sample CEOs' birth county (and county-level control variables) with a CEO birth county randomly chosen from the 10 nearest counties. This is done for each firm-CEO in the sample, forming a single pseudo sample. This process is repeated 100 times, forming an empirical pseudo-nearest CEO birthplace bootstrap resampling distribution.
Air Quality Index	Used in unreported robustness checks only. The annual county-level exposure to air pollution variables obtained from the EPA Air Quality index database.

Variable	Definition
Corporate cash, leverage, and payout policy variables	
Cash/Assets	The ratio of cash and short-term investments to the book value of total assets.
Leverage	The ratio of the book value of total long-term debt over total assets.
Ln(1+Share repurchase)	The natural logarithm of one plus dollar amounts of share repurchase.
Corporate debt aggressiveness variable	
Kink	The amount of hypothetical interest where the expected marginal tax-shield benefit function becomes downward sloping, expressed as a proportion of actual interest expense (Graham (2000); Malmendier, Tate, and Yan (2011)).
Corporate credit risk and default risk variables	
Credit rating	Credit ratings provided by Standard & Poor's (S&P), Moody's, Fitch, and Duff and Phelps, which are given a numerical score increasing by 1 for each increase in credit rating, with a 0 corresponding to a rating of D and 24 corresponding to a rating of AAA. Since the S&P Rating database was discontinued after February 2017, we fill the missing data and data after February 2017 using Mergent Fixed Income Securities Database (FISD).
Junk rating (0,1)	An indicator variable that equals one if the Standard & Poor's domestic long-term issuer credit ratings or converted credit ratings from other agencies are lower than BBB− in a given year and zero otherwise.
Bankruptcy score	Zmijewski (1984) bankruptcy score, which is $-4.3-(4.5\times ROA)+(5.7\times Leverage)-(0.004\times Current\ Ratio)$; higher scores indicate higher levels of financial distress.
Default probability	The estimated probability of default based on KMV-Merton's (1974) model (Bharath and Shumway (2008)).
Corporate cost of borrowing variables	
Interest expense/Debt	Interest expense divided by total debt.
Bank loan all-in-spread	All-in-spread over LIBOR inclusive of all fees, in basis points, for bank loans at the time of loan initiation. Bank loan data are from DealScan.
Bond issue spread	Spread over the U.S. Treasury yields of equivalent maturity, in basis points, for the firm's newly issued bonds' yield-to-maturity. Bond issue data are from Mergent Fixed Income Securities Database (FISD).
Corporate equity risk variables	
$\sigma_{\text{Stock return}}$	The annualized standard deviation of a firm's stock return.
$\sigma_{\text{Specific return}}$	The annualized square root of the residual variance from an expanded index model regressing a firm's weekly returns on the contemporaneous, two leads, and two lags of CRSP weekly value-weighted market index returns and the relevant Fama-French (1997) weekly value-weighted industry index returns. We allow for nonsynchronous trading by including two leads and two lags for the market and industry indexes (Hutton, Marcus, and Tehranian (2009)).
Negative skewness	Negative one multiplied by the skewness (the third standardized moment) of firm-specific weekly returns (defined in $\sigma_{\text{Specific return}}$) for each firm-year (Xu, Xuan, and Zheng (2021)).
$\sigma_{\text{Down-to-up}}$	Natural logarithm of the ratio of the standard deviation of firm-specific weekly returns in down weeks to the standard deviation of firm-specific weekly returns in up weeks (Xu, Xuan, and Zheng (2021)). Down (up) weeks are weeks with firm-specific weekly returns below (above) the annual mean.
Crash risk	The frequency that a firm-year experiencing crash weeks during the fiscal-year. Crash weeks are the frequencies with which the firm-specific weekly returns fall 3.09 standard

	deviations (probability 0.001 events for a normal distribution) below the annual mean (Kim, Li, and Zhang (2011)).
Corporate M&A announcement abnormal returns and the propensity of unrelated acquisitions variables	
CAR(-1,1) Market model	The acquirer's cumulative abnormal return (CAR) during trading days [–1, +1] around the M&A announcement (day 0) is based on the market model regressions of daily stock returns on the CRSP value-weighted market index. The estimation period for the market model is from day −131 through day −31 before the M&A announcement (day 0). We obtain merger and acquisition (M&A) announcements that involve U.S. public acquiring firms in the Securities Data Corporation's (SDC) U.S. Mergers and Acquisitions database.
CAR(-1,1) FF4 model	The acquirer's cumulative abnormal return (CAR) during trading days [–1, +1] around the M&A announcement (day 0) is based on the Carhart (1997) four-factor model regressions of daily stock returns on the CRSP value-weighted market index, size, book-to-market, and momentum factor. The estimation period for the Carhart (1997) four-factor model is from day −131 through day −31 before the M&A announcement (day 0).
Unrelated acquisition (0,1)	An indicator variable that equals one if the target is not in the same Fama–French (1997) 48 industry as the acquirer and zero otherwise. We obtain merger and acquisition (M&A) announcements that involve U.S. public acquiring firms in the Securities Data Corporation's (SDC) U.S. Mergers and Acquisitions database.
Firm performance variables	
ROA	The ratio of operating income before depreciation scaled by total assets.
Tobin's Q	The ratio of market-to-book value of assets.
Stock return	Annual buy-and-hold stock return, including dividends.
Ind.adj. ROA	The focal firm's ROA adjusted by the median ROA of firms from the same industry (based on Fama-French (1997) 48-industry classification) as the focal company in a given year.
Ind.adj. Tobin's Q	The focal firm's Tobin's Q adjusted by the median Tobin's Q of firms from the same industry (based on Fama-French (1997) 48-industry classification) as the focal company in a given year.
Ind.adj. Stock return	The focal firm's stock returns adjusted by the median stock returns of firms from the same industry (based on Fama-French (1997) 48-industry classification) as the focal company in a given year.
CEO turnover variables	
Generic CEO turnover (0,1)	An indicator variable for all CEO turnover events excluding turnover in which the CEO leaves the firm to immediately accept a position elsewhere or where the CEO leaves the firm for health reasons. The generic CEO turnover indicator equals one in year t if the incumbent CEO is in office for the larger part of fiscal year *t* but is no longer in office in fiscal year *t*+1.
Forced CEO turnover (0,1)	An indicator variable for CEO involuntary departure events in which a news article indicates a forced departure. The forced CEO turnover indicator equals one in year *t* if the incumbent CEO is in office for the larger part of fiscal year *t* but is no longer in office for fiscal year *t*+1.
Severance payment CEO if turnover (0,1)	An indicator variable for all CEO turnover events in which the CEO received severance payments upon departure. We collect severance payment information from the explicit CEO severance pay contracts or explicit CEO employment contract terms including golden handshakes or golden parachutes.
County-level control variables	
County poverty status	The percentage of the county population with income that falls below the appropriate official poverty threshold. The data source is IPUMS USA database variable POVERTY, which was created using detailed income and family structure information about each

	individual and calculating the family income as a percentage of the appropriate official poverty threshold.
County employment status	The percentage of the county population that is employed. The data source is IPUMS USA database variable EMPSTAT.
County earnings per capita	The average personal total pre-tax wage and salary income for each county. The data source is IPUMS USA database variable INCWAGE.
CEO characteristics control variables	
Ln(CEO age)	The natural logarithm of the age of the CEO.
CEO age≥ 60 (0,1)	An indicator variable that equals one if the CEO's age (measured in years) is at least 60.
Ln (1+CEO tenure)	The natural logarithm of one plus the number of years the current CEO has held her position.
CEO duality (0,1)	An indicator variable that equals one if the CEO also holds the title of chairman of the board of directors and zero otherwise. CEO duality data are obtained from RiskMetrics and SEC filings.
Founder CEO (0,1)	An indicator variable that equals one if the current CEO founded the firm and zero otherwise. The CEO's founder status is obtained from Equilar Consultants and SEC filings.
Outside CEO (0,1)	An indicator variable that equals one if the individual joined the firm and became CEO in no more than two years and zero otherwise (Gopalan, Milbourn, and Song (2010)).
CEO employment contract (0,1)	An indicator variable that equals one if the CEO has an explicit employment agreement and zero otherwise. CEO employment agreement data are obtained from Equilar Consultants and SEC filings.
CEO ownership	The percentage of the firm's total common stock owned by the CEO.
Ln(1+Delta)	The natural logarithm of one plus the change in the risk-neutral (Black-Scholes) value a CEO's total portfolio of all current and prior grants of shares and options for a 1% change in the price of the underlying stock.
Firm and industry characteristics control variables	
Ln(Assets)	The natural logarithm of the firm's book value of total assets.
Capex	The ratio of capital expenditures to the book value of total assets.
R&D	The ratio of research and development expense to the book value of total assets. We code missing values of research and development expense as zero.
Dividend (0,1)	An indicator variable that equals one if the firms pay cash dividends and zero otherwise.
Cash flow/Assets	The ratio of cash flow from operations (operating income before depreciation minus interest minus taxes minus cash dividends) to the book value of total assets.
NWC/Assets	The ratio of net working capital (current assets minus cash minus current liabilities plus debt in current liabilities) to the book value of total assets.
Acquisition/Assets	The ratio of cash outflows associated with acquisitions (Compustat data item AQC) to the book value of total assets.
PP&E/Assets	The ratio of net property, plant and equipment to the book value of total assets.
Growth in sales	Sales less lagged sales over the lagged sales.
Inst. ownership	Total institutional ownership based on data from the Thomson-Reuters Institutional Holdings (13F) database.
Outside directors	The number of independent directors divided by the total number of directors on the firm's board.
NOL carryforward (0,1)	An indicator variable that equals one if the firms have a net operating loss (NOL) carryforward (Compustat data item TLCF>0) and zero otherwise.
ECOST	The expected cost of financial distress (ECOST), which is the product of the standard deviation of the first difference in the firm's historical EBIT, divided by the mean level of

	book assets, and the sum of research and development expense and advertising expense divided by sales.
CYCLICAL	The standard deviation of operating earnings divided by mean assets, calculated for each firm, and then averaged in a given Fama-French (1997) 48 industry and year; the means and the standard deviation are estimated on a rolling basis.
Z-score	Modified Altman's (1968) Z-score; (3.3×EBIT +1×Sales +1.4×Retained Earnings + 1.2×Working Capital)/Total Assets.
Ln(Sales)	The natural logarithm of sales.
Quick ratio	The ratio of cash, short-term investments, and receivables to current liabilities.
Current ratio	The ratio of current assets to current liabilities.
R&D/Sales	The ratio of research and development expense to sales. We code missing values of research and development expense as zero.
AD/Sales	The ratio of advertising expense to sales. We code missing values of advertising expense as zero.
Computer industry (0,1)	An indicator variable that equals one if the firms are in computer industry (three-digit SIC code 357) and zero otherwise.
Semiconductor industry (0,1)	An indicator variable that equals one if the firms are in semiconductor industry (three-digit SIC code 367) and zero otherwise.
Chemicals industry (0,1)	An indicator variable that equals one if the firms are in chemicals and allied products industries, including drugs (three-digit SIC codes 280 to 289) and zero otherwise.
Aircraft industry (0,1)	An indicator variable that equals one if the firms are in aircraft, guided missiles, and space vehicles industry (three-digit SIC codes 372 and 376) and zero otherwise.
Other sensitive industry (0,1)	An indicator variable that equals one if the firms are in other sensitive industries (three-digit SIC codes 340 to 400, excluding 357, 367, 372, and 376) and zero otherwise.
Opacity	Following Hutton, Marcus, and Tehranian (2009), we employ a measure of opacity based on measures of accruals quality: the three-year moving sum of the absolute value of annual discretionary accruals proposed by Dechow and Dichev (2002).
Ln(B/M)	The natural logarithm of the ratio of the book-to-market value of equity.
TNIC total similarity	Total product similarity scores, which are the sum of firm pairwise similarity scores based on text-based network industry classifications (TNIC) (Hoberg and Phillips (2016)).
PP&E/Sales	The ratio of net property, plant and equipment over sales.
Intangibles	The ratio of sum of research and development expense and advertising expense over sales. We code missing values of research and development expense as zero.
Dividend yield	The ratio of common stock dividends and preferred stock dividends (Compustat data items DVC+DVP) scaled by the market value of common stock and the par value of preferred stock (Compustat data items PRCC_F × CSHO+ PSTK).
Ln(Local peers)	The natural log of the number of Compustat firms from the same industry (based on Fama-French (1997) 48-industry classification) and within a 150-mile-radius circle around the focal company headquarters.
Non-compete index	The state-level index that measures how difficult it is to enforce a non-compete clause in an employment contract. Larger index numbers indicate that the strength of enforcement of a non-compete clause is stronger. The data source for the non-compete index is Garmaise (2011) Table A1.
Ind. return percentile	The industry median annual buy-and-hold stock returns measured on a percentile basis within the annual cohort of all Compustat firms from the same industry (based on Fama-French (1997) 48-industry classification) as the focal company.
Firm abnormal return percentile	The focal firm's industry-adjusted annual buy-and-hold stock returns measured on a percentile basis.
Ind. return risk	Industry stock return volatility computed from daily value-weighted returns on the same industry (based on Fama-French (1997) 48-industry classification) as the focal company.

	The daily return data on the 48-industry portfolio are obtained from the Kenneth R. French data library.
Firm abnormal return volatility	The focal firm's industry-adjusted stock return volatility over the fiscal year.
Bank loan and bond issuance contract characteristics variables	
Previous lending relationship	An indicator variable that equals one if over the previous three years the same lead bank arranged other loans for the same borrower and zero otherwise (Ivashina (2009)). We use the variable LeadArrangerCredit from DealScan to identify if a lender is also a lead arranger.
Ln(Facility amount)	Natural logarithm of the offering amount of the largest facility within the same loan package with the earliest active date. Bank loan data are from DealScan.
Maturity (in months)	Maturity, measured in months, of the largest facility within the same loan package with the earliest active date. Bank loan data are from DealScan.
Number of facilities	The number of facilities within the same loan package. Bank loan data are from DealScan.
Collateral	An indicator variable that equals one if the loan is securitized and zero otherwise. Bank loan data are from DealScan.
Financial covenants	An indicator variable that equals one if the loan has financial covenants and zero otherwise. Bank loan data are from DealScan.
Prime base rate	An indicator variable that equals one if the base rate for the loan is prime and zero otherwise. Bank loan data are from DealScan.
Performance pricing	An indicator variable that equals one if the loan has a performance pricing provision and zero otherwise. Bank loan data are from DealScan.
Ln(Amount)	Natural logarithm of the bond offering amount. Bond issue data are from Mergent FISD.
Covenants	An indicator variable that equals one if the bond has covenant protection and zero otherwise. Bond issue data are from Mergent FISD.
Callable	An indicator variable that equals one if the bond is callable and zero otherwise. Bond redemption data are from Mergent FISD.
Corporate M&A deal characteristics variables	
All stock (0,1)	An indicator variable that equals one if the M&A transaction is completely paid in stock, and zero otherwise.
% acquired	Fraction of the target firm exchanged in the M&A transaction.
Hostile (0,1)	An indicator variable that equals one if the target board officially rejects the offer yet the acquirer persists with the acquisition, and zero otherwise.
Competing bidders	The number of third-party launching offers for the same target while the original bid was pending, and zero otherwise.
Tender offer (0,1)	An indicator variable that equals one when a tender offer is launched for the target and zero otherwise.
Termination fees (0,1)	An indicator variable that equals one if the target or acquirer has made a termination fee agreement whereby failure to consummate the M&A transaction results in a payment made by one party to the other and zero otherwise.
Public status (target) (0,1)	An indicator variable that equals one if the target is listed on a stock exchange and zero otherwise.
Toehold (0,1)	An indicator variable that equals one if the acquirer owns more than 0.5% ownership in the target prior to the M&A announcement.
CAR(-131,-31) (acquirer)	Run-up (or run-down) measured by the acquirer's cumulative abnormal return (CAR) during trading days [–131, -31] prior to the M&A announcement (day 0) based on the market model.

Figure 1. Geographic distribution of Superfund sites listed on the National Priorities List (NPL)

This Figure illustrates the number of Superfund sites in each county in the United States. These Superfund sites include all the sites as of December 31, 2018, that were, have been, or are being listed on the National Priorities List (NPL). This Figure does not show Superfund sites in the five U.S. territories (Puerto Rico, American Samoa, Commonwealth of Northern Marianas, Virgin Islands, and Guam) and the Federated States of Micronesia.

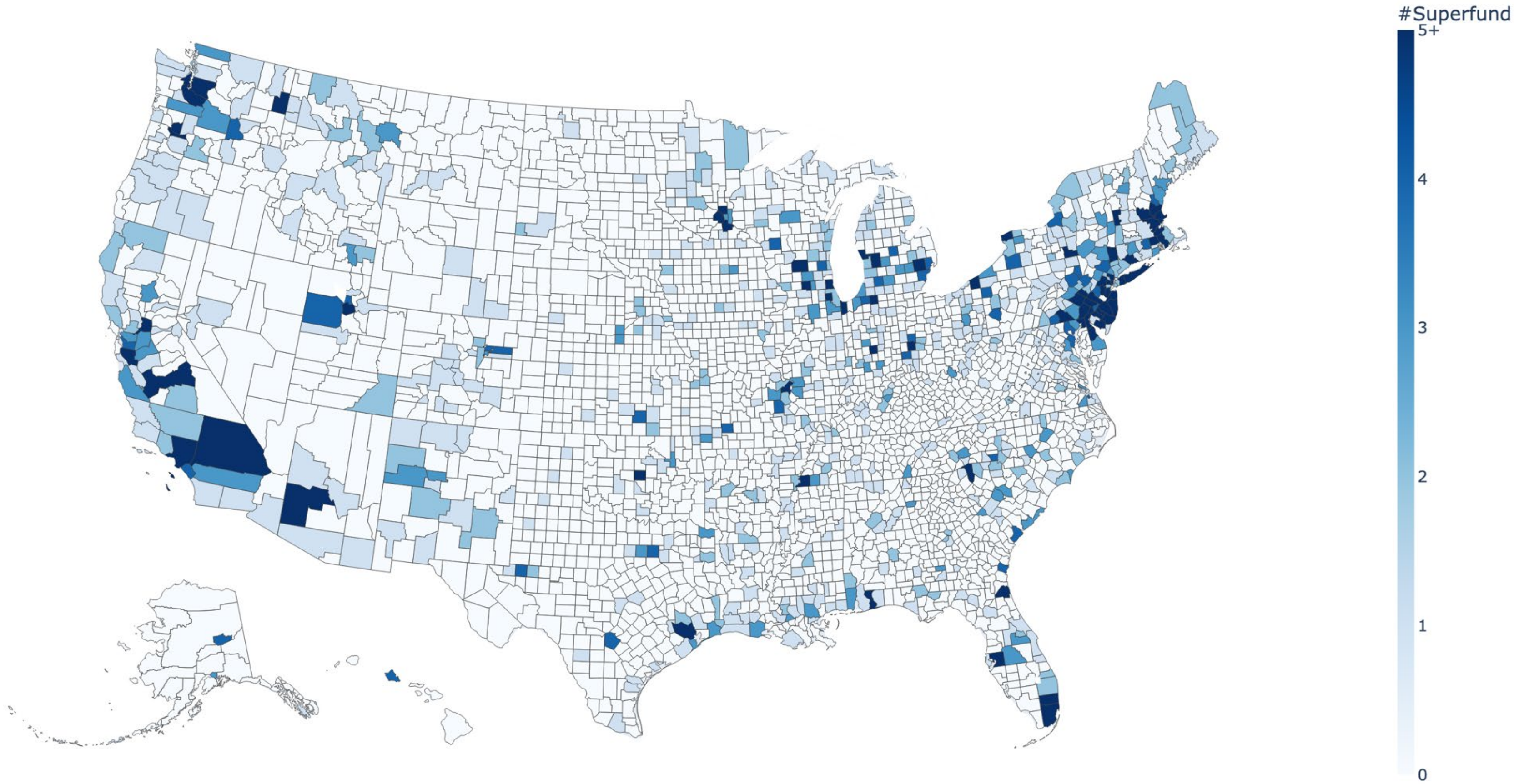

Table 1. Summary statistics for the Superfund program 1981-2018

This Table presents summary statistics on Superfund sites placed on the NPL before December 31, 2018. The duration (in years) of accumulation of the worst hazardous contaminants at the later-designated NPL sites is the period of rendering the U.S. worst hazardous contaminants at the later-designated NPL sites.

	Observations
Number of Superfund sites proposed to NPL	1,803
1981–1985	796
1986–1989	418
1990–1994	122
1995–1999	127
2000–2004	124
2005–2009	79
2010–2014	86
2015–2018	51

	Mean	Median	First quartile	Third quartile	Standard deviation	Observations
Duration (in years) of accumulation of the worst hazardous contaminants at the later-designated NPL sites	25.519	19.000	11.000	32.000	22.782	1,786
Hazard Ranking System scores	43.850	43.70	35.108	50.000	9.961	1,780
Size of Superfund site (in acres)	6852.15	38.00	9.50	200.00	81,812.34	1,783
Superfund cleanup durations (years) from NPL proposal date until:						
Remedial action started date	8.583	7.831	5.235	11.088	4.996	1,406
Construction completion date	13.201	12.358	9.211	16.250	6.035	1,205
Deletion from NPL date	15.238	13.693	10.448	19.750	7.487	412
Reuse and redevelopment date	24.002	24.128	20.803	27.925	5.937	871
Contaminated environmental media						
Air medium	4.881%	0.000%	0.000%	0.000%	21.553%	1,803
Ground medium	82.03%	100.000%	100.00%	100.00%	38.404%	1,803
Water medium	87.97%	100.000%	100.00%	100.00%	32.547%	1,803

Table 2. Comparisons of proportions of Superfund infants, infant mortality rates, and low birthweight rates

Panel A compares the percentage of Superfund CEOs among all CEOs in our sample with the percentage of Superfund infants (newborns in a county with at least one Superfund site during its actively polluting period) among all infants. Panel B and C compare the infant mortality rates and low birthweight rates between counties with Superfund sites during the pollutant-accumulation periods and (1) all counties, (2) counties with Superfund sites during periods before or after the pollutant-accumulation periods, or (3) counties without Superfund sites. Newborns weighing less than 2,500 grams are classified as low birthweight newborns. ∗∗∗, ∗∗, and ∗ denote a significant difference at the 1%, 5%, and 10% levels, respectively. Tests of differences in means (medians) are two-sample t-tests (Kruskal-Wallis H tests), and one of the two samples is the sample of counties during pollutant-accumulation periods. Data for infant mortality and low birthweight rates are from Bailey et al. (2016) U.S. County-Level Natality and Mortality Data, 1915-2007 (available at https://www.openicpsr.org/openicpsr/project/100229/version/V4/view).

Panel A. Comparison of the percentage of Superfund CEOs and the percentage of Superfund infants

	Percentage of Superfund infants among all infants	Percentage of Superfund CEOs among all CEOs
Annual mean	30.3749%	24.4585% (=734/(734+2,267))

Panel B. Comparison of infant mortality rates

	Infant mortality rate in all counties	Infant mortality rate in counties during pollutant-accumulation periods	Infant mortality rate in counties during other periods	Infant mortality rate in the remaining counties
Annual mean	1.8571%	2.0477%	1.5520%***	1.8248%****
Annual median	1.2658%	2.0270%	1.1881%***	0.5952%****

Panel C. Comparison of low birthweight rates

	Low birthweight rate in all counties	Low birthweight rate in counties during pollutant-accumulation periods	Low birthweight rate in counties during other periods	Low birthweight rate in the remaining counties
Annual mean	7.9607%	9.2372%	7.9821%***	7.5429%***
Annual median	8.4279%	10.4790%	8.3985%***	7.2315%***

Table 3. Comparisons of firms run by Superfund CEOs with the universe of firms and CEOs

Panel A reports summary statistics for various firm-year variables. Columns (1) to (3) restrict the sample to firms managed by the CEOs in our sample (including both Superfund and non-Superfund CEOs). Columns (4) to (6) report summary statistics for the Compustat firms. Columns (7) to (9) report similar statistics for the Execucomp firms. Panel B reports comparisons between firms managed by the Superfund CEOs and other CEOs. The Superfund CEOs subsample includes all firm-year observations for firms having a Superfund CEO at that year. The rest of the firm-year observations with valid CEO birth years and birthplaces in the U.S. are in the non-Superfund CEOs subsample. Tests of differences in means (medians) are two-sample t-tests (Kruskal-Wallis H-tests). ∗∗∗, ∗∗, and ∗ denote significant differences at the 1%, 5%, and 10% levels, respectively.

Panel A: Comparison of firms run by the sample CEOs (both Superfund and non-Superfund) with full Compustat and Execucomp universe

	All sample CEOs			Compustat universe			Execucomp universe			*t*-stat Sample vs. Compustat	*t*-stat Sample vs. Execucomp
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.		
Size											
Ln(Assets)	19,488	8.1273	1.9171	240,935	5.1418	2.9240	52,659	7.4037	1.8921	199.44***	45.17***
Ln(Sales)	19,453	7.6998	1.7207	222,449	4.7316	2.8293	52,488	6.9762	1.7641	216.37***	49.76***
Performance											
ROA	19,517	0.0415	0.0632	258,354	-0.1354	0.3884	52,970	0.0375	0.0699	210.45***	7.19***
Tobin's Q	18,378	1.7587	0.9384	226,134	2.2736	2.2489	51,778	1.8360	1.0275	-61.42***	-9.36***
Stock return	17,460	0.2290	0.7611	169,216	0.1397	0.8715	47,069	0.1827	0.6595	14.54***	7.11***
Growth opportunities											
PP&E/Assets	19,172	0.2894	0.2455	236,969	0.2662	0.2761	51,721	0.2587	0.2413	12.50***	14.86***
Capex	18,543	0.0554	0.0588	227,049	0.0660	0.9094	50,797	0.0524	0.0605	-5.42***	5.87***
R&D	19,488	0.0239	0.0881	240,935	0.1266	6.1920	52,659	0.0313	0.1191	-8.14***	-9.10***
Debt risk											
Leverage	19,453	0.2120	0.2015	259,370	0.3233	10.4563	52,836	0.2042	0.2152	-5.41***	4.53***
Cash/Assets	19,518	0.1219	0.1526	259,765	0.1907	0.2444	52,994	0.1427	0.1712	-57.67***	-15.78***
Credit rating	13,027	16.1893	3.5057	71,655	14.2963	4.0439	26,915	15.3060	3.4898	55.31***	23.64***
Default probability	15,208	0.1061	0.2364	116,183	0.8458	1.6611	41,477	0.1058	0.2244	-141.25***	0.16
Interest expense/Debt	17,575	0.1978	4.6365	204,864	0.5691	19.6879	45,502	0.4044	14.2940	-6.65***	-2.73***
Equity risk											
Dividend (0,1)	19,482	0.6826	0.4655	241,131	0.4199	0.4936	52,642	0.5845	0.4928	75.41***	24.72***
Ln(1+Share repurchase)	17,790	2.5869	2.7171	238,966	0.6583	1.5598	49,239	2.0398	2.4197	93.53***	23.68***
$\sigma_{\text{Stock return}}$	16,849	0.3902	0.1658	198,603	0.5733	0.4609	48,952	0.4385	0.2401	-111.42***	-28.84***
$\sigma_{\text{Specific return}}$	15,677	0.3046	0.1544	169,765	0.4275	0.3729	45,156	0.3484	0.2330	-80.37***	-26.51***
Other risk											
Acquisition (0,1)	19,573	0.3387	0.4733	310,598	0.1193	0.3241	53,398	0.2828	0.4504	63.94***	14.34***

Panel B: Comparison between firms run by Superfund CEOs and non-Superfund CEOs

	Superfund CEOs (Observations=4,852)				Non-Superfund CEOs (Observations=14,721)				t-test Superfund vs. Non-Super.	(Kruskal-Wallis H test) Superfund vs. Non-Super.
	N	Mean	Median	Std. Dev.	N	Mean	Median	Std. Dev.		
# of Unique CEOs	734				2,267					
Size										
Ln(Assets)	4,831	8.3960	8.3938	1.9528	14,657	8.0388	7.9522	1.8970	11.10***	(129.23***)
Ln(Sales)	4,823	7.9233	7.9994	1.7877	14,630	7.6261	7.6123	1.6917	10.14***	(110.19***)
Performance										
ROA	4,843	0.0371	0.0372	0.0659	14,674	0.0429	0.0408	0.0622	-5.38***	(26.33***)
Tobin's Q	4,558	1.7480	1.4101	0.9089	13,820	1.7622	1.3953	0.9479	-0.90	(0.14)
Stock return	4,378	0.2247	0.1258	0.8328	13,082	0.2304	0.1258	0.7356	-0.40	(0.11)
Growth opportunities										
PP&E/Assets	4,751	0.2606	0.1840	0.2399	14,421	0.2989	0.2401	0.2465	-9.47***	(101.07***)
Capex	4,649	0.0506	0.0350	0.0556	13,894	0.0570	0.0429	0.0598	-6.73***	(98.57***)
R&D	4,831	0.0275	0.0000	0.0630	14,657	0.0227	0.0000	0.0950	3.99***	(20.44***)
Debt risk										
Leverage	4,827	0.2144	0.1762	0.1999	14,626	0.2111	0.1823	0.2020	0.95	(0.13)
Cash/Assets	4,843	0.1346	0.0726	0.1587	14,675	0.1176	0.0560	0.1503	6.55***	(75.38***)
Credit rating	3,351	16.0185	16.000	3.5836	9,676	16.2485	16.000	3.4765	-3.23***	(6.49**)
Default probability	3,813	0.1127	0.0000	0.2434	11,395	0.1039	0.0000	0.2340	1.95*	(4.37**)
Interest expense/Debt	4,340	0.1927	0.0616	3.2866	13,235	0.1994	0.0684	5.0006	-0.10	(164.34***)
Equity risk										
Dividend (0,1)	4,830	0.6433	1.0000	0.4791	14,652	0.6955	1.0000	0.4602	-6.64***	(29.77***)
Ln(1+Share repurchase)	4,495	2.9589	2.6391	2.8479	13,295	2.4611	1.6095	2.6598	10.30***	(95.86***)
$\sigma_{\text{Stock return}}$	4,201	0.4018	0.3485	0.2121	12,648	0.3863	0.3497	0.1470	4.39***	(3.03*)
$\sigma_{\text{Specific return}}$	3,942	0.3114	0.2557	0.2087	11,735	0.3023	0.2677	0.1312	2.57***	(23.46***)
Other risk										
Acquisition (0,1)	4,852	0.3510	0.0000	0.4773	14,721	0.3347	0.0000	0.4719	2.07**	(2.91*)
County-level variables										
County poverty status	4,843	14.4837	12.3976	8.3924	14,691	21.8896	17.1784	13.6853	-44.83***	(1561.80***)
County employment status	4,459	40.1133	40.0141	5.3299	13,900	39.0507	38.6680	12.1561	8.15***	(308.86***)
Ln(County earnings per capita)	4,843	7.7478	7.8011	0.6985	14,619	7.3048	7.5938	1.0061	33.97***	(1059.48***)

Table 4. Effects of CEOs' prenatal Superfund exposure on capital structure

This table reports coefficients from OLS regressions of *Cash/Assets*, *Leverage*, and *Ln*(1+*Share repurchase*) for fiscal year *t* on our CEOs' prenatal Superfund exposure measure and control variables (of lagged firms, lagged CEOs, and counties characteristics) with fixed effects. County-level variables are measured in the CEO's birth year and the CEO's birth county. Variables are defined in the Appendix. Constant terms are not reported. *t*-values are based on robust standard errors clustered by CEO-firm and by year (two-way) and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	Cash/Assets	Leverage	Ln(1+Share repurchase)
	(1)	(2)	(3)
Ln(1+ CEO #Superfund exposure$_t$)	-0.0191*	0.0451***	-0.7948**
	(-1.66)	(2.92)	(-2.41)
Assets volatility$_{t-1}$	0.1149***	-0.1386***	
	(7.07)	(-8.15)	
Tobin's Q$_{t-1}$	-0.0027***	-0.0005	
	(-3.42)	(-0.53)	
Ln(Assets)$_{t-1}$	-0.0288***	-0.0050	0.4647***
	(-7.66)	(-1.23)	(6.90)
Capex$_{t-1}$	-0.1463***	0.0282	
	(-5.21)	(0.74)	
R&D$_{t-1}$	0.0869	-0.2185***	
	(1.00)	(-2.69)	
Dividend (0,1)$_t$	-0.0012	-0.0098*	
	(-0.30)	(-1.76)	
Cash flow/Assets$_{t-1}$	-0.0735***		
	(-3.09)		
NWC/Assets$_{t-1}$	-0.1274***		
	(-5.10)		
Acquisition/Assets$_{t-1}$	-0.1033***		
	(-6.90)		
Leverage$_t$	-0.0762***		-1.4735***
	(-5.17)		(-5.40)
ROA$_{t-1}$		-0.1184***	1.4795***
		(-6.44)	(3.31)
PP&E/Assets$_{t-1}$		0.0017	
		(0.07)	
Growth in sales$_{t-1}$		-0.0068*	-0.1384*
		(-1.92)	(-1.77)
Cash/Assets$_t$			-0.0227
			(-0.08)
Ln(CEO age)$_{t-1}$	-0.0687	0.1561	-2.7869
	(-0.51)	(0.82)	(-1.01)
Ln(1+CEO tenure)$_{t-1}$	-0.0052	0.0001	0.0465
	(-1.46)	(0.02)	(0.50)
CEO duality (0,1)$_{t-1}$	-0.0013	0.0169***	0.1238
	(-0.29)	(3.32)	(1.16)
Founder CEO (0,1)$_{t-1}$	0.0027	-0.0271	-0.6357*
	(0.24)	(-1.46)	(-1.92)
CEO ownership$_{t-1}$ (%)	-0.0000	0.0005	-0.0076
	(-0.16)	(1.63)	(-1.38)
Inst. ownership$_{t-1}$ (%)	0.0044	-0.0397***	-0.1777
	(0.40)	(-3.02)	(-0.80)
County poverty status	-0.0004	0.0001	0.0670*
	(-0.38)	(0.09)	(1.78)
County employment status	-0.0006*	0.0018***	-0.0144
	(-1.84)	(3.47)	(-1.39)

Ln(County earnings per capita)	-0.0201	0.0428**	0.2938
	(-1.47)	(2.40)	(0.64)
Firm, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes
Clustered by CEO-firm and year	Yes	Yes	Yes
Adj R^2	0.8553	0.7917	0.6950
Observations	8,298	8,955	9,136

Table 5. Effects of CEOs' prenatal Superfund exposure on corporate debt aggressiveness

This table reports coefficients from censored Tobit (column 1) and fixed effects OLS (column 2) regressions of *kink* for fiscal year *t* on our CEOs' prenatal Superfund exposure measure and control variables (of lagged firms, lagged CEOs, and counties characteristics) with fixed effects. In the Tobit model, observations are left censored at 0 and right censored at 8. Variables are defined in the Appendix. Constant terms are not reported. *t*-values are based on robust standard errors clustered by CEO-firm and by year (two-way) and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	**Kink Tobit**	**Kink OLS**
	(1)	**(2)**
Ln(1+ CEO #Superfund exposure$_t$)	-0.7161***	-1.1758***
	(-30.78)	(-4.90)
Dividend (0,1)$_t$	0.0738***	-0.0573
	(2.98)	(-0.57)
NOL carryforward (0,1)$_t$	-0.3936***	-0.6161***
	(-21.47)	(-8.76)
ECOST$_t$	-5.2221***	-4.4243
	(-7.76)	(-1.37)
CYCLICAL$_t$	0.0080***	0.0049
	(7.18)	(1.14)
ROA$_t$	17.7599***	6.8840***
	(136.52)	(7.73)
Ln(Sales)$_t$	0.3185***	0.3732***
	(146.55)	(3.95)
Z-score$_t$	2.2349***	0.6204***
	(296.88)	(3.05)
Quick ratio$_t$	0.5214***	0.3329***
	(45.37)	(2.83)
Current ratio$_t$	-0.5843***	-0.3704***
	(-65.89)	(-3.47)
PP&E/Assets$_t$	-0.8684***	-0.8862**
	(-29.47)	(-2.01)
Tobin's Q$_t$	1.0894***	0.2295***
	(96.16)	(5.38)
R&D/Sales$_t$	-4.7964***	0.5934**
	(-16.03)	(2.03)
AD/Sales$_t$	0.3164	-3.8864**
	(1.04)	(-2.08)
Computer industry (0,1)	0.2779***	-0.4894
	(2.80)	(-0.33)
Semiconductor industry (0,1)	14.8542***	3.3349**
	(154.66)	(2.01)
Chemicals industry (0,1)	3.3040***	0.1949
	(85.24)	(0.10)
Aircraft industry (0,1)	2.8714***	0.6179
	(49.92)	(0.36)
Other Sensitive industry (0,1)	3.5062***	1.2026
	(125.15)	(0.72)
Ln(CEO age)$_{t-1}$	-10.4142***	-7.4851**
	(-2258.43)	(-2.53)
Ln(1+CEO tenure)$_{t-1}$	0.4554***	0.2591***
	(56.96)	(3.37)
CEO duality (0,1)$_{t-1}$	-0.3341***	-0.2591***
	(-19.12)	(-2.78)

Founder CEO (0,1)$_{t-1}$	0.1540***	0.3856
	(4.74)	(1.45)
CEO ownership$_{t-1}$ (%)	-0.0145***	-0.0084*
	(-11.38)	(-1.77)
Inst. ownership$_{t-1}$ (%)	1.1209***	0.9066***
	(42.94)	(3.83)
County poverty status	-0.0458***	0.0307
	(-76.21)	(1.49)
County employment status	0.0249***	-0.0192***
	(54.61)	(-2.71)
Ln(County earnings per capita)	-0.4963***	-0.4951*
	(-196.15)	(-1.81)
Firm, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes
Adj R^2	0.4386	0.7842
Observations	8,740	8,740

Table 6. Effects of CEOs' prenatal Superfund exposure on corporate credit risk and default risk

This table reports coefficients from ordered Probit and OLS regressions of *Credit rating*, *Junk rating*, *Bankruptcy score*, and *Default probability* for fiscal year *t* on our CEOs' prenatal Superfund exposure measure and control variables (of lagged firms, lagged CEOs, and counties characteristics) with fixed effects. Our control variables are similar to those reported in the leverage regression in Table 4. Variables are defined in the Appendix. Constant terms are not reported. *t*-values are based on robust standard errors clustered by CEO-firm and by year (two-way) and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	**Credit rating Ordered Probit**	**Junk rating (0,1) OLS**	**Bankruptcy score OLS**	**Default probability OLS**
	(1)	**(2)**	**(3)**	**(4)**
Ln(1+CEO #Superfund exposure$_t$)	-0.9963**	0.0907	0.2731**	0.1029***
	(-2.52)	(1.55)	(1.99)	(3.22)
Assets volatility$_{t-1}$	0.6664*	-0.1078*	0.3172**	-0.2057***
	(1.77)	(-1.83)	(2.09)	(-5.44)
Tobin's Q$_{t-1}$	0.0396	-0.0080	0.0182*	0.0024
	(0.89)	(-1.47)	(1.66)	(0.93)
Ln(Assets)$_{t-1}$	0.8908***	-0.1000***	0.0915***	0.0317***
	(10.41)	(-6.26)	(2.59)	(3.92)
Capex$_{t-1}$	5.3197***	-0.6127***	0.7059**	-0.0667
	(7.24)	(-4.27)	(2.23)	(-0.85)
R&D$_{t-1}$	14.0291***	-1.1331***	-1.2359*	-0.1693
	(5.72)	(-3.26)	(-1.85)	(-1.47)
Dividend (0,1)$_{t-1}$	0.8038***	-0.0808***	-0.0112	-0.0127
	(7.66)	(-3.87)	(-0.24)	(-1.10)
ROA$_{t-1}$	2.6272***	-0.2616**	-0.2735*	-0.2245***
	(2.79)	(-2.23)	(-1.83)	(-3.83)
PP&E/Assets$_{t-1}$	1.1642***	-0.0858	0.0134	0.0441
	(2.90)	(-1.16)	(0.06)	(0.86)
Growth in sales$_{t-1}$	-0.2346**	0.0330*	-0.1671*	-0.0169**
	(-2.08)	(1.95)	(-1.84)	(-2.13)
Ln(CEO age)$_{t-1}$	9.7135**	-2.2709***	-0.3365	-0.6523**
	(2.41)	(-3.44)	(-0.26)	(-2.14)
Ln(1+CEO tenure)$_{t-1}$	0.1396	-0.0100	0.0185	0.0134
	(1.23)	(-0.48)	(0.47)	(1.55)
CEO duality (0,1)$_{t-1}$	-0.0404	-0.0246	0.0983**	0.0109
	(-0.43)	(-1.32)	(2.07)	(1.00)
Founder CEO (0,1)$_{t-1}$	-0.2701	0.0810	-0.4741***	0.0447*
	(-0.97)	(0.97)	(-3.04)	(1.73)
CEO ownership$_{t-1}$ (%)	-0.0108*	0.0006	0.0042	0.0012**
	(-1.70)	(0.67)	(1.44)	(2.07)
Inst. ownership$_{t-1}$ (%)	0.2388	-0.0681	0.1481	-0.1433***
	(0.97)	(-1.60)	(1.25)	(-4.99)
County poverty status	0.0718**	-0.0090**	-0.0112	-0.0007
	(2.49)	(-2.20)	(-0.97)	(-0.27)
County employment	0.0157	0.0002	0.0097**	0.0025***
	(1.51)	(0.12)	(2.53)	(2.97)
Ln(County earnings per capita)	-2.1558***	0.0667	-0.0141	0.0314
	(-4.51)	(1.01)	(-0.09)	(1.02)
Firm, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes	Yes
Clustered by CEO-firm and year	Yes	Yes	Yes	Yes
Pseudo/Adj R^2	0.5321	0.8471	0.7478	0.5677
Observations	5,630	5,630	8,962	8,174

Table 7. Effects of CEOs' prenatal Superfund exposure on cost of borrowing

This table reports coefficients from OLS regressions of *Interest expense/Debt*, *Bank loan all-in-spread,* and *Bond issue spread* for fiscal year *t* on our CEOs' prenatal Superfund exposure measure and control variables (of lagged firms, lagged CEOs, loans/bonds, and counties characteristics) with fixed effects. Each observation in columns (2) and (3) corresponds to each loan/bond issue. Variables are defined in the Appendix. Constant terms are not reported. *t*-values are based on robust standard errors clustered by CEO-firm and by year (two-way) and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	Interest expense/Debt	Bank loan all-in-spread	Bond issue spread
	(1)	(2)	(3)
Ln(1+CEO #Superfund exposure$_t$)	0.3587	16.8135**	92.9586***
	(0.99)	(2.03)	(3.99)
Assets volatility$_{t-1}$	-0.0293		
	(-0.07)		
Tobin's Q$_{t-1}$	0.0054		
	(0.40)		
Ln(Assets)$_{t-1}$	-0.0565	5.3618	34.6749**
	(-0.88)	(1.21)	(2.40)
Capex$_{t-1}$	-2.2620		
	(-1.01)		
R&D$_{t-1}$	3.2572		
	(1.37)		
Dividend (0,1)$_{t-1}$	0.0559		
	(0.78)		
ROA$_{t-1}$	0.3256	-22.6039	-68.1358
	(1.54)	(-1.04)	(-0.96)
PP&E/Assets$_{t-1}$	-1.2891		
	(-1.30)		
Growth in sales$_{t-1}$	-0.0782		
	(-1.37)		
Ln(CEO age)$_{t-1}$	-4.9900		
	(-1.43)		
Ln(1+CEO tenure)$_{t-1}$	0.1295		
	(1.31)		
CEO duality (0,1)$_{t-1}$	-0.1219		
	(-0.90)		
Founder CEO (0,1)$_{t-1}$	-0.2733		
	(-1.03)		
CEO ownership$_{t-1}$ (%)	0.0387		
	(0.99)		
Inst. ownership$_{t-1}$ (%)	-0.4529		
	(-0.77)		
Credit rating$_{t-1}$		-11.2940***	2.0166
		(-12.84)	(0.70)
Previous lending relationship$_t$		-6.5777***	
		(-4.71)	
Ln(Sales)$_{t-1}$		-1.3785	-24.1376
		(-0.31)	(-1.57)
Leverage$_{t-1}$		20.7259	19.2789
		(1.52)	(0.45)
Ln(Facility amount)$_t$		-12.5337***	
		(-8.71)	
Maturity (in months)$_t$		0.1243**	0.3210***
		(2.13)	(17.70)
Number of facilities$_t$		7.4039***	
		(5.01)	
Collateral$_t$		58.2976***	-138.5135**
		(13.78)	(-2.42)
Financial covenants$_t$		-1.9909	

		(-0.64)	
Prime base rate$_t$		184.1533***	
		(11.48)	
Performance pricing$_t$		-17.8439***	
		(-5.12)	
Ln(Amount)$_t$			-31.4236***
			(-7.26)
Covenants$_t$			-8.1138
			(-0.96)
Callable$_t$			-55.5740***
			(-3.59)
County poverty status	0.0048	-0.0303	5.3009
	(0.51)	(-0.01)	(1.54)
County employment status	0.0067	0.4013**	0.9394
	(0.65)	(2.19)	(1.01)
Ln(County earnings per capita)	-0.0393	4.1257	78.6634*
	(-0.31)	(0.36)	(1.78)
Firm, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes
Clustered by CEO-firm and year	Yes	Yes	Yes
Lead lender FE	No	Yes	No
Adj R^2	0.1295	0.8258	0.7672
Observations	7,833	11,693	6,273

Table 8. Effects of CEOs' prenatal Superfund exposure on equity risk

This table reports coefficients from OLS regressions of $\sigma_{Stock\ return}$, $\sigma_{Stock\ return}$, $\sigma_{Specific\ return}$, *Negative skewness*, $\sigma_{Down\text{-}to\text{-}up}$, and *Crash risk* for fiscal year *t* on our CEOs' prenatal Superfund exposure measure and control variables (of lagged firms, lagged CEOs, and counties characteristics) with fixed effects. Variables are defined in the Appendix. Constant terms are not reported. *t*-values are based on robust standard errors clustered by CEO-firm and by year (two-way) and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	$\sigma_{Stock\ return}$	$\sigma_{Specific\ return}$	Negative skewness	$\sigma_{Down\text{-}to\text{-}up}$	Crash risk
	(1)	(2)	(3)	(4)	(5)
Ln(1+CEO #Superfund exposure$_t$)	0.0322***	0.0278*	0.3323*	0.0790**	0.1673*
	(2.58)	(1.73)	(1.85)	(2.14)	(1.82)
Opacity$_{t-1}$			0.0047*	0.0011**	0.0016
			(1.91)	(2.12)	(1.30)
Stock return$_{t-1}$	0.0055***	-0.0003	0.0019	0.0083**	-0.0242**
	(3.44)	(-0.16)	(0.11)	(2.19)	(-2.49)
Ln(Assets)$_{t-1}$	-0.0252***	-0.0288***	0.1346***	0.0311***	0.0562***
	(-8.72)	(-8.49)	(4.29)	(4.61)	(3.14)
Ln(B/M)$_{t-1}$	0.0126***	0.0106***	-0.2067***	-0.0447***	-0.0856***
	(5.37)	(3.89)	(-7.93)	(-8.10)	(-5.85)
Leverage$_{t-1}$	0.0277**	0.0174	-0.0897	-0.0548**	-0.0037
	(2.46)	(1.25)	(-0.69)	(-1.98)	(-0.05)
PP&E/Assets$_{t-1}$	-0.0043	-0.0117	-0.1351	-0.0811**	0.0283
	(-0.25)	(-0.58)	(-0.74)	(-2.00)	(0.25)
Cash/Assets$_{t-1}$	-0.0025	-0.0249	0.0551	-0.0388	0.0321
	(-0.19)	(-1.63)	(0.38)	(-1.28)	(0.39)
Dividend (0,1)$_{t-1}$	-0.0047	0.0070	0.0311	-0.0023	0.0312
	(-1.16)	(1.48)	(0.67)	(-0.23)	(1.23)
ROA$_{t-1}$	-0.0637***	-0.0192*	0.2741***	0.0744***	0.0666
	(-4.26)	(-1.68)	(3.39)	(3.87)	(1.47)
Growth in sales$_{t-1}$	0.0009	0.0020	-0.0366	-0.0034	-0.0317
	(0.44)	(1.32)	(-1.21)	(-0.51)	(-1.39)
Ln(CEO age)$_{t-1}$	-0.1839	-0.4797***	-2.6059*	-0.2266	-1.2226
	(-1.43)	(-3.44)	(-1.77)	(-0.72)	(-1.48)
Ln(1+CEO tenure)$_{t-1}$	0.0069*	0.0094**	0.0777**	0.0162**	0.0470**
	(1.89)	(2.35)	(1.96)	(1.99)	(2.04)
CEO duality (0,1)$_{t-1}$	0.0041	0.0065	0.0342	0.0067	0.0034
	(0.90)	(1.29)	(0.76)	(0.68)	(0.12)
Founder CEO (0,1)$_{t-1}$	0.0358***	0.0185	0.0606	0.0274	-0.0304
	(2.84)	(1.08)	(0.34)	(0.77)	(-0.32)
CEO ownership$_{t-1}$ (%)	0.0005**	0.0006*	0.0034	0.0004	0.0022
	(2.43)	(1.91)	(1.21)	(0.71)	(1.35)
Inst. ownership$_{t-1}$ (%)	-0.0404***	-0.0075	0.2144**	0.0575***	0.1196**
	(-4.34)	(-0.69)	(2.05)	(2.65)	(2.01)
County poverty status	-0.0018*	-0.0012	-0.0292**	-0.0038	-0.0087
	(-1.80)	(-0.98)	(-2.39)	(-1.44)	(-1.28)
County employment status	0.0022***	0.0022***	0.0082*	0.0018**	0.0028
	(7.64)	(5.09)	(1.85)	(2.02)	(1.27)
Ln(County earnings per capita)	0.0405***	0.0086	0.0806	0.0491	0.0354
	(2.99)	(0.47)	(0.44)	(1.31)	(0.39)
Firm, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes	Yes	Yes
Clustered by CEO-firm and year	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.8575	0.7477	0.2346	0.2374	0.2228
Observations	8,692	8,022	8,237	8,237	8,238

Table 9. Effects of acquirer CEOs' prenatal Superfund exposure on M&A announcement abnormal returns and the propensity of unrelated acquisitions

Columns (1) and (2) of this table report coefficients from OLS regressions of acquirers' *CAR* (-1,1) *Market model* announcement returns, and acquirers' *CAR* (-1,1) *FF4 model* announcement returns for fiscal year *t* on the acquirers CEOs' prenatal Superfund exposure measure, control variables (of acquirers, acquirer CEOs, M&A deal characteristics, and counties characteristics) and fixed effects. In columns (3) and (4), we use probit and linear probability models, respectively, to regress unrelated acquisitions (0,1) for fiscal year *t* on the same explanatory variables and fixed effects as columns (1) and (2). Unrelated acquisitions (0,1) is defined using the Fama-French 1(1997) 48 industry definition. Each observation corresponds to each M&A announcement. Variables are defined in the Appendix. Constant terms are not reported. *t*-values are based on robust standard errors clustered by CEO-acquirer and by year (two-way) and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	**CAR(-1,1) Market model**	**CAR(-1,1) FF4 model**	**Unrelated acquisition (0,1) (Probit)**	**Unrelated acquisition (0,1) (Linear probability)**
	(1)	**(2)**	**(3)**	**(4)**
Ln(1+ CEO #Superfund exposure$_t$)	-0.0081***	-0.0063**	0.2816***	0.0751***
(acquirer)	(-2.64)	(-2.06)	(2.76)	(2.86)
All stock (0,1)	-0.0035	-0.0025	0.0033	0.0083
	(-1.07)	(-0.76)	(0.04)	(0.35)
% acquired	-0.0002***	-0.0002***	0.0014	0.0004
	(-3.45)	(-3.70)	(1.09)	(1.13)
Hostile (0,1)	-0.0160	-0.0177	0.7528**	0.2090*
	(-1.21)	(-1.40)	(2.01)	(1.93)
Competing bidders	-0.0039	-0.0030	-0.7188***	-0.1431***
	(-0.50)	(-0.42)	(-3.64)	(-3.43)
Tender offer (0,1)	0.0216***	0.0202***	-0.3027**	-0.0663**
	(5.41)	(5.11)	(-2.47)	(-2.18)
Termination fees (0,1)	-0.0058	-0.0048	0.0612	0.0129
	(-1.53)	(-1.28)	(0.55)	(0.47)
Public status (target) (0,1)	-0.0112***	-0.0110***	-0.2091**	-0.0483*
	(-3.11)	(-3.18)	(-1.98)	(-1.86)
Toehold (0,1)	-0.0026	-0.0019	0.0170	0.0086
	(-0.60)	(-0.45)	(0.14)	(0.28)
Ln(Assets)$_{t-1}$ (acquirer)	-0.0029***	-0.0026***	0.1254***	0.0352***
	(-3.79)	(-3.38)	(5.29)	(5.69)
Ln(B/M)$_{t-1}$(acquirer)	0.0015	0.0020	0.0099	-0.0037
	(0.37)	(0.45)	(0.09)	(-0.15)
Leverage$_{t-1}$(acquirer)	0.0188***	0.0198***	-0.1751	-0.0364
	(2.85)	(2.92)	(-0.83)	(-0.68)
Cash/Assets$_{t-1}$(acquirer)	-0.0097	-0.0087	-0.3500	-0.0509
	(-1.18)	(-1.05)	(-1.44)	(-0.86)
CAR(-131,-31) (acquirer)	-0.013***	-0.0121***	-0.0351	-0.0100
	(-4.73)	(-4.13)	(-0.48)	(-0.55)
Ln(CEO age)$_{t-1}$ (acquirer)	-0.1123	-0.1117	-0.1626	0.2989
	(-1.45)	(-1.34)	(-0.07)	(0.54)
Ln(1+CEO tenure)$_{t-1}$ (acquirer)	-0.0025*	-0.0019	0.0481	0.0052
	(-1.67)	(-1.31)	(1.03)	(0.42)
CEO duality (0,1)$_{t-1}$ (acquirer)	0.0016	0.0009	0.1179*	0.0328*
	(0.72)	(0.39)	(1.69)	(1.80)
Founder CEO (0,1)$_{t-1}$ (acquirer)	-0.0045	-0.0052	0.0269	-0.0058
	(-1.00)	(-1.16)	(0.25)	(-0.21)
County poverty status	0.0003	0.0004	-0.0096	-0.0027
	(0.82)	(1.05)	(-0.89)	(-0.97)
County employment status	-0.0000	0.0001	-0.0099*	-0.0013
	(-0.01)	(0.34)	(-1.81)	(-1.27)
Ln(County earnings per capita)	0.0079*	0.0081**	-0.0317	-0.0069
	(1.96)	(2.03)	(-0.21)	(-0.18)

Acquirer industry, Year, Birth Year, Birth County, and Acquirer HQ State FE	Yes	Yes	Yes	Yes
Clustered by CEO-Acquirer and year	Yes	Yes	Yes	Yes
Adj R^2	0.1670	0.1645	0.3345	0.4258
Observations	6,798	6,798	6,065	6,798

Table 10. Effects of CEOs' prenatal Superfund exposure on industry-adjusted firm performance

This table reports coefficients from OLS regressions of industry-adjusted (labeled *Ind. adj.*) *ROA*, *Tobin's Q,* and *Stock return* for fiscal year *t* on our CEOs' prenatal Superfund exposure measure and control variables (of the lagged dependent variable, lagged firms, lagged CEOs, and counties characteristics) with fixed effects. Variables are defined in the Appendix. Constant terms are not reported. *t*-values are based on robust standard errors clustered by CEO-firm and by year (two-way) and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	**Ind. adj. ROA**	**Ind. adj. Tobin's Q**	**Ind. adj. Stock return**
	(1)	**(2)**	**(3)**
Ln(1+CEO #Superfund exposure$_{t-1}$)	-0.0060***	-0.0475**	-0.0499**
	(-2.87)	(-2.22)	(-2.54)
Ln(Local peers)$_{t-1}$	0.0009**	0.0276***	-0.0035
	(2.01)	(2.58)	(-0.36)
Non-compete index	0.0016	0.0122	0.0368*
	(0.68)	(0.71)	(1.67)
Lagged respective industry-adjusted performance	0.1555***	0.1917***	-0.0796***
	(3.98)	(4.35)	(-4.13)
Ln(Assets)$_{t-1}$	-0.0008	-0.0437***	-0.0081
	(-1.40)	(-5.42)	(-1.40)
$\sigma_{\text{Stock return},t-1}$	-0.0487***	-0.5348***	1.1186***
	(-3.11)	(-3.62)	(3.15)
Ln(B/M)$_{t-1}$	-0.0315***	-0.4361***	0.0596***
	(-16.28)	(-10.43)	(4.24)
TNIC total similarity$_{t-1}$	-0.0001*	0.0000	0.0000
	(-1.79)	(0.03)	(0.04)
PP&E/Sales$_{t-1}$	0.0005	0.0417**	-0.0055
	(0.43)	(2.33)	(-0.45)
Leverage$_{t-1}$	-0.0554***	-0.7500***	0.0844
	(-9.89)	(-8.97)	(1.62)
Intangibles$_{t-1}$	-0.0027**	0.0256***	0.0114
	(-2.33)	(2.84)	(1.18)
Dividend yield$_{t-1}$	0.0036	-0.0693	-0.1246
	(0.32)	(-0.60)	(-1.09)
Ln(CEO age)$_{t-1}$	0.0989	1.3951**	-0.1799
	(1.60)	(2.11)	(-0.34)
Ln(1+CEO tenure)$_{t-1}$	-0.0012	-0.0059	-0.0029
	(-1.10)	(-0.50)	(-0.24)
CEO duality (0,1)$_{t-1}$	0.0008	-0.0573***	-0.0000
	(0.49)	(-3.43)	(-0.00)
Founder CEO (0,1)$_{t-1}$	-0.0002	0.0293	0.0357
	(-0.11)	(1.09)	(1.52)
CEO ownership$_{t-1}$ (%)	-0.0001	-0.0026**	0.0006
	(-0.76)	(-1.98)	(0.51)
Inst. ownership$_{t-1}$ (%)	0.0047	-0.0787*	-0.1786***
	(1.07)	(-1.90)	(-3.91)
Ln(1+Delta)$_{t-1}$	0.0025***	0.0369***	-0.0069
	(4.11)	(3.48)	(-1.21)
County poverty status	-0.0001	-0.0018	0.0010
	(-0.56)	(-0.89)	(0.49)
County employment status	0.0001	0.0001	-0.0012
	(1.11)	(0.11)	(-0.77)
Ln(County earnings per capita)	-0.0013	0.0018	0.0040
	(-0.60)	(0.07)	(0.15)
Industry, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes
Clustered by CEO-firm and year	Yes	Yes	Yes
Adj R^2	0.6546	0.6898	0.1362
Observations	10,542	10,452	10,519

Table 11. Effects of CEOs' prenatal Superfund exposure on career outcomes

This table presents coefficients from OLS and Probit regressions predicting the length of tenure, and CEO turnover, respectively. Specifically, we regress the length of CEO tenure (model 1), CEO forced turnover, generic turnover, and severance payment turnover (models 2 to 4) on our CEOs' prenatal Superfund exposure measure and control variables (of lagged firms, lagged industries, lagged CEOs, and counties characteristics) with fixed effects. Variables are defined in the Appendix. Constant terms are not reported. Z-values are based on robust standard errors clustered by CEO-firm and by year (two-way) and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	**Ln(1+CEO tenure)** (1)	**Forced CEO turnover (0,1)** (2)	**Generic CEO turnover (0,1)** (3)	**Severance payment if CEO turnover (0,1)** (4)
Ln(1+CEO #Superfund exposure$_t$)	-0.0502**	0.2757***	0.0200	-0.0568
	(-2.36)	(3.24)	(0.25)	(-0.51)
Ln(Local peers)$_{t-1}$	-0.0243**	0.0742**	0.0082	0.0119
	(-2.49)	(1.97)	(0.23)	(0.23)
Non-compete index	0.0254	-0.0473	-0.2148**	0.0330
	(1.07)	(-0.46)	(-2.45)	(0.24)
Ind. return percentile$_{t-1}$	-0.0002	0.0004	-0.0007	-0.0006
	(-1.25)	(0.51)	(-1.09)	(-0.62)
Firm abnormal return percentile$_{t-1}$	-0.0009***	-0.0020**	-0.0029***	-0.0021**
	(-4.56)	(-2.36)	(-3.83)	(-2.18)
Ind. return risk$_{t-1}$	-0.1442	1.3879	0.6332	2.5771
	(-0.36)	(0.74)	(0.39)	(1.17)
Firm abnormal return volatility$_{t-1}$	-0.2599*	2.3612***	1.3795**	1.0343
	(-1.87)	(4.35)	(2.53)	(1.44)
Ln(Assets)$_{t-1}$	-0.1058***	0.0870***	0.0382*	0.0230
	(-19.05)	(4.19)	(1.80)	(0.78)
Tobin's Q$_{t-1}$	-0.0052***	0.0004	-0.0028	-0.0089*
	(-5.62)	(0.11)	(-0.77)	(-1.74)
CEO age≥ 60 (0,1)$_{t-1}$	2.0755***	-0.1437**	0.3537***	0.1612*
	(4.00)	(-2.03)	(5.83)	(1.94)
Ln(1+CEO tenure)$_{t-1}$		-0.0198	0.2221***	0.3026***
		(-0.45)	(5.37)	(5.10)
Outside CEO (0,1)$_{t-1}$	0.0141	-0.0569	0.0299	-0.0176
	(-0.99)	(-0.99)	(0.53)	(-0.24)
Founder CEO (0,1)$_{t-1}$	0.4140***	0.0358	-0.2036**	-0.3695***
	(18.24)	(0.46)	(-2.43)	(-3.15)
CEO duality (0,1)$_{t-1}$	0.2474***	-0.1573***	0.0407	0.0609
	(16.98)	(-2.64)	(0.72)	(0.76)
CEO ownership$_{t-1}$ (%)	0.0022*	0.0057	-0.0206***	-0.0106*
	(1.80)	(1.44)	(-3.75)	(-1.69)
CEO employment contract (0,1)$_{t-1}$	-0.1224***	-0.0782	-0.1172**	3.1745***
	(-9.03)	(-1.47)	(-2.27)	(9.81)
Inst. ownership$_{t-1}$ (%)	0.0023	-0.0997	0.0112	-0.1298
	(0.06)	(-0.65)	(0.08)	(-0.69)
Ln(1+Delta)$_{t-1}$	0.1027***	-0.0520***	-0.0275	-0.0416*
	(19.57)	(-2.88)	(-1.59)	(-1.71)
County poverty status	0.0003	-0.0079	0.0098	0.0202
	(0.12)	(-0.84)	(1.17)	(1.57)
County employment status	0.0051***	0.0001	-0.0002	-0.0036
	(4.64)	(0.02)	(-0.05)	(-0.44)
Ln(County earnings per capita)	0.1269***	-0.0539	-0.1983*	-0.1033
	(4.52)	(-0.47)	(-1.84)	(-0.76)
Industry, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes	Yes
Clustered by CEO-firm and year	Yes	Yes	Yes	Yes
Adj R^2/Pseudo R^2	0.6187	0.3486	0.1550	0.2866
Observations	11,117	7,731	10,085	8,670

Table 12. Effects of CEOs' prenatal Superfund exposures on the likelihood of becoming a CEO

This table presents coefficients from a Probit regression of Outside CEO, which is a dummy variable set equal to one if the individuals joined the firm and became CEO in no more than two years and zero otherwise. County-level variables are measured in the CEO's birth year and the CEO's birth county. Variables are defined in the Appendix. Constant terms are not reported. Z-values are based on robust standard errors clustered by CEO-firm and by year (two-way) and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	**Outside CEO (0,1)**
Ln(1+CEO #Superfund exposure$_t$)	-0.4188**
	(-2.48)
Departing forced CEO turnover (0,1)	0.6390***
	(6.64)
Ln(Local peers)$_{t-1}$	0.1925**
	(2.53)
Non-compete index	-0.2047
	(-1.03)
Ind. return percentile$_{t-1}$	0.0003
	(0.21)
Firm abnormal return percentile$_{t-1}$	-0.0007
	(-0.49)
Ind. return risk$_{t-1}$	6.4275**
	(2.36)
Firm abnormal return volatility$_{t-1}$	5.1498***
	(5.07)
Ln(Assets)$_{t-1}$	-0.3100***
	(-8.02)
Tobin's Q$_{t-1}$	-0.0340***
	(-4.95)
Departing CEO age	-1.6888***
	(-3.45)
Ln(1+ Departing CEO tenure)	-0.3840***
	(-4.76)
Departing Founder CEO (0,1)	-0.1810
	(-1.11)
Departing CEO duality (0,1)	0.1668
	(1.36)
Departing CEO employment contract (0,1)	0.2311**
	(2.19)
Inst. ownership$_{t-1}$ (%)	0.3146
	(1.10)
Outside directors$_{t-1}$ (%)	1.3615***
	(4.71)
County poverty status	-0.0884***
	(-5.91)
County employment status	-0.0026
	(-0.65)
Ln(County earnings per capita)	-0.9880***
	(-3.17)
Industry, Year, Birth Year, Birth County, and HQ State FE	Yes
Clustered by CEO-firm and year	Yes
Pseudo R^2	0.4714
Observations	2,980

Online Appendix

Table OA1. Robustness test: Effect of CEOs' prenatal exposures to only developmental toxic chemicals

This table repeats tests in Tables 4 to 11, focusing on CEOs' prenatal exposure to developmental toxic chemicals. Here, we regress our models on *Developmental toxic chemical* (0,1), which identifies whether the contaminant the CEO was exposed to is a developmental toxic substance. Each observation corresponds to one CASRN chemical released by the Superfund sites. In each case, we control for the same control variables as in the corresponding previous tables and add chemical fixed effects. *t*-values are based on robust standard errors clustered by CEO-firm and by year (two-way) and are reported in parentheses. Variables are defined in the Appendix. *, **, and *** indicates significance at the 10%, 5%, and 1% level, respectively.

Corresponding table	**4**	**4**	**4**	**5**
Dependent variable	**Cash/Assets**	**Leverage**	**Ln(1+Share repurchase)**	**Kink**
	(1)	**(2)**	**(3)**	**(4)**
Developmental toxic chemical $(0,1)_t$	-0.0028***	-0.0061***	0.0998***	-0.0270
	(-3.26)	(-5.03)	(5.40)	(-0.90)
Chemical, Industry, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes	Yes
Adj R^2	0.7753	0.6030	0.5792	0.3372
Observations	299,148	326,240	332,184	310,401

Corresponding table	**6**	**6**	**6**	**6**	**7**	**7**	**7**
Dependent variable	**Credit rating Ordered Probit**	**Junk rating (0,1) OLS**	**Bankruptcy score OLS**	**Default probability OLS**	**Interest expense/Debt**	**Bank loan all-in-spread**	**Bond issue spread**
	(5)	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
Developmental toxic chemical $(0,1)_t$	-0.0489***	0.0038	0.0448***	0.0065***	0.1492***	2.2208***	7.6080***
	(-9.82)	(1.46)	(2.65)	(4.37)	(4.75)	(3.60)	(4.74)
Chemical, Industry, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lead lender FE	-	-	-	-	No	Yes	No
Adj R^2/Pseudo R^2	0.6093	0.6786	0.4614	0.4615	0.0895	0.8096	0.6932
Observations	218,591	218,591	326,730	293,698	286,064	518,689	216,585

Table OA1, continued

Corresponding table	8	8	8	8	8
Dependent variable	$\sigma_{Stock\ return}$	$\sigma_{Specific\ return}$	**Negative skewness**	$\sigma_{Down\text{-}to\text{-}up}$	**Crash risk**
	(12)	**(13)**	**(14)**	**(15)**	**(16)**
Developmental toxic chemical $(0,1)_t$	0.0043***	0.0054***	0.0636***	0.0102***	0.0226***
	(5.10)	(7.29)	(7.70)	(5.76)	(5.14)
Chemical, Industry, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.7247	0.6356	0.1519	0.1532	0.1312
Observations	308,598	286,321	289,994	289,994	290,048

Corresponding table	9	9	9	10	10	10
Dependent variable	**CAR(-1,1) Market model**	**CAR(-1,1) FF4 model**	**Unrelated acquisition (0,1)**	**Ind. adj. ROA**	**Ind. adj. Tobin's Q**	**Ind. adj. Stock return**
	(17)	**(18)**	**(19)**	**(20)**	**(21)**	**(22)**
Developmental toxic chemical $(0,1)_t$	-0.0004*	-0.0002	0.0708***	-0.0022***	-0.0290***	-0.0205***
	(-1.79)	(-0.81)	(5081)	(-4.20)	(-4.80)	(-4.94)
Chemical, (Acquirer) Industry, Year, Birth Year, Birth County, and (Acquirer) HQ State FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2/Pseudo R^2	0.2004	0.1879	0.3647	0.6647	0.6759	0.1434
Observations	323,404	323,404	308,017	394,204	389,569	393,372

Corresponding table	11	11
Dependent variable	**Ln(1+CEO tenure)**	**Forced CEO turnover (0,1)**
	(23)	**(24)**
Developmental toxic chemical $(0,1)_t$	-0.0299***	0.1645***
	(-8.31)	(8.76)
Chemical, Industry, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes
Adj R^2/Pseudo R^2	0.6950	0.5158
Observations	484,128	355,197

Table OA2. Robustness test: Effect of Superfund CEOs' postnatal pollution exposure

This table repeats tests in Tables 4 to 11, focusing on the non-moving Superfund CEOs' likely postnatal exposure to pollution up to adolescence. Non-moving Superfund CEOs are Superfund CEOs born and went to high school in the same county or attended college in the same state. *Ln*(*length of CEO postnatal exposure*) is the natural log of the length of likely CEO postnatal exposure to pollution. It is calculated as the minimum (maximum polluting period length of all Superfund sites in the CEO's county after the CEO's birth year, 15 (age of entry into senior high school)). In each case, we control for the same control variables as in the corresponding previous tables. *t*-values are based on robust standard errors clustered by CEO-firm and by year (two-way) and are reported in parentheses. Variables are defined in the Appendix. *, **, and *** indicates significance at the 10%, 5%, and 1% level, respectively.

Corresponding table	**4**	**4**	**4**	**5**
Dependent variable	**Cash/Assets**	**Leverage**	**Ln(1+Share repurchase)**	**Kink**
	(1)	**(2)**	**(3)**	**(4)**
Ln(length of CEO postnatal exposure)	0.6439	3.9679***	1.9184	0.3394
	(1.11)	(5.07)	(0.13)	(0.00)
Firm, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes	Yes
Adj R^2	0.8874	0.8290	0.7311	0.7819
Observations	2,054	2,231	2,275	2,161

Corresponding table	**6**	**6**	**6**	**6**	**7**	**7**	**7**
Dependent variable	**Credit rating Ordered Probit**	**Junk rating (0,1) OLS**	**Bankruptcy score OLS**	**Default probability OLS**	**Interest expense/Debt**	**Bank loan all-in-spread**	**Bond issue spread**
	(5)	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
Ln(length of CEO postnatal exposure)	-0.2496***	0.1052**	13.2074**	-5.0409***	44.6186	302.6094**	-24105.39***
	(-2.68)	(2.14)	(2.03)	(3.30)	(1.08)	(2.23)	(-2.91)
Firm, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lead lender FE	-	-	-	-	No	Yes	No
Adj R^2/Pseudo R^2	0.5451	0.6992	0.7423	0.6136	0.2006	0.8374	0.7417
Observations	1,531	1,531	2,137	1,978	1,927	3,359	1,806

Corresponding table	8	8	8	8	8
Dependent variable	$\sigma_{\text{Stock return}}$	$\sigma_{\text{Specific return}}$	Negative skewness	$\sigma_{\text{Down-to-up}}$	Crash risk
	(12)	(13)	(14)	(15)	(16)
Ln(length of CEO postnatal exposure)	0.5349	-0.8936	44.0869***	9.4558***	-13.1457***
	(0.99)	(-1.30)	(2.68)	(2.86)	(-3.40)
Firm, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.8709	0.8478	0.2289	0.2339	0.2198
Observations	2,131	2,131	1,977	1,977	1,978

Corresponding table	9	9	9	10	10	10
Dependent variable	CAR(-1,1) Market model	CAR(-1,1) FF4 model	Unrelated acquisition (0,1)	Ind. adj. ROA	Ind. adj. Tobin's Q	Ind. adj. Stock return
	(17)	(18)	(19)	(20)	(21)	(22)
Ln(length of CEO postnatal exposure)	0.0080	0.0041	-0.0568	0.0003	-0.1065***	0.0283
	(0.81)	(0.40)	(-0.67)	(0.08)	(-3.25)	(0.97)
(Acquirer) industry, Year, Birth Year, Birth County, and (Acquirer) HQ State FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.2653	0.2740	0.5094	0.7026	0.6834	0.1831
Observations	1,691	1,691	1,691	2,692	2,662	2,686

Corresponding table	11	11
Dependent variable	Ln(1+CEO tenure)	Forced CEO turnover (0,1)
	(23)	(24)
Ln(length of CEO postnatal exposure)	0.0446	0.6864
	(0.93)	(1.55)
Industry, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes
Pseudo R^2/Adj R^2	0.7169	0.6537
Observations	2,853	1,642

Table OA3. Robustness test: CEOs' current exposure to pollutants at work

This table repeats tests in Tables 4 to 11 with additional controls for firms' relationships with pollution. We add three variables for firms' different relationships with pollution. *Current Firm Polluter?* (0,1) identifies whether the firm is a polluter listed on EPA's databases. *HQ current pollution exposure* (0,1) and *Facility current pollution exposure* (0,1) capture whether the firm's headquarters and its facilities are currently exposed to toxic pollutants, respectively. In each column, we include the same control variables and fixed effects as the corresponding previous tables. *t*-values are based on robust standard errors clustered by CEO-firm and by year (two-way) and are reported in parentheses. Variables are defined in the Appendix. *, **, and *** indicates significance at the 10%, 5%, and 1% level, respectively.

Corresponding table	**4**	**4**	**4**	**5**
Dependent variable	**Cash/Assets**	**Leverage**	**Ln(1+Share repurchase)**	**Kink**
	(1)	**(2)**	**(3)**	**(4)**
Ln(1+CEO #Superfund exposure$_t$)	-0.0180	0.0437***	-0.7189**	-0.6574***
	(-1.56)	(2.82)	(-2.19)	(-28.22)
Firm current polluter? (0,1)$_t$	-0.0035	0.0124*	-0.3483**	0.0023
	(-0.50)	(1.68)	(-2.35)	(0.12)
HQ current pollution exposure (0,1)$_t$	-0.0017	-0.0171***	0.0753	0.2242***
	(-0.37)	(-3.31)	(0.73)	(12.41)
Facility current pollution exposure (0,1)$_t$	-0.0052	-0.0105	-0.2528*	-0.0220
	(-0.82)	(-1.55)	(-1.77)	(-1.16)
Firm, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes	Yes
Adj R^2/Pseudo R^2	0.8553	0.7922	0.6959	0.4387
Observations	8,298	8,955	9,136	8,740

Corresponding table	**6**	**6**	**6**	**6**	**7**	**7**	**7**
Dependent variable	**Credit rating Ordered Probit**	**Junk rating (0,1) OLS**	**Bankruptcy score OLS**	**Default probability OLS**	**Interest expense/Debt**	**Bank loan all-in-spread**	**Bond issue spread**
	(5)	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
Ln(1+CEO #Superfund exposure$_t$)	-0.9889**	0.0919	0.2737**	0.1045***	0.2922	16.6494**	91.7241***
	(-2.49)	(1.57)	(1.99)	(3.27)	(0.91)	(2.01)	(3.91)
Firm current polluter? (0,1)$_t$	-0.0549	-0.0063	-0.0307	-0.0264	0.0533	9.6089*	53.0752***
	(-0.29)	(-0.22)	(-0.43)	(-1.53)	(0.57)	(1.12)	(2.84)
HQ current pollution exposure (0,1)$_t$	0.0326	-0.0021	-0.0569	0.0086	-0.4473	9.0600**	-22.2886**
	(0.34)	(-0.11)	(-1.16)	(0.80)	(-1.07)	(2.03)	(-1.96)
Facility current pollution exposure (0,1)$_t$	0.0295	-0.0221	0.0027	0.0120	0.0497	-7.6088	-11.5610
	(0.18)	(-0.90)	(0.04)	(0.75)	(0.62)	(-0.77)	(-0.63)
Firm, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lead lender FE	-	-	-	-	No	Yes	No
Adj R^2/Pseudo R^2	0.5321	0.8471	0.6324	0.5679	0.1305	0.8260	0.7681
Observations	5,630	5,630	8,962	8,174	7,833	11,693	6,273

Table OA3, continued

Corresponding table	8	8	8	8	8
Dependent variable	$\sigma_{Stock\ return}$	$\sigma_{Specific\ return}$	Negative skewness	$\sigma_{Down\text{-}to\text{-}up}$	Crash risk
	(12)	(13)	(14)	(15)	(16)
Ln(1+CEO #Superfund exposure$_t$)	0.0321***	0.0270*	0.3442*	0.0801**	0.1771*
	(2.58)	(1.68)	(1.91)	(2.17)	(1.93)
Firm current polluter? (0,1)$_t$	0.0025	0.0018	-0.1293	-0.0278	-0.0557
	(0.36)	(0.22)	(-1.57)	(-1.56)	(-1.26)
HQ current pollution exposure (0,1)$_t$	0.0049	-0.0018	0.0419	0.0063	0.0063
	(1.24)	(-0.34)	(0.81)	(0.60)	(0.23)
Facility current pollution exposure (0,1)$_t$	0.0056	0.0078	0.0556	0.0243	-0.0187
	(0.86)	(1.03)	(0.71)	(1.46)	(-0.42)
Firm, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.8576	0.7478	0.2351	0.2378	0.2234
Observations	8,692	8,022	8,237	8,237	8,238

Corresponding table	9	9	9	10	10	10
Dependent variable	CAR(-1,1) Market model	CAR(-1,1) FF4 model	Unrelated acquisition (0,1)	Ind. adj. ROA	Ind. adj. Tobin's Q	Ind. adj. Stock return
	(17)	(18)	(19)	(20)	(21)	(22)
Ln(1+CEO #Superfund exposure$_t$)	-0.0082***	-0.0065**	0.2695***	-0.0058***	-0.0468**	-0.0489**
	(-2.67)	(-2.11)	(2.63)	(-2.80)	(-2.18)	(-2.49)
Firm current polluter? (0,1)$_t$	-0.0006	-0.0008	0.0749	0.0044	0.0002	0.0457*
	(-0.16)	(-0.25)	(0.60)	(1.48)	(0.01)	(1.73)
HQ current pollution exposure (0,1)$_t$	0.0002	0.0010	-0.0975	-0.0018	0.0169	0.0123
	(0.09))	(0.43)	(-1.23)	(-0.95)	(0.94)	(0.68)
Facility current pollution exposure (0,1)$_t$	0.0020	0.0020	0.0934	0.0032	0.0254	0.0017
	(0.61)	(0.62)	(0.81)	(1.09)	(0.84)	(0.06)
(Acquirer) industry, Year, Birth Year, Birth County, and (Acquirer) HQ State FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2/Pseudo R^2	0.1670	0.1646	0.3353	0.6554	0.6899	0.1371
Observations	6,799	6,799	6,065	10,542	10,452	10,519

Table OA3, continued

Corresponding table	**11**	**11**
Dependent variable	**Ln(1+CEO tenure)**	**Forced CEO turnover (0,1)**
	(23)	**(24)**
Ln(1+CEO #Superfund exposure$_t$)	-0.0508**	0.2693***
	(-2.39)	(3.14)
Firm current polluter? (0,1)$_t$	0.0379	0.0339
	(1.15)	(0.25)
HQ current pollution exposure (0,1)$_t$	0.0525***	0.1294*
	(2.98)	(1.66)
Facility current pollution exposure (0,1)$_t$	-0.0719**	-0.4572***
	(-2.25)	(-3.39)
Industry, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes
Adj R^2/Pseudo R^2	0.6194	0.3545
Observations	11,117	7,731

Table OA4. Robustness test: Superfund CEOs versus Non-Superfund CEOs – Nearest birthplace matching sample

This table repeats tests in Tables 4 to 11 contrasting Superfund CEOs versus Non-Superfund CEOs using the nearest birthplace matching sample. This matching sample comprises CEO-firm-year pairs with Superfund CEOs matched with non-Superfund CEOs. Matched CEO-firm-year pairs satisfy: (1) their CEOs were born in the same year (if feasible, or in the same decade, if not), and (2) they are in the same FF48 industry. For those satisfying the above requirements, we choose our control non-Superfund CEO as the one born in the nearest neighboring counties to the Superfund CEO. In each column, we include the same control variables and fixed effects as the corresponding previous tables. *t*-values are based on robust standard errors clustered by CEO-firm and by year (two-way) and are reported in parentheses. Variables are defined in the Appendix. *, **, and *** indicates significance at the 10%, 5%, and 1% level, respectively.

Corresponding table	**4**	**4**	**4**	**5**
Dependent variable	**Cash/Assets**	**Leverage**	**Ln(1+Share repurchase)**	**Kink**
	(1)	**(2)**	**(3)**	**(4)**
Ln(1+CEO #Superfund exposure$_t$)	-0.8693***	1.5276***	-5.4005*	-4.3419*
	(-6.58)	(5.92)	(-1.66)	(-1.74)
Firm, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes	Yes
Adj R^2/Pseudo R^2	0.8935	0.6259	0.5988	0.4625
Observations	3,720	3,016	3,115	3,851

Corresponding table	**6**	**6**	**6**	**6**	**7**	**7**	**7**
Dependent variable	**Credit rating Ordered Probit**	**Junk rating (0,1) OLS**	**Bankruptcy score OLS**	**Default probability OLS**	**Interest expense/Debt**	**Bank loan all-in-spread**	**Bond issue spread**
	(5)	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
Ln(1+CEO #Superfund exposure$_t$)	-12.3076***	0.8318*	5.9016***	0.0106**	0.2418*	362.3219***	472.2387*
	(-3.45)	(1.76)	(3.03)	(2.36)	(1.72)	(3.61)	(1.91)
Firm, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lead lender FE	-	-	-	-	No	Yes	No
Adj R^2/Pseudo R^2	0.5635	0.8743	0.6320	0.6107	0.4978	0.8636	0.5047
Observations	2,604	2,604	3,702	3,647	3,455	5,267	2,164

Table OA4, continued

Corresponding table	8	8	8	8	8
Dependent variable	$\sigma_{Stock\ return}$	$\sigma_{Specific\ return}$	Negative skewness	$\sigma_{Down\text{-}to\text{-}up}$	Crash risk
	(12)	(13)	(14)	(15)	(16)
Ln(1+CEO #Superfund exposure$_t$)	0.0472**	0.0356***	4.7756**	0.7769*	2.8611**
	(2.17)	(2.56)	(2.02)	(1.79)	(2.08)
Firm, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.6884	0.6647	0.2922	0.2927	0.2812
Observations	3,889	3,890	3,701	3,701	3,702

Corresponding table	9	9	9	10	10	10
Dependent variable	CAR(-1,1) Market model	CAR(-1,1) FF4 model	Unrelated acquisition (0,1)	Ind. adj. ROA	Ind. adj. Tobin's Q	Ind. adj. Stock return
	(17)	(18)	(19)	(20)	(21)	(22)
Ln(1+CEO #Superfund exposure$_t$)	-0.0193***	-0.0181**	0.7678***	-0.0114	-0.0379	-0.0481
	(-2.73)	(-2.48)	(2.58)	(-1.26)	(-0.89)	(-1.37)
(Acquirer) industry, Year, Birth Year, Birth County, and (Acquirer) HQ State FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2/Pseudo R^2	0.2574	0.2628	0.3825	0.6143	0.6995	0.1999
Observations	2,789	2,789	2,326	4,836	4,774	4,825

Corresponding table	11	11
Dependent variable	Ln(1+CEO tenure)	Forced CEO turnover (0,1)
	(23)	(24)
Ln(1+CEO #Superfund exposure$_t$)	-0.1516***	1.3064***
	(-4.43)	(4.84)
Industry, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes
Adj R^2/Pseudo R^2	0.6835	0.5142
Observations	5,133	2,974

Table OA5. Robustness test: Superfund CEOs versus Non-Superfund CEOs – Nearest firm headquarters matching sample

This table repeats tests in Tables 4 to 11 contrasting Superfund CEOs versus Non-Superfund CEOs using the nearest firm's headquarters matching sample. This matching sample comprises CEO-firm-year pairs with treated CEOs with Superfund pollution exposure matched with CEOs without such Superfund pollution exposure. Matched CEO-firm pairs satisfy: (1) their CEOs were born in the same year (if feasible, or in the same decade, if not), and (2) they are in the same FF48 industry. For those satisfying the above requirements, we choose the control firm managed by a non-Superfund CEO with headquarter located in the nearest neighboring counties to the treated firm managed by a Superfund CEO. In each column, we include the same control variables and fixed effects as the corresponding previous tables. *t*-values are based on robust standard errors clustered by CEO-firm and by year (two-way) and are reported in parentheses. Variables are defined in the Appendix. *, **, and *** indicates significance at the 10%, 5%, and 1% level, respectively.

Corresponding table	**4**	**4**	**4**	**5**
Dependent variable	**Cash/Assets**	**Leverage**	**Ln(1+Share repurchase)**	**Kink**
	(1)	**(2)**	**(3)**	**(4)**
Ln(1+CEO #Superfund exposure$_t$)	-1.0406**	0.7763**	-12.9506***	0.1029***
	(-2.45)	(2.40)	(-2.65)	(2.93)
Firm, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes	Yes
Adj R^2/Pseudo R^2	0.6227	0.8444	0.4565	0.4703
Observations	3,134	4,322	4,141	4,296

Corresponding table	**6**	**6**	**6**	**6**	**7**	**7**	**7**
Dependent variable	**Credit rating Ordered Probit**	**Junk rating (0,1) OLS**	**Bankruptcy score OLS**	**Default probability OLS**	**Interest expense/Debt**	**Bank loan all-in-spread**	**Bond issue spread**
	(5)	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
Ln(1+CEO #Superfund exposure$_t$)	-8.3166***	-0.4487	4.7935**	2.7135***	0.1151**	2286.412*	438.67**
	(-5.93)	(-0.35)	(2.16)	(6.39)	(5.49)	(1.89)	(2.12)
Firm, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lead lender FE	-	-	-	-	No	Yes	No
Adj R^2/Pseudo R^2	0.1785	0.8743	0.6281	0.5768	0.5131	0.8712	0.7434
Observations	3,504	2,980	4,179	4,023	2,901	4,313	2,630

Table OA5, continued

Corresponding table	**8**	**8**	**8**	**8**	**8**
Dependent variable	**$\sigma_{Stock\ return}$**	**$\sigma_{Specific\ return}$**	**Negative skewness**	**$\sigma_{Down\text{-}to\text{-}up}$**	**Crash risk**
	(12)	**(13)**	**(14)**	**(15)**	**(16)**
Ln(1+CEO #Superfund exposure$_t$)	0.3908*	0.3969***	6.6943***	1.0262**	2.4864**
	(1.80)	(2.61)	(3.41)	(2.35)	(2.10)
Firm, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.8731	0.8062	0.3351	0.3277	0.1360
Observations	4,229	4,229	4,058	4,058	4,059

Corresponding table	**9**	**9**	**9**	**10**	**10**	**10**
Dependent variable	**CAR(-1,1) Market model**	**CAR(-1,1) FF4 model**	**Unrelated acquisition (0,1)**	**Ind. adj. ROA**	**Ind. adj. Tobin's Q**	**Ind. adj. Stock return**
	(17)	**(18)**	**(19)**	**(20)**	**(21)**	**(22)**
Ln(1+CEO #Superfund exposure$_t$)	-0.0109*	-0.0212*	2.5571***	-0.0313*	-0.1576**	-0.1583***
	(-1.81)	(-1.67)	(3.21)	(-1.82)	(-2.50)	(-2.80)
(Acquirer) industry, Year, Birth Year, Birth County, and (Acquirer) HQ State FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2/Pseudo R^2	0.3507	0.4357	0.4282	0.4056	0.3892	0.1621
Observations	2,670	2,670	2,080	5,595	5,352	5,541

Corresponding table	**11**	**11**
Dependent variable	**Ln(1+CEO tenure)**	**Forced CEO turnover (0,1)**
	(23)	**(24)**
Ln(1+CEO #Superfund exposure$_t$)	-0.1147**	3.5779***
	(-2.37)	(4.67)
Industry, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes
Adj R^2/Pseudo R^2	0.8281	0.7171
Observations	5,764	1,994

Table OA6. Robustness test: Difference-in-differences (DID) analysis on CEOs' sudden deaths

This table repeats tests in Tables 4 to 11 using DID analysis on CEOs' sudden deaths. We contrast the firm-year observations for the three years before and the three years after the CEO demise using *Post CEO demise* (0,1) on the treatment of deceased CEOs' prenatal Superfund exposures (i.e., *Ln*(1+*deceased CEO #Superfund exposure*)). In each column, we include the same fixed effects as in the corresponding previous tables. *t*-values are based on robust standard errors clustered by CEO-firm and by year (two-way) and are reported in parentheses. Variables are defined in the Appendix. *, **, and *** indicates significance at the 10%, 5%, and 1% level, respectively.

Corresponding table	**4**	**4**	**4**	**5**
Dependent variable	**Cash/Assets**	**Leverage**	**Ln(1+Share repurchase)**	**Kink**
	(1)	**(2)**	**(3)**	**(4)**
Post CEO demise $(0,1)_t \times$ Ln(1+ deceased CEO #Superfund exposure$_t$)	0.7155**	-1.5846***	2.3378	3.5273***
	(1.96)	(-4.05)	(0.29)	(2.91)
CEO-firm, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes	Yes
Adj R^2/Pseudo R^2	0.9421	0.9780	0.8879	0.2753
Observations	206	205	205	225

Corresponding table	**6**	**6**	**6**	**6**	**7**	**7**	**7**
Dependent variable	**Credit rating Ordered Probit**	**Junk rating (0,1) OLS**	**Bankruptcy score OLS**	**Default probability OLS**	**Interest expense/Debt**	**Bank loan all-in-spread**	**Bond issue spread**
	(5)	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
Post CEO demise $(0,1)_t \times$ Ln(1+ deceased CEO #Superfund exposure$_t$)	397.5393***	-1.2334***	-1.8951**	-0.0448*	-0.0334*	-448.4504***	-649.7348***
	(11.33)	(-3.71)	(-2.05)	(-1.84)	(-1.68)	(-4.88)	(-17.05)
CEO-firm, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lead lender FE	-	-	-	-	No	Yes	No
Adj R^2/Pseudo R^2	0.8334	0.9201	0.7931	0.7611	0.8821	0.9792	0.8724
Observations	105	105	170	164	164	114	94

Table OA6, continued

Corresponding table	8	8	8	8	8
Dependent variable	**$\sigma_{Stock\ return}$**	**$\sigma_{Specific\ return}$**	**Negative skewness**	**$\sigma_{Down\text{-}to\text{-}up}$**	**Crash risk**
	(12)	**(13)**	**(14)**	**(15)**	**(16)**
Post CEO demise $(0,1)_t$ × Ln(1+deceased CEO #Superfund exposure$_t$)	-0.2394**	-0.3109***	-2.3685*	-0.6099**	-1.6384***
	(-2.05)	(-2.87)	(-1.83)	(-2.51)	(-2.74)
CEO-firm, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.8074	0.8414	0.6320	0.6200	0.6372
Observations	187	187	184	165	165

Corresponding table	**9**	**9**	**9**	**10**	**10**	**10**
Dependent variable	**CAR(-1,1) Market model**	**CAR(-1,1) FF4 model**	**Unrelated acquisition (0,1)**	**Ind. adj. ROA**	**Ind. adj. Tobin's Q**	**Ind. adj. Stock return**
	(17)	**(18)**	**(19)**	**(20)**	**(21)**	**(22)**
Post CEO demise $(0,1)_t$ ×	-0.0677*	-0.0479	0.5670***	0.3284***	2.3568***	1.7643**
Ln(1+deceased CEO #Superfund exposure$_t$)	(-1.72)	(-0.95)	(1890)	(7.85)	(2.75)	(2.48)
(Acquirer) firm, Year, Birth Year, Birth County, and (Acquirer) HQ State FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2/Pseudo R^2	0.4354	0.4304	0.2927	0.8094	0.9185	0.3655
Observations	113	113	44	274	269	274

	11
	Ln(1+CEO tenure)
	(23)
Post CEO demise $(0,1)_t$ ×	-0.6532**
Ln(1+deceased CEO #Superfund exposure$_t$)	(-2.41)
Industry, Year, Birth Year, Birth County, and HQ State FE	Yes
Adj R^2	0.9895
Observations	274

Table OA7. Placebo test: Random assignment of the CEO's birthplace

This table repeats tests in Tables 4 to 11 using randomly assigned CEO's birthplaces for two empirical bootstrap resampling distributions. To construct each empirical distribution, we replace the sample CEOs' birth county (and county-level control variables) with a pseudo CEO birth county. In column (1), for each firm-CEO in the sample, the pseudo-county is randomly chosen from all U.S. counties (not limited to the counties containing CEOs' birthplaces in our sample). The main regressions are run on this pseudo-sample. This process is repeated 1,000 times, forming an empirical bootstrap resampling distribution. In column (2), for each firm-CEO in the sample, the pseudo-county is randomly chosen from the 10 nearest counties to the CEO birth county and the main regressions are run on this pseudo-sample. This process is repeated 100 times, forming the second empirical bootstrap resampling distribution. In both columns, we use *Ln*(1+ *Pseudo-random CEO #Superfund exposure*) to capture the effect of randomly assigning the CEO's prenatal Superfund exposures for the bootstrap resampling distributions. In each column, we include the same control variables and fixed effects as the corresponding previous tables. We report the fraction of the total number of bootstrap regressions that report similar significant (p-value ≤0.05) coefficients *Ln*(1+ *Pseudo-random CEO #Superfund exposure*) as our main tables. Variables are defined in the Appendix. Bolded values signify cases when the pseudo-random procedure results in significant (p-value ≤0.05) coefficients similar to our main results more than 5% of the time.

		Fraction of significant bootstrapped coefficients	
Dependent variable	Corresponding table	Pseudo-random CEO #Superfund exposure (Random assignment of CEO birth county to all counties in the US) (1)	Pseudo-nearest CEO #Superfund exposure (Random assignment of CEO birth county to one of closest 10 counties) (2)
Cash/Assets	4	**0.095**	0.030
Leverage	4	**0.087**	0.000
Ln(1+Share repurchase)	4	**0.097**	0.010
Kink	5	0.019	0.000
Credit rating	6	**0.130**	**0.250**
Junk rating (0,1)	6	**0.062**	0.030
Bankruptcy score	6	0.032	0.000
Default probability	6	0.018	0.000
Interest expense/Debt	7	0.002	0.000
Bank loan all-in-spread	7	0.047	0.000
Bond issue spread	7	**0.098**	0.000
$\sigma_{\text{Stock return}}$	8	**0.134**	0.000
$\sigma_{\text{Specific return}}$	8	**0.138**	0.030
Negative skewness	8	0.009	0.000
$\sigma_{\text{Down-to-up}}$	8	0.019	0.000
Crash risk	8	0.019	0.000
CAR(-1,1) Market model	9	0.013	0.000
CAR(-1,1) FF4 model	9	0.011	0.000
Unrelated acquisition (0,1)	9	0.004	0.000
Ind. adj. ROA	10	0.003	**0.270**
Ind. adj. Tobin's Q	10	0.016	0.000
Ind. adj. Stock return	10	0.002	0.000
Ln(1+CEO tenure)	11	**0.081**	0.020
Forced CEO turnover (0,1)	11	**0.070**	**0.190**