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

Lok-Si Ieong* Baruch College

P. Raghavendra Rau** University of Cambridge

YiLin Wu*** National Taiwan University

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Abstract

Over the past several decades, there has been intense scrutiny on the effect of pollution on human health. This literature typically examines health consequences at the individual level. In this paper, we document the impact of prenatal exposure to pollution on CEOs, individuals who are likely to make consequential real decisions that affect large sections of society. Specifically, we draw on the extensive medical literature documenting the harm caused by developmental pollutants released by the most hazardous plants in the U.S. These effects were plausibly unknown when the CEO was born. We find that the CEOs with greater prenatal exposure to Superfund sites take more risks, but the risks do not pay off, adversely affecting the firm's value, and the CEOs experience higher forced turnover. Our results point to an indirect effect of pollution beyond the immediate health effects. They also demonstrate the role that prenatal exposure to pollution plays in affecting CEO managerial styles.

JEL classification: D22; G30; J31; J33; I10; Q50; Q53
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* Ieong: Zicklin School of Business, Baruch College, City University of New York, US. Email: loksi.ieong@baruch.cuny.edu. ** Rau: Cambridge Judge Business School, University of Cambridge, Trumpington Street, Cambridge, CB2 1AG, UK. Email: r.rau@jbs.cam.ac.uk. *** Wu: Department of Economics and Center for Research in Econometric Theory and Applications (CRETA), College of Social Sciences, National Taiwan University, Taipei City, Taiwan, R.O.C. Email: yilinwu@ntu.edu.tw.

"*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

1. Introduction

Over the past several decades, the impact of pollution on human health has been the subject of intense scrutiny. However, most papers examining the impact of pollution have typically focused on health outcomes, such as deleterious effects on health or cognition, hospitalizations, or deaths, for the individuals affected. A growing literature in economics examines the causal effect of pollution on real non-health consequences including worker productivity (Graff Zivin and Neidell (2012) or Lichter, Pestel, and Sommer (2017)), school performance (Graff Zivin et al. (2020) or Persico, Figlio, and Roth (2021)), and crime (Herrnstadt et al. (2021)). In this paper, we build on this literature to examine the long-term real consequences of prenatal pollution on chief executive officers' (CEO) risk judgments. Examining this issue is important because CEOs are typically successful individuals who plausibly make consequential real decisions that affect large sections of stakeholders in the firm and society.

A major issue in this analysis is endogeneity. It is plausible that family 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 passed on to their offspring. A growing body of literature has shown that chief executive officers' (CEO) managerial styles explain a significant portion of the variation in firm capital structure, investment, and other corporate policies (e.g., Bertrand and Schoar (2003), Bamber, Jiang, and Wang (2010), Graham, Li, and Qiu (2012)). However, the evidence that links this heterogeneity in CEOs' managerial styles to variations in the CEO's life and career experiences (e.g., Malmendier and Tate (2005), Malmendier and Nagel (2011), Malmendier, Tate, and Yan (2011), Benmelech and

[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 40m×14% = 5.6m Americans typically move across states and around 12.4m 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.

Frydman (2015), Dittmar and Duchin (2016), Bernile, Bhagwat, and Rau (2017), Schoar and Zuo (2017)) is subject to this endogeneity problem. 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 exposure to disasters shapes the CEO's preferences for risk-taking. However, it is plausible that although the decision to live in a disaster-prone area is not taken by the child, the decision to move to the area may reflect the parents' risk preferences and the latter rather than the disaster experience would affect the CEO's preferences. Natural disasters like wildfires and tornadoes occur in specific states in the United States, and the existence of these natural disasters 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 this issue by examining the effect of a clearly exogenous event that likely directly affected CEO risk preferences during the prenatal development period without simultaneously being affected by the risk preferences of the parent. Specifically, we examine the effect on the subsequent risk-taking behavior of the CEO who was born in a heavily polluted area, an area later designated as a Superfund site, without either the CEO or her parents making a deliberate choice to live in the polluted area. We refer to these CEOs as Superfund CEOs. To measure the impact of inadvertent exposure to pollution, we use the establishment of the U.S. Environmental Protection Agency (EPA), and its Superfund program.

Prior to the publication of "Silent Spring," by Rachel Carson in 1962, there was not much information about the use of pesticides (e.g., DDT, which was banned in 1972) and the harm they cause to animals, human health, and the environment. "Silent Spring" was the beginning of the U.S. environmental movement.[2] In 1970, President Nixon signed the National Environmental Policy Act (NEPA) and officially formed the Environmental Protection Agency (EPA). Though several other environmental acts have been proposed since then, such as the Resource Conservation and Recovery Act (RCRA) and the Toxic Substances Control Act (TSCA), the general public was not aware 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. Partly to address the problems of these toxic waste dumps, on June 13, 1979, President

[2] See "Milestones in EPA and environmental history" available at https://www.epa.gov/history/milestones-epa-and-environmental-history.

Carter proposed the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA) to Congress to fund the cleanups of the sites. CERCLA was passed in 1980.[3]

What effect does exposure to Superfund sites have on cognitive development? In the medical literature, Superfund contaminants, whether released through the air, ground, or water, have been documented to have severe adverse developmental effects on neurodevelopment, psychophysical, and cognitive dimensions for children. These effects include impaired inhibitory control, greater levels of depression, anxiety, and somatic symptoms (e.g., Guxens et al., (2018) or Persico, Figlio, and Roth (2020)), increased risk for attention deficit hyperactivity disorder (ADHD) (Ke et al. (2021)) and a reduction in serotonin levels (Yokota, et al. (2016)). Low levels of serotonin have been associated with increased aggression and impulsivity in adults, children, and animals. Margolis et al. (2016) show that prenatal exposure to pollutants produces long-lasting effects on deficits in self-regulation and that these deficits have real-world consequences for high-risk adolescent behaviors. The perceived benefits from risk-taking plays a significant role in explaining the association between ADHD and increased engagement in risk-taking behaviors. Shoham et al. (2016) and Shoham et al. (2021) show that the association between ADHD and increased engagement in risk-taking behaviors (such as gambling or financial investment) is mediated by the overestimated benefits from the risky behaviors. Even short-term exposure to hazardous waste sites and ambient air pollution has been shown to reduce performance in highly skilled, mentally demanding jobs (Archsmith, Heyes, and Saberian (2018), Heyes, Rivers, Schaufele (2019), Chang, Graff Zivin, Gross, and Neidell (2019), Ebenstein, Lavy, and Roth (2016), Zhang, Chen, and Zhang (2018), Huang, Xu, and Yu (2020); Li, Massa, Zhang, and Zhang (2021); Dong, Fisman, Wang, and Xu (2021)).

We primarily focus on inadvertent prenatal exposure to hazardous toxicity to examine the impact on CEOs' ability to gauge risks. One advantage of our setting is that most of the CEOs in our sample were born during periods when people did not realize the harm caused by these industrial chemicals or the location of hazardous sites near their neighborhoods. It is unlikely that the CEO's parents would know about this potentially dangerous exposure. Hence, it is implausible that our sample Superfund CEOs are disproportionately represented by CEOs with risk-taking

[3] The Superfund Program deals only with the most polluted hazardous waste sites. A number of other major environmental laws—such as the RCRA, the Clean Water Act, the Clean Air Act, TSCA, and the Safe Drinking Water Act—were enacted to deal with other types of pollution.

genotypes. Our research design enables us to rule out this type of self-selection bias and omitted variables such as intrinsic risk-taking preferences as potential confounders that affect both the CEOs' risk-taking behaviors and their prenatal pollution exposure.

Based on the extensive medical literature, we argue that the primary underlying channel is the harm caused by developmentally toxic chemicals contained in the Superfund sites. In other words, we conjecture that Superfund CEOs' prenatal exposure to toxic chemicals impairs their ability to judge risks. We focus on three major dimensions of corporate consequences: the risk-taking policies of the firm, firm valuation, and CEO performance. The results are strikingly consistent across all three dimensions – Superfund CEOs take more risks, the risks do not pay off, adversely affecting the value of the firm, and the CEOs are more likely to be fired.

More specifically, the greater the CEO's prenatal exposure to Superfund sites, the risker the capital structure of the firm – the firm holds less cash, has higher leverage levels, and makes fewer cash payouts. The debt issued by these firms tend to be inefficient and riskier – they have smaller kinks, as defined in Graham (2000), have lower credit ratings, are more likely to be rated lower than BBB-, have higher bankruptcy scores, higher estimated default probabilities. The cost of the debt is higher – the firms have greater interest expenses, 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, more likely to have negatively skewed firm-specific returns, larger ratios of volatilities in up weeks over in down weeks, and more likely to have a crash week. They earn smaller abnormal returns after M&A announcements and 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, the forced turnover rate for these CEOs is significantly higher.

To mitigate the potential omitted variable issue, in all our models, we control for firm, year, CEO's birth year, county of birth, and firm's headquarter state fixed effects. We include a host of firm and CEO control variables that are likely to affect debt and equity risk, performance, and turnover. We control for macroeconomic effects, including county poverty, employment status, and wealth.

We also conduct a number of additional tests to exclude other channels that may drive our results. We examine CEOs' *post-natal* exposure, that is, whether the effect is driven by continuous exposure to Superfund pollution during the developmental years of the child. Relative to prenatal exposure, postnatal exposure does not appear to have an incrementally large effect.

We next focus on CEO exposure specifically to toxic chemicals that are important during the development process in the womb. According to the EPA, four significant prenatal outcomes related to developmental chemicals are death, structural abnormality, altered growth, and functional deficit. Among infants who survive to adulthood, developmental toxicity includes detrimental effects such as growth retardation or functional impairment by exposure during the embryonic stages of development. Our results remain largely unchanged when we consider only developmentally toxic chemicals.

Another explanation for our results is that the CEO ends up managing a local firm that is still exposed to the pollution from the Superfund site. Alternatively, the firm might be a current polluter. Indicator variables for whether the firm is a current polluter or whether the firm's headquarters or facilities are exposed to pollution are rarely significant. In contrast, the Superfund CEO variable is consistently significant across all our dependent variables.

Our results are robust to a battery of robustness tests. For every CEO, we next match the 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 FF48 industry. Our results are largely unaffected. In a second robustness test, we match 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). Again, our results are largely unchanged. Third, we contrast the firm-year observations for the three years before and the three years after a sudden death of a Superfund CEO. The difference-in-difference (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 exposure to developmentally toxic chemicals take more risks, both with respect to debt and equity, the risks do not appear to pay off, and this has strong negative consequences for CEO turnover.

Our paper contributes to the vast literature on environmental pollution in economics. For example, Heyes, Neidell, and Saberian (2016) show air pollution in Manhattan affects the return on S&P 500 on the same day via health and behavior channels. Huang, Xu, and Yu (2020) find that air pollution worsens individual investors' trade performance. Li, Massa, Zhang, and Zhang (2021) argue that individual investors suffering from air pollution-induced depressed moods may trigger the increases in investors' disposition effects.

Relative to other pollutants, only a small number of economic papers focus on Superfund sites, the most hazardous polluted plants in the United States. 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, Timmins (2023)), enforcements (Akey and Appel (2021)), and health (Klemick, Mason, and Sullivan (2020), Persico, Figlio, and Roth (2020)). We add to this literature by showing that prenatal exposure to hazardous chemicals via the health channel affects CEOs' financing decisions, risk-taking, firm performance, and their own performance.

Our paper also points to the real consequences of pollution. From the perspective of human capital, our paper is consistent with Persico, Figlio, and Roth (2020) and Sanders (2012) who use school tests to show that prenatal exposure to Superfund and other pollution has long-term effects on human cognitive performance. We provide novel evidence to show prenatal exposure to Superfund sites has lifetime consequences on human capital. Our results are especially noteworthy in the sense that (1) our sample is composed of individuals who have *ex-post* the highest socio-economic status in the United States, (2) we mitigate the selection bias issue by focusing on the polluting period when people did not know much about Superfund pollution exposure, (3) our observations contain much longer horizons and are widely spread in their geographical scale compared to the previous studies, and (4) the cognitive trials for CEOs are much more complicated than the high-school tests.

Pollution is positively correlated with poverty (O'Neill et al. (2003)). Hence it is possible to argue that our results are actually being driven by poverty. Alternatively, it is possible to argue that the real effects on the economy are not likely to be large since poor individuals typically have smaller economic impacts than rich, successful individuals.

We note, however, that in all our models, among other effects, we control for the county of birth and the state of the firm's headquarters fixed effects. We also control for macroeconomic effects, including county poverty, employment status, and wealth. Hence, our results are unlikely to be driven by a positive correlation between local socio-economic status and pollution. Beyond this, our data shows that though Superfund sites are spread nationwide across the U.S., they are concentrated in six states in the United States (e.g., California, Massachusetts, Michigan, Pennsylvania, New Jersey, and New York). These states are relatively wealthy. Finally, the medical literature documents that pollution has significant deleterious effects on wealthy families as well. For instance, Forastiere et al. (2007) document that people with higher area-based income and socioeconomic status (SES) are exposed to greater environmental risk. Tyrrell et al. (2013) find that rich families have higher levels of environmental pollutant concentrations, such as mercury, arsenic, thallium, and perfluorononanoic acid associations due to their greater consumption of fish and shellfish. Overall, our results imply that prenatal exposure to pollution for eventually wealthy, successful individuals who have substantial influences on society through their management of corporations is likely to have significant effects on the economy beyond just a measurement of the direct effects of pollution.

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

2. The federal Superfund program

2.1. Brief overview of the federal Superfund program[4]

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 EPA developed a nationwide program to react to emergency responses, collect information and analyze, identify and provide liability for responsible parties for their releases of contaminations,

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

and perform site cleanup. The CERCLA also establish a trust fund (also known as "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) unless EPA finds that no action will be assigned to the site if placed on NPL.[5] No Further Remedial Action Planned (NFRAP) status is provided to those not suitable for NPL, and their cleanups are the responsibilities of states, tribes, and other federal government agencies. The assessment process ensures that only the most toxic polluted plants, the Superfund sites, are selected and listed on NPL.

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 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 requirements for listing, it is formally listed on the NPL. The first stage of the cleanup process, remedial investigation, and feasibility study (RI/FS), serves as the mechanism for collecting data to characterize site conditions, determines the precise nature and extent of contamination at the site, tests whether certain technologies are capable of treating the contamination and evaluates 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 actions to be implemented. The first milestone in the cleanup process is when a site is labeled as "construction complete." It indicates that all physical or construction engineering tasks required for the site's cleanup have been completed, and both immediate and long-term threats to the public health or the environment have been addressed. Note that construction complete does not mean that all threats have been neutralized.[6] The post construction completion (PCC) phase may involve a number of different activities necessary for

[5] Officially, the Record of Decision (ROD) for such sites would be "no action," following the Guide to Preparing Superfund Proposed Plans, Records of Decision, and Other Remedy Selection Decision Documents.

[6] For example, though a groundwater treatment system has been constructed, it may need to operate for a prolonged period of time in order for all contaminants to be removed from the groundwater. It is possible for the source of the contamination to have been completely removed but the surrounding media may remain toxic and thus not ready for being returned to general use.

achieving the ultimate cleanup goals of returning hazardous waste sites to 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.

2.2. The effect of exposure to hazardous waste sites and air pollution on cognitive, physical, and mental health outcomes

There is an extensive literature that looks at the deleterious effects of environmental pollutants on cognitive, physical, and mental health outcomes. Research shows higher levels of cancer incidence rates (e.g., Kirpich and Leary (2017); Amin, Nelson, and McDougall (2018); Zhang, McDermott, Davis, and Hussey (2020)), poor infant birth outcomes (e.g., higher infant mortality, lower birth weight, and a higher incidence of congenital anomalies) (Currie and Neidell (2005); Berkowitz, Price-Green, Bove, Kaye (2006); Currie, Greenstone, and Morettis (2011)), and significant physical health threats for exposures to environmental pollutants from Superfund sites.[7]

Relevant to our study, the extant literature also shows significant negative cognitive and behavioral development for children (Persico, Figlio, and Roth (2020), Sanders (2012)). Superfund sites release endocrine disrupting chemicals, which are the source of several anomalies such as anxiety, depression, and hyperactivity (Shoaff, Calafat, Schantz, and Korrick (2019); Seibert, Quesada, Bergamasco, Borba, and Pellenz (2019)). In particular, Persico, Figlio, and Roth (2020) examine the long-run impacts of prenatal exposure to Superfund sites on a range of cognitive outcomes,[8] and show that children exposed to pollutants from Superfund sites in the prenatal period show lower test scores, increases in behavioral incidents at school, higher likelihood of repeating a grade, and an increased likelihood of having a cognitive disability, compared to their siblings conceived after the cleanup of the Superfund sites.

[7] For adults living in communities near Superfund sites, studies show adverse effects on immune (Williamson, White, Poole, Kleinbaum, Vogt, and North (2006)), cardiovascular (Davis, McDermott, McCarter, and Ortaglia (2019)), endocrine (Shoaff, Calafat, Schantz, and Korrick (2019)), reproductive (Moline, Golden, Bar-Chama, Smith, Rauch, Chapin, Perreault, Schrader, Suk, and Landrigan (2000)), hepatic (Ala, Stanca, Bu-Ghanim, Ahmado, Branch, Schiano, Odin, and Bach (2006)), hematologic (Karouna-Renier, Rao, Lanza, Davis, and Wilson (2007)), respiratory (Kudyakov, Baibergenova, Zdeb, and Carpenter (2004)), nervous (Kilburn and Warshaw (1995); Zhang, McDermott, Davis, and Hussey (2020)), dermal (Hailer, Peck, Calhoun, West, and Siciliano (2017)), urinary (Budnick, Logue, Sokal, Fox, and Falk (1984)), ocular (Gill and Mix (2020)), and on gastrointestinal systems (Sonwalkar, Fang, and Sun (2010)).

[8] 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 human brain is highly vulnerable to toxic chemical exposures (Lanphear (2015)).

Herrnstadt, Heyes, Muehlegger, and Saberian (2021) offer several channels through which pollution causes increased aggression and impulsivity. One channel is that pollutants inflame nerve tissues in humans (a dopaminergic effect), which, in turn, causes aggressive behavior. Morris, Counsell, McGonnell, and Thornton (2021) show that early-life exposure to air pollution, comprising particulate matter (PM), metals, black carbon, and gases such as ozone (O_3), nitrogen dioxide (NO_2) and carbon monoxide (CO), may cause neuro inflammation, resulting in aggressive behavior and neurodevelopmental and neuropsychiatric disorders. A second channel is that pollution directly affects brain chemistry by lowering levels of serotonin, which, in turn, is associated with increased aggression and impulsivity. González-Guevara et al. (2014) and Murphy et al. (2013) provide evidence linking short-term pollution exposure to decreased serotonin in animals. Yokota, Oshio, Moriya, and Takeda (2016) document that prenatal exposure to pollution decreases serotonin levels. In turn, low levels of serotonin are associated with increased aggression and impulsivity in adults, children, and animals. Pollution has also been shown to increase ADHD in children. For example, Perera et al. (2014), Myhre et al. (2018), and Thygesen et al. (2020) show that early-life exposure to air pollution is associated with a significantly increased risk of ADHD. Lee et al. (2018) show that environmental toxicants such as lead, cadmium, and antimony contribute to the risk of ADHD. Ke et al. (2021) show that prenatal exposure to the neurotoxin methylmercury is associated with an increased risk for ADHD and argues that eliminating exposure to heavy metals may help to prevent neurodevelopmental disorders in children.

The 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 study 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 deficits in self-regulation and that these deficits have real-world consequences for high-risk adolescent behaviors. The perceived 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) and Shoham et al. (2021) show that the association between ADHD and increased engagement in risk-taking behaviors (such as gambling, financial investment) is mediated by the overestimated benefits from the risky behaviors. Currie, Greenstone, and Morettis (2011) and Persico, Figlio, and Roth (2020) show the substantial health benefits of Superfund cleanups.

There is also substantial evidence that even short-term exposures to hazardous waste sites and ambient air pollution reduces performance in highly skilled, mentally demanding jobs, assuming that cognition or mental acuity is the potential underlying mechanism; 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 highly skilled, 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.

Still another potential mechanism underlying the decline in performance is pollution-induced negative human emotions —anxiety, depression, or impatience. Li, Massa, Zhang, and Zhang (2021) argue that individual investors suffering from air pollution-induced depressed moods may trigger the increases in investors' disposition effects. Dong, Fisman, Wang, and Xu (2021) show that higher air pollution during corporate site visits by investment analysts leads to lower earnings forecasts in the weeks immediately following visits, suggestive of the pollution-induced depressed moods mechanism.

3. Sample construction, variable definitions, and descriptive statistics

3.1. Superfund sites and other EPA programs

We begin with a list of 1,803 Superfund sites collected from the EPA's websites as of December 31, 2018.[9] Figure 1 shows the number of Superfund sites located in each county over the United States. These sites are spread throughout 50 states and the District of Columbia and are concentrated in highly populous states like California, Massachusetts, Michigan, Pennsylvania, New Jersey, and New York. For example, Silicon Valley, home to more than 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. The rest are in the five U.S. territories (America Samoa, Guam, the Northern Mariana Island, Puerto Rico, and the U.S. Virgin Islands) and the Federated States of Micronesia.

As described in Section 2.1, based on their status, these sites can be classified as proposed NPL sites, NPL sites, and deleted NPL sites. Our sample consists of 412 sites deleted from NPL, 1,338 sites currently listed, and 53 sites proposed to be listed on NPL. Regardless of their current cleanup status, we use all three types of Superfund sites for our study because our research design relies on whether CEOs were exposed to the hazardous pollutants released from these sites in the prenatal state. We collect the following information for each Superfund site: name, state, city, EPA ID, HRS score, status date, an indicator for Federal facility, links for location, and additional information. Specifically, the location of Superfund sites allows us to match CEOs' birthplaces. Moreover, for each Superfund site, EPA provides the site progress profile and discloses extra information about the site[10]. We manually collect the size of each Superfund site and, more importantly, its polluting period from the page. The actively polluting period then allows us to identify the contamination period for each Superfund sites.

Table 1 presents summary statistics on the Superfund sites through 2018. The summary statistics are similar to those reported in Greenstone and Gallagher (2008). For all 1,803 Superfund sites, 796 (44%) were proposed in 1981-1985, 418 (23%) were proposed in 1986-1990, 249 (14%) were proposed in the 1990s, 203 (11%) were proposed in the 2000s, and 137 (8%) were proposed in 2010-2018. There are 23 proposed sites with missing HRS scores, and one with an HRS score

[9] The latest list of Superfund sites is available here: https://www.epa.gov/superfund/superfund-national-priorities-list-npl

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

less than 28.5 were added by the state as its top-priority site, and such cases are limited to one per state. The mean (median) HRS score on the NPL listing date is 43.85 (43.70). The mean Superfund site size at 6,852 acres is substantially larger than the median site size (at 38 acres) due to some huge sites.

Table 1 also documents the lengthy nature of the Superfund cleanup process. It reports the mean (median) years until the sites reach key milestones.[11] The median years from the NPL proposal date until the remedial action started date (the date when a site achieved the construction completion milestone, the date when the cleanup goals have been achieved and the sites are deleted from the NPL) is around 7.83 (12.36, 13.69) years. It takes over two decades (median 24.13 years) before the site can be reused or redeveloped. The three contaminated environmental media at Superfund sites: air, water, and ground, are non-mutually exclusive.[12] For example, liquid contaminants can flow down through the soil to the groundwater due to gravity or rainfall. Table 1 reveals that air as an environmental medium is less common at Superfund sites; only 4.88% of Superfund sites report toxic releases to air, while 82.03% and 87.97% of Superfund sites report toxic releases to ground and water, respectively.

To show the negative impact of exposure to Superfund sites, 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 that was actively polluting) among all infants and the counterpart for CEOs. Superfund CEOs form a lower proportion of CEOs relative to the proportion of Superfund infants among all infants. One explanation is that Superfund infants are less likely to become CEOs than other infants. An alternative explanation is that the relatively higher socio-economic status for CEO families makes them less likely to give birth to Superfund infants. We control for the latter possibility by using CEOs birth year and county fixed effects and the county's demography characteristics in all our models. Panel B and C compare the infant mortality rates and low birthweight rates of (1) all counties, (2) counties with Superfund sites

[11] There are 397 sites with remedial action started date marked as "not yet achieved," which means that the remedial action has not started yet at this particular site. There are 598 sites with construction completion date marked as "not yet achieved." There are 1,391 sites with deletion status marked as "not yet achieved." There are 932 sites with ready for reuse and redevelopment status marked as "not yet achieved."

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

during the pollutant-generating periods, (3) counties with Superfund sites during periods before or after the pollutant-generating periods, and (4) counties without Superfund sites. The key takeaway from these two panels is that the most negative impact on human health for the Superfund sites was during the pollutant-generating periods.

Every Superfund site was polluted by different levels of different types of contaminants with accompanying distinct effects on human health. The health and environment section contains the contaminant list in the Superfund sites' progress profiles. Specifically, the section provides the name of the contaminants with their contaminated media, the chemical abstracts service (CAS) code, and the Agency for Toxic Substances and Disease Registry (ATSDR) profiles. We especially focus on exposure to the developmental toxic chemical. Developmental toxicity includes detrimental effects such as growth retardation and functional impairment by exposure during the embryonic stages of development. We then match the contaminants' CAS codes with their chemical assessments in the EPA's Integrated Risk Information System (IRIS) and classify them based on the human health risk assessment and developmental toxicity studies in laboratory animals. The contamination information gives us the precise health effect that could have been had through CEOs' exposure to Superfund sites.

Even if a CEO was not exposed to a Superfund site in the prenatal period, she could be later connected to a Superfund site or other environmental programs under the EPA. As mentioned in Section 2.1, the EPA identifies the potentially responsible parties (PRPs) and provides them with liability for their responsibility of cleanup at each Superfund site. Typically, the EPA uses "general notice letters" and "special notice letters" to communicate with PRPs for their identification and potential liabilities.[13] Though PRPs may have been responsible for their contamination of Superfund sites in the past, if the Superfund CEO is managing a firm that is named a PRP, it could potentially affect the interpretation of our results. For example, Advanced Micro Devices, Inc was identified as a Superfund PRP, following which they settled with the EPA.[14] The current polluting behavior of an executive working for a PRP might be correlated with her risk-judgment ability. We collect our PRPs' information from two sources to control for this possibility. We acquire the file Noticed Parties at Sites in SEMS (FOIA 11) from the EPA's Superfund Data and Reports. This

[13] For more details about EPA's use of notice letters, please refer to the EPA's website: https://www.epa.gov/enforcement/superfund-notice-liability-letters.
[14] AMD's disclosure is on SEC EDGAR available at https://www.sec.gov/Archives/edgar/data/2488/000101287003001181/d10k.htm.

list consists of both NPL and non-NPL sites with their PRPs and the corresponding actions (e.g., the use of notice letters and enforcement instruments). We also submitted a FOIA request, EPA-2021-000409, to get the estimated values of the PRPs' response for each Superfund.[15]

However, a firm and its facilities might have other pollutants that are documented in other EPA programs such as the Toxic Release Inventory (TRI) program. After the passage of the Emergency Planning and Community Right-to-Know Act (EPCRA) in 1986, firms with certain scales were required to self-report their emissions of specific hazardous pollutants to the EPA using various forms. These forms are then verified and compiled in the Toxic Release Inventory (TRI) database. Among them, Form R is used by firms with large amounts of emissions. We collected the complete list of TRI Form R reports with information such as name, TRI facility ID, reporting year, address, an indicator for Federal facility, parent company, and contaminations. The identities of PRPs and TRI facilities' parent company together allow us to figure out if a firm is a polluter who releases hazardous chemicals. We use the indicator variable "*Firm current polluter?* (0,1)" to denote these firms.

A firm may also be affected by pollution released by other firms. Hence, our effects may be driven by current pollution exposure at the firm's headquarters or facilities. To address this issue, we collect the locations for firms' headquarters and facilities. Since 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.[16] In addition, we obtain data on headquarters missing from this database from the header sections of the 10-Ks and 10-Qs filed on SEC EDGAR. We then convert the HQs to obtain corresponding longitude-latitude coordinates using geocoding. We collect key information about facility-level information including facility name, address, geospatial information, and its parent company from EPA.[17] 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 in EPA to Compustat firms based on at least three shared web search URLs in cases where the parent name

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[15] Our FOIA request, EPA-2021-000409, can be found on FOIA online: https://foiaonline.gov/foiaonline/action/public/submissionDetails?trackingNumber=EPA-2021-000409&type=Request.

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

[17] We obtain the 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.

strings on EPA and Compustat firm records do not match exactly. We focus only on the three-mile radius circle around the company HQ that is likely to pose a significant threat to human health (Greenstone and Gallagher (2008); Persico, Figlio, and Roth (2020)). Finally, 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.[18]

3.2. CEOs' characteristics

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

We begin with the S&P 1500 firms on Compustat Execucomp from 1992 to 2018. Our initial set of CEOs consists of 7,937 CEOs. We begin with CEO birthplace data obtained from Bernile, Bhagwat, and Rau (2017), and Lei, Petmezas, Rau, and Yang (2022). For CEOs without a reported birthplace, we manually collect their birthplace and birth year from textual, visual, and audio sources, including Bloomberg, Forbes, Legacy.com (from their obituaries), 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 (partial) birthplace information for 3,095 CEOs and a complete birthplace record at the county level for 2,761 CEOs born in the United States.

Using the locations of the Superfund sites and CEOs' birthplace, we identify 638 CEOs whose birth counties experienced the U.S. worst hazardous contaminants during the birth year. These CEOs are denoted our "*Superfund CEOs*." Our key explanatory variable, "*CEO #Superfund exposure*," measures the number of Superfund sites that were 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 a total of 5 Superfund sites. Three of them were polluted before 1961 and were not cleaned up until well after she was born. Therefore, Mary T. Barra is identified as a "*Superfund CEO,*" and her "*CEO #Superfund exposure*" is 3. In addition, we use the indicator variable "*Developmental toxic chemical* (0,1)" to identify whether the contaminant the CEO was exposed to during her birth year is a developmental toxic substance.

[18] Our results are similar if we use a distance of 2 miles and hence do not tabulate these results for brevity.

To measure CEO post-natal exposure to Superfund pollution, we next collect the records of their high schools and higher education. We collect CEOs' high school records via yearbooks, alumni, and official high school websites. To confirm these records, we use a combination of CEOs' names, ages, and birthplaces to prevent misidentification with people with the same name. This process gives us 1,591 CEOs' high school records, with 1,475 in the United States. For CEOs where we were unable to find a high school record, we assume that they grew up in the same county they were born in if they attended a university in the same state. Making this further assumption allows us to identify an additional 742 CEOs who were born and grew up in the same county in the United States.

3.2.2. Other CEO characteristics

To address concerns that other CEO characteristics drive our findings, we include CEO age, CEO tenure, CEO duality (an indicator variable that equals one if the current CEO also chairs the board), Founder CEO (an indicator variable that equals one if the current CEO founded the firm), Outside CEO (indicator variables for whether or not the individual joined the firm and became CEO in no more than two years), whether or not CEO has an explicit employment contract, CEO ownership, and CEO equity-based compensation (change in the risk-neutral (Black-Scholes) value of a CEO's stock and option portfolio in response to a 1% change in stock price). Data on CEO characteristics are obtained from ExecuComp, Equilar Consultants, Risk Metrics and Compustat. Missing data on CEO characteristics are collected from proxy statements and other SEC filings when available. Detailed descriptions of the construction of these variables can be found in the Appendix.

3.3. Firm characteristics

Our sample consists of all publicly traded U.S. firms that were listed in S&P 1500 in Compustat between 1992 and 2018. Our research design requires us to limit our focus to firm-year observations where we can track the CEOs' birthplace record, implying that their birthplaces have to be in the United States. We exclude firm-year observations where the principal executive office is listed as being located outside the U.S. We also exclude financial and utility firms (with Standard Industrial Classification (SIC) codes 4900-4999 and 6000-6999). Detailed definitions of all variables used in this study can be found in the Appendix.

To illustrate the characteristics of our sample, we provide two sets of comparisons in Table 3. Panel A compares the firm characteristics of our sample with all firms in Compustat and ExecuComp. Intuitively, given our sample was drawn from ExecuComp, our sample characteristics should be more like firms in ExecuComp than Compustat. Also, our sample comprises the firms listed in the S&P 1500, among the largest firms in the Compustat universe. Following our expectations, mainly because of the nature of our sample construction process, Panel A shows our sample firms are more similar to those in ExecuComp than Compustat on average. The last column suggests that our sample firms are still larger than typical firms in the ExecuComp universe. This is because larger firms have better CEO birthplace availability. CEOs working for more prominent firms are more famous, and thus their birthplace records are more accessible, for example, through media coverage. The rest of the table shows similar patterns: firms in our sample are more alike to those in ExecuComp than Compustat.

Panel B compares our sample of Superfund CEOs and non-Superfund CEOs. Here, we have a total of 638 unique Superfund CEOs and 2,109 non-Superfund CEOs. We also note that 14 CEOs with complete birthplace records are dropped from the exclusion of the financial and utilities firms we mention above. Strikingly, Superfund CEOs are typically hired by larger firms than non-Superfund CEOs. Consistent with our initial hypotheses, firms managed by Superfund CEOs perform worse across all three measures of performance: ROA, Tobin's Q, and stock return. In addition, these firms have more significant leverage ratios and interest expenses but hold less cash and are less likely to pay dividends. Not surprisingly, they bear higher equity and debt risks. These univariate comparisons serve as preliminary evidence for our main research questions.

4. Empirical results: Baseline tests

4.1. CEOs' exposure to Superfund sites and firms' capital structure

We begin our analysis by examining the effect of CEOs' prenatal exposure to the Superfund sites on firms' capital structure. As discussed in Section 2.2, considerable medical evidence has documented the detrimental impacts on the human health of those pollutants released in Superfund sites. Accordingly, prenatal exposure to Superfund sites has been shown to have long-term negative impacts on cognitive performance and behavioral outcomes, such as high-stakes student test scores (Persico, Figlio, and Roth (2020), Sanders (2012)). Based on these facts, we conjecture that CEOs with greater prenatal exposure to Superfund sites have dampened their ability to gauge tasks that are likely to be much more complicated than pupils' school tests (e.g., risk assessments). Thus, the CEOs' impaired judgement of risks should be reflected in their firms' capital structure.

To test our conjecture, we consider three dimensions of firms' capital structure – the cash-to-asset ratio ($\text{Cash/Assets}_{i,j,t}$), the year-end book financial leverage ($\text{Leverage}_{i,j,t}$), and the amount of cash returned to the shareholders in the form of share repurchases ($\text{Ln(1 + Share Repurchase)}_{i,j,t}$) for firm i, CEO j, and year t. We examine share repurchases instead of dividends because the former are largely discretionary while the latter are sticky. We include the lagged control variables, measured as of the year *t*-1 for the firm's and CEO's characteristics, the county-level macroeconomic variables following Bates, Kahle, and Stulz (2009), Custódio and Metzger (2014), and Bernile, Bhagwat, and Rau (2017). In addition, we control for firm, year, CEO's birth year, birth county, and firm's headquarters' state fixed effects to mitigate potential omitted variable concerns. We then estimate equation (1) using OLS and cluster standard errors by CEO-firm and by year (two way).

The results are reported in Table 4. Column (1) reports a negative relationship between the CEO's prenatal Superfund exposure and her firm's cash holdings. Column (2) shows that CEOs with more Superfund sites exposure tend to increase their firms' leverage. Similarly, Column (3) suggests that CEOs' exposure to Superfund sites results in lower levels of share repurchase. In terms of economic magnitude, a firm with a CEO born in a county with one polluting Superfund site holds 1.32% ($= -0.0191 \times (\text{Ln}(2) - \text{Ln}(1))$) less cash, has 3.13% ($= 0.0451 \times (\text{Ln}(2) - \text{Ln}(1))$) greater leverage and repurchases 57.6% (= exp ($-0.7948 \times (\text{Ln}(2) - \text{Ln}(1))$)) fewer shares than firms managed by non-Superfund CEOs. The effects of prenatal exposure to only one Superfund site are almost the same as the impact of medium fatality experience documented in Bernile, Bhagwat, and Rau (2017) who report that CEOs with medium fatality experience in their sample have 1% lower cash holdings and a 3% higher leverage ratio on average. If there are multiple Superfund sites polluting the CEO's birthplace, these results indicate that our effects will be further amplified.

Is the debt accrued by the Superfund CEOs beneficial for the firm? To answer this question, we compute the kink, which captures the effect of debt on the firm's tax function, as defined by Graham (2000). The kink measures 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) and Malmendier, Tate, and Yan (2011)). Therefore, the kink captures the conservatism of a firm's debt policy from the tax benefits of increasing debts.

However, perhaps not surprisingly, Table 5, using either a censored Tobit model (column 1) or a fixed effects OLS regression (column 2), shows that the more severe CEOs' prenatal Superfund exposure, the smaller their firms' kink, suggesting that Superfund CEO firms are more likely to issue debt beyond the amount where the marginal benefit from the tax shield turns negative. To quantify the economic magnitude, using the linear OLS model for ease of interpretation, contrasting a Superfund CEO born with one polluting site in her birth county and a non-Superfund CEO, with a Superfund CEO, the firm's kink decreases by 0.82 ($= -1.1758 \times (\mathrm{Ln}(2) - \mathrm{Ln}(1))$). CEOs' Superfund exposure effect on the kink is greater than the effect of an overconfident CEO captured by the *Longholder* dummy and *Depression Baby* in Malmendier, Tate, and Yan (2011) (0.63 ($= 16\% \times 3.93$) and 0.51 ($= 13\% \times 3.93$) increase in kink), with a full set of controls. Again, the impact is likely to be amplified if the CEO was exposed to multiple polluting Superfund sites as a fetus.

4.2. CEOs' exposure to Superfund sites, credit risk and cost of debt

If the debt financing decisions by Superfund CEOs are not beneficial for firm value, they should negatively affect the credit risk and the cost of debt of the firm. Table 6 reports how firm credit ratings and likelihood of bankruptcy vary with CEO Superfund exposure.

To conduct the ratings analysis, we obtain credit ratings from Standard & Poor's (S&P), Moody's, Fitch, and Duff and Phelps. These ratings 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 Compustat S&P Rating database was discontinued after February 2017, we then fill the missing data and data after February 2017 using bond credit ratings from Mergent Fixed Income Securities Database (FISD).

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 extreme credit risk and examine how the likelihood of obtaining a "Junk" rating (i.e., if the Standard & Poor's domestic long-term issuer credit ratings are lower than BBB−) varies with Superfund exposure. We find no effect of firms managed by Superfund CEOs on obtaining a below-investment grade rating. In the last two columns of Table 6, we examine the effect on the firm's bankruptcy score (Zmijewski (1984)) (where higher scores indicate higher levels of financial distress) (column 3) and the estimated probability of default based on KMV-Merton's (1974) and Bharath and Shumway's (2008) model (column 4). In both columns, the CEO prenatal Superfund exposure has a significant positive effect on the likelihood of bankruptcy and default.

Next, in Table 7, we investigate whether the increased credit risk for the firm shows up in its cost of debt capital. All models reported in the table explicitly control for firm leverage. Hence, the estimated effect of Superfund exposure on the cost of debt capital is incremental relative to the effect of firm leverage. This is important given that our earlier results show that there is a strong relation between financial leverage and pollution exposure.

We begin by measuring the cost of debt as reported interest expenses scaled by the amount of long-term debt. Column 1 of Table 7 shows that firms with Superfund CEOs, on average, do not report significantly higher annual interest expenses per dollar of outstanding long-term debt than firms managed by non-Superfund CEOs. However, interest expenses for long-term debt may be driven by debt issued a long time prior, perhaps even prior to the current CEO taking her position. We therefore examine the relationship between CEO pollution exposure and the cost of debt at the issue-level at the time of the issue. The main advantage of this approach is the direct link between the cost of debt and the CEO leading the firm at the time of the issue. Table 7 Columns 2-3 report the results of this analysis for bank loans and bond issues, respectively. We calculate the all-in-spread over LIBOR inclusive of all fees, in basis points, for bank loans at the time of loan initiation using bank loan data from DealScan. We compute the bond issue spread as the spread over the U.S. Treasury yields of equivalent maturity, in basis points, for the firm's newly issued bonds' yield-to-maturity, using bond issue data from Mergent Fixed Income Securities Database (FISD). Following Ivashina (2009), we control for a wide array of factors that may affect the cost of new debt. Conditional on receiving a bank loan, firms with Superfund CEOs pay 16.8 basis points higher spread than firms with non-Superfund CEOs (column 2). Column 3 shows that firms managed by Superfund CEOs also pay significantly higher bond issue spreads. The results in Table 7 are comparable to the medium fatality experience reported by Bernile, Bhagwat, and Rau (2017). CEOs' prenatal exposure to one Superfund site has an impact on bank loan all-in-spread similar to CEOs' median fatality experience, and the effect is much more significant on bond issue spread.

The combined evidence in Tables 4-7 is largely consistent with the notion that the effect of prenatal exposure to pollution on CEOs is uniformly negative – Superfund CEOs aggressively take on more debt, beyond the points when the marginal benefit of tax shields turns negative. The aggressiveness of this policy ultimately affects the firm's credit risk and cost of debt capital. In addition to statistical significance, these results are also economically significant – similar in magnitudes as other factors documented in the previous studies (e.g., Malmendier, Tate, and Yan (2011), Bernile, Bhagwat, and Rau (2017)).

4.3. CEOs' exposure to Superfund sites, and equity risk

The results in Table 4 suggest that the leverage policy of the firm should also affect the risk borne by shareholders in the firm. Table 8 examines this conjecture reporting estimates from fixed effects OLS regressions of firm stock return risk on our Superfund CEO pollution exposure measure. Specifically, in columns 1-5, we regress the annualized standard deviation of a firm's stock return ($\sigma_{Stock\ return}$), the annualized square root of the residual variance ($\sigma_{Specific\ return}$), the negative skewness (the third standardized moment) of firm-specific weekly returns (*Negative skewness*), the 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 ($\sigma_{Down\text{-}to\text{-}up}$), and an indicator variable for a firm-year experiencing at least one crash week during the fiscal-year (*Crash risk* (0,1)), respectively, on our CEOs' Superfund exposure measure and control variables (of firms, CEOs, and counties characteristics) with fixed effects in columns (1) – (5). Our control variables are similar to those in Hutton, Marcus, and Tehranian (2009), Kim, Li, and Zhang (2011), and Xu, Xuan, and Zheng (2021).

Across all regressions in Table 8, the Superfund exposure variable is always consistently positively related to the five measures of equity risk. Specifically, firms managed by Superfund CEOs have significantly higher stock volatility (column 1), higher idiosyncratic volatility (column 2), higher negative skewness (column 3), a greater standard deviation in down weeks than in up weeks (column 4), and a higher crash risk (column 5) than firms managed by non-Superfund CEOs. Our results are again economically comparable to the previous studies. Compared with non-Superfund CEOs, firms with Superfund CEOs with pre-natal exposure to at least one Superfund site show 3.22% higher stock return volatilities and 2.78% higher idiosyncratic volatilities. These sizes are similar to those of medium fatality experiences reported in Bernile, Bhagwat, and Rau (2017).

4.4. CEOs' exposure to Superfund sites, and acquisition activity

Existing studies suggest that CEOs exert significant decision-making power in the context of mergers and acquisitions and may engage in acquisitions at the expense of the firm's shareholders whether for agency reasons (Jensen (1986)) or hubris (Roll (1986)). Corporate acquisitions are inherently riskier compared to organic internal growth due to the typically large commitment of time and resources required. Therefore, in our next set of tests, we examine whether CEO Superfund exposure explains corporate acquisition activity.

To conduct these tests, we obtain merger and acquisition (M&A) transactions 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 10,486 M&A transactions for 5,154 acquirer-year observations. Then, we estimate a series of OLS, probit, and linear probability models to assess whether CEO attitude toward risk, as measured by pollution exposure, has a material impact on firm acquisitiveness. We find that it does.

Specifically, we regress the CAR (-1,1) Market model and CAR (-1,1) FF4 model on the CEOs' Superfund exposure measure of the acquirers and control variables (of acquirers, their CEOs, M&As, and counties characteristics). Here, we include the acquirer industry, year, acquirer's CEO birth year, birth county, and the acquirer's headquarters state fixed effects in Columns (1) and (2). In Columns (3) and (4), we use probit and linear probability models to regress the propensity of an unrelated acquisition (i.e., Unrelated acquisition (0,1)) on the same set of control variables and fixed effects as the previous columns. We use the linear probability model to estimate the economic magnitude of our results. Table 9 reports the results.

The first two columns shows that prenatal Superfund pollution exposure is negatively related to the announcement period excess returns earned by the acquirer, whether excess returns are measured using the market model or the FF4 model. In Columns (3) and (4), the probability of making an unrelated acquisition is significantly higher for a firm managed by a Superfund CEO than a non-Superfund CEO. These results are also economically significant and similar to prior studies (e.g., Bernile, Bhagwat, and Rau (2017)). Acquiring firms with Superfund CEOs (with exposure to one Superfund site) earn 0.56% ($= -0.0081 \times (\mathrm{Ln}(2) - \mathrm{Ln}(1))$, or 0.44% $= -0.0063 \times (\mathrm{Ln}(2) - \mathrm{Ln}(1))$) lower abnormal returns using the market and FF4 models, respectively in the three trading days around the announcement. Also, from column (4), these firms are 5.21% $(= 0.0751 \times (\mathrm{Ln}(2) - \mathrm{Ln}(1)))$ more likely to announce unrelated acquisitions comparing with those managed by non-Superfund CEOs. Together with Table 8, our results show that shareholders of firms managed by Superfund CEOs bear increased risks following their CEOs' prenatal exposure to environmental toxicants.

4.5. The effect on firm performance

In the previous tests, we show that Superfund CEOs make poor financial decisions regarding capital structure which shows up in the cost of debt, credit risk, and equity risk. Do these policies also hurt the firm's performance?

In this section, we examine three typical firm performance measures: ROA, Tobin's Q, and stock return. We control for lagged firm performance, along with firm, CEO, and the CEO birthplace characteristics. In addition, current findings in CEO literature suggest that the presence of local CEO labor market shocks significantly affect CEOs' incentives and thus their firms' performance. Examples include the staggered recognition of the Inevitable Disclosure Doctrine by US states that reduces the mobility of top executives relative to other employees (e.g., Klasa, Ortiz-Molina, Serfling, and Srinivasan (2018)), the changes in legal protection against hostile takeovers in Delaware in year 1995 (Low (2009); Bereskin and Cicero (2013)), and the limited corporate officers' and directors' litigation risk in Nevada in year 2001 (Donelson and Yust (2014)). To mitigate the influence of these exogenous shocks and to control for unobserved factors that are related to local CEO labor market conditions, we include *Non-compete index* defined as state-level enforcement of non-compete laws (Garmaise (2011)), and *Ln*(*local peers*) defined as the natural logarithm of the number of peer firms in the same Fama-French (1997) 48-industry within a 150-mile-radius circle around the company HQ (Jochem, Ladika, and Sautner (2018)).

Table 10 reports the results with industry, year, CEO's birth year and county, headquarters' effects. These three columns show that firms managed by Superfund CEOs perform significantly worse than those managed by non-Superfund CEOs. Firms managed by Superfund CEOs' with prenatal exposure to one polluting Superfund site earn an industry-adjusted ROA that is lower than the ROA for their peer non-Superfund CEO firms by 0.42% $(= -0.0060 \times (\mathrm{Ln}(2) - \mathrm{Ln}(1)))$, an industry-adjusted Tobin's Q lower by 3.29% $(= -0.0475 \times (\mathrm{Ln}(2) - \mathrm{Ln}(1)))$, and an industry-adjusted stock return by 3.46% $(= -0.0499 \times (\mathrm{Ln}(2) - \mathrm{Ln}(1)))$.

We repeat all models with unadjusted firm performance measures (results not tabulated for brevity). Without adjusting for industry performance, ROA drops by 0.85% ($= -0.0123 \times (\mathrm{Ln}(2) - \mathrm{Ln}(1))$), Tobin's Q by 3.37% ($= -0.0486 \times (\mathrm{Ln}(2) - \mathrm{Ln}(1))$), and stock returns by 2.90% ($= -0.0418 \times (\mathrm{Ln}(2) - \mathrm{Ln}(1))$) for firms managed by Superfund CEOs with prenatal exposure to one polluting site. Hence our results show up both at the raw and industry-adjusted levels - firms run by Superfund CEOs have lower operating performance and worse stock returns.

4.6. The effect on CEO turnover

Our final baseline test sheds light on the consequences of CEOs' prenatal exposure to Superfund sites and their career outcomes. Given the negative impacts on firms' policies and performance that we document, we expect that Superfund CEOs should have higher forced turnover rates. We examine the effect on forced turnover rather than generic turnover since the latter may be caused by other reasons apart from risk misjudgments. For example, the CEO could be in poor health (perhaps due to the pre-natal pollution exposure) and step down voluntarily. This would not be related to her risk-judging ability. To test this conjecture, we regress our *Forced CEO turnover* (0,1) variable on the local CEO labor market measures, the firm's and its industry's performance measures, along with the firm's and the CEO's characteristics. Table 11 reports the results with the fixed effects we used in Table 10. Consistent with our conjecture, Superfund CEOs are more likely to lose their positions from their worse performance, and thus results in higher forced turnover rates (Column 2). They do not have higher generic turnover rates (column 1). If a CEO is dismissed without cause, or resigns for good reason, the CEO usually collects a severance payment. Column 3 shows that Superfund CEOs are not more likely to receive severance payments than non-Superfund CEOs.

In sum, all the results in this section show that Superfund CEOs take more risks without earning higher returns and thus adversely affect their own careers. We also contrast our results with other studies on CEOs' early-life experience (e.g., Malmendier, Tate, and Yan (2011), Bernile, Bhagwat, and Rau (2017)). Our results are comparable to theirs in both economic and statistical magnitudes, even in the most conservative calculations (i.e., only one Superfund polluting CEOs' birthplaces). In other words, the negative impact of greater exposure to Superfund sites would further aggravate firms' capital structures, risk-taking, performances, and CEOs' forced turnover.

5. Additional empirical analyses

In this section, we address other plausible channels that could potentially explain our results. We first consider CEOs' postnatal exposure to Superfund sites. We then focus solely on the exposure to the *developmental* toxicity released in Superfund sites, which we conjecture is the primary channel harming human cognitive performance. Next, we take the firms' current pollution exposure into account. Finally, we perform two matching samples, a difference-in-difference analysis on CEOs' sudden deaths, and two falsification tests to consolidate our results.

5.1. Postnatal exposures to Superfund sites

An alternative explanation for our results is that our CEOs' prenatal exposure to Superfund measure, in fact, captures the effects of their postnatal Superfund exposure if the CEOs typically lived in the same states from birth to adulthood. Since the exogeneity we rely on is the timing when people learn about the hazard of Superfund sites, the timing of exposure is critical to our analyses. Most of this information became available well after the CEOs in our sample grew up. Finally, in addition to prenatal exposure in our baseline tests, postnatal exposure per se could also significantly influence our results. Indeed, most prior literature measures early-life experience starting 5 years and ending 15 years after the CEO's birth year (Bernile, Bhagwat, and Rau, 2017)). The literature focuses on this period because medical research shows that the formation of lasting childhood memories tends to start around the 5th birthday, while the 15th birthday is a natural stopping time for "early childhood" memories (Nelson (1993)). Hence, our results may be due to the formation of negative childhood memories, not from the prenatal exposure of the CEO.

We, therefore, reexamine our results on CEOs with additional controls for CEOs' postnatal exposures to Superfund sites, specifically, the number of Superfund sites they were exposed to over the period when they grew up. As described in Section 3.2, we collect CEOs' high school and higher education records. Using these records, we assume that CEOs were born and grew up in the same county if (1) they were born in one county and attended high schools there, and (2) they were born in one county and attended universities in the same state of that county. We then define "*born and grew up* (0,1)" to represent it. We repeat all our regression models in Tables 4 to 11 with "*born and grew up* (0,1)" and its interaction term with "*Ln*(1+*CEO #Superfund exposure*)". Since our sample size drops significantly, we do not use this specification in our main tests. The results (not tabulated for brevity) show that the interaction term is largely insignificant in most of the regressions suggesting that the continued exposure to developmental chemicals does not have a large impact on the risk-judgment of the CEO compared to the initial pre-natal exposure.

5.2. CEO exposures to developmental toxic chemicals only

Persico, Figlio, and Roth (2020) document that early-life exposure to Superfund pollutants contributes to their long-term cognitive and developmental outcomes that were underemphasized in the previous studies. However, pollutants besides developmental toxicants might have other health effects on CEOs like cancers, which may require long-term medical treatment and cause other side effects. Therefore, it could be a potential omitted variable that contaminates our results.

To address this issue, as described in Section 3.1, we collect contamination lists for each Superfund site on the EPA websites and then match their CASRN (CAS Registry Number) code to the EPA's IRIS database. Unfortunately, data from the Superfund site-related reports and documents gives us the period when the most hazardous contaminants were being released but does not break it down to the period when each toxic chemical was being released. Hence, we run a regression at the CASRN chemical level, where our primary independent variable is an indicator variable. Specifically, for each pollutant found in the Superfund sites near a CEO's birth county, we define our "*Developmental toxic chemical* (0,1)" variable as an indicator variable that equals one if it is a *developmental* poisonous substance and zero otherwise. Then, we construct a pollutant-firm-year sample and repeat our analyses by replacing "*Ln*(1+*CEO #Superfund exposure*)" with "*Developmental toxic chemical* (0,1)". Table OA1 confirms that developmental toxic chemicals are the primary channel that drives our results. Across nearly all our regressions, with the exception of leverage and share repurchases, the coefficient on exposure to a developmental toxic chemical is significant and has the same sign as our baseline results.

5.3. Firms' current exposure to pollutants

Exposure to hazardous pollutants might also affect people's attitudes toward environmental issues in differing ways. For example, due to personal attachment to their hometowns, Superfund CEOs may choose to work in their hometowns ignoring potential pollution effects. Alternatively, the desensitization to pollution may make them less hesitant to work in other highly polluted places. In either case, the continued exposure of the CEO to pollutants during the time she is heading the firm might have the effect on risk-taking and performance that we document here. In yet another explanation, 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.

We first consider whether a firm's headquarters and facilities are currently exposed to Superfund site pollution. Following Greenstone and Gallagher (2008) and EPA's reports, we define our "*HQ current pollutant exposure* (0,1)" and "*facility current pollutant exposure* (0,1)" as indicator variables to account for Superfund sites within three miles of firms' current headquarters and facilities, respectively.[19] Furthermore, we control for the possibility that the firm CEOs work for is currently a polluter. Using the list of the potentially responsible parties (PRPs) and the self-reported Form R in Toxic Release Inventory (TRI) database, we define our "*Firm current polluter?* (0,1)" indicator variable identifying firms as a polluter if they are currently listed on them for their releases. These control variables thus allow us to separate Superfund CEOs' past and current exposures to pollutants and account for their potential environmental liabilities. Our results in Table OA2 show that our findings are mostly unaltered after controlling for the firms' current exposure to pollution or to its polluting behavior.

5.4. Matching sample analysis

Although we have already controlled for various fixed effects, including the CEO's birth county and the state of the firm's headquarters, there may still be potential omitted variables in our analysis. To validate our results, we construct two matching samples. Our first matching sample consists of CEO-firm-year pairs with Superfund CEOs matched with non-Superfund CEOs. Matched CEO-firm pairs satisfy the following criteria: (1) the matched CEOs were born in the same year (if feasible) or in the same decade, and (2) they are in the same FF48 industry. For those CEOs that satisfy 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. Using this matching sample, we rerun our analyses. Table OA3 shows that most of our findings remain unchanged. Hence our results do not appear to be driven by omitted variables at the birth county-year level.

Our second matching sample is composed of CEO-firm-year pairs with Superfund CEOs matched with non-Superfund CEOs. In this matching sample, every matched CEO-firm pair

[19] We also consider the distance of 2 miles. The results do not change and thus are not tabulated.

satisfies: (1) their CEOs were born in the same year (if feasible) or in the same decade, 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 whose firm headquarters is 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. Similarly, using this matching sample, we repeat the tests in Table OA4. 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-difference analysis on CEOs' sudden deaths

We next perform a difference-in-difference analysis on CEOs' sudden deaths. If there is indeed a causal relation between Superfund CEOs' prenatal exposure and the policies (and poor performance) followed by the firm, 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, where the cause of death of the CEO is indicated as a heart attack, stroke, plane crash, car accident, cancer within a year of diagnosis, and other similar unexpected death events. These exogenous events allow us to mitigate concerns that the policy reversals took place because the CEO was replaced following poor performance.

To test our conjecture, we first contrast the firm-year observations for the three years before and after the CEO decease. Then, we define our "*Post CEO demise period* (0,1)" variable as one for the three years after the CEOs' deaths and zero otherwise. We also record the deceased CEO's Superfund exposure as "*Ln*(1+*deceased CEO #Superfund exposure*)". Finally, we perform a difference-in-difference analysis using the "*Post CEO demise period* (0,1)" on the treatment of "*Ln*(1+*deceased CEO #Superfund exposure*)" and report the results in Table OA5. The test for CEOs' forced turnover is not feasible because the model did not converge. Otherwise, in almost every case, our results reverse in sign (though they continue to be significant) from the previous results, suggesting that subsequent CEOs reverse the firm policies of Superfund CEOs who died suddenly.

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 (i.e., the Superfund exposures and county-level control variables) with pseudo birth counties. In Table OA6 column (1), the pseudo county is randomly chosen from all U.S. counties (not limited only 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 entire process is then repeated 1,000 times forming an empirical bootstrap resampling distribution. In Table OA6 column (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 then 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 control for the same set of 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.

Table OA6 shows that our pseudo-Superfund-exposure variable is largely insignificant in most of our specifications. In model 1, out of 23 specifications, we obtain the same significant results in a random assignment more than 5% of the time only in 9 cases. In model 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

Empirical studies that examine the effect of pollution on economic outcomes typically focus on the individual level. In this paper, we examine the effect of pollution on the risk judgments of CEOs, successful and influential individuals who have large impacts on their stakeholders and society. We address the potential concern of endogeneity – that prior variation in the CEO's life and career that causes an impact on the policies of the firm is in turn driven by innate risk preferences of the CEO or the CEO's family – by examining the impact of prenatal exposure to pollution that was plausibly unknown at the time the CEO was born.

We draw on the extensive medical literature investigating the harm caused by environmental pollutants released by Superfund sites in the U.S. during the twentieth century. It is plausible that the Superfund CEOs' parents would not have been aware of this pollution in their local community at the time of the CEO's birth. Our research design, therefore, allows us to eliminate the possibility that our prenatal exposure to toxicants measures capture their parents' risk preferences.

We find that the CEOs with greater prenatal exposure to Superfund sites take more risks, but the risks do not pay off, adversely affecting the firm's value, and the CEOs experience higher forced turnover. These results demonstrate the role that prenatal exposure to pollution, nurture, plays in affecting CEO managerial styles. These results cannot be explained by alternative channels and are robust over our tests. In addition, by documenting the impact of pollution on individuals who plausibly make consequential real decisions, we also point to an indirect effect of pollution beyond the immediate health effects.

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Appendix A

Variable Name	Definition
Pollution exposure variables	
Superfund CEO	An indicator variable that takes the value of one if CEO's birth county during her birth year generated the U.S. worst hazardous contaminants, and zero otherwise. These sites are later designated as Superfund sites.
CEO #Superfund exposure	The number of 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 the CEO was exposed to during her birth year, released by later designated Superfund sites, is a developmental toxic substance and zero otherwise. Developmental toxicity includes detrimental effects such as growth retardation and functional impairment by exposure during the embryonic stages of 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.
Firm current polluter? (0,1)	An indicator variable that equals one when either the firm-year observations are listed on the U.S. EPA TRI Form R and with positive levels of toxic releases for the firm-year, 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 active Superfund sites or facilities of other firms releasing toxic pollutants within three miles of the firm's headquarters (HQ) for the firm-year and zero otherwise.
Facility current pollution exposure (0,1)	An indicator variable that equals one when there are active Superfund sites within three miles of the firm's facilities for the year and zero otherwise.
Post CEO demise period (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 attacks, strokes, plane crashes, car accidents, cancer within a year of diagnosis, and other similar unexpected death events.
Deceased CEO #Superfund exposure	The CEO #Superfund exposure for the deceased CEO. In the three years before the CEO's sudden death, this measure is the same as the firm-year's CEO #Superfund exposure. In the three years after the sudden death of the CEO, this measure is the CEO #Superfund exposure of the deceased CEO.
Pseudo-random CEO #Superfund exposure	The corresponding CEO #Superfund exposure using an empirical distribution. To construct the empirical distribution, we replace the sample CEOs' birth county (i.e., the Superfund exposures 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 on which we run all the main regressions. This entire process is then repeated 1,000 times forming an empirical bootstrap resampling distribution.
Pseudo-nearest CEO #Superfund exposure	The corresponding CEO #Superfund exposure using an empirical distribution for the nearest random county. To construct the empirical distribution, we replace the sample CEOs' birth county (i.e., the Superfund exposures 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 on which we run all the main regressions. This entire process is then repeated 100 times forming an empirical bootstrap resampling distribution.
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 share repurchase.

Corporate capital structure sensitivity and corporate debt aggressiveness variables	
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) and Malmendier, Tate, and Yan (2011)).
Corporate credit 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. For missing values prior to February 2017 and for data after February 2017, when Compustat S&P Ratings database was discontinued, we obtain bond credit ratings from 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 are lower than BBB− in a given year and zero otherwise.
Bankruptcy score	Zmijewski (1984) bankruptcy score, which is -4.3−(4.5×ROA)+(5.7× Leverage)−(0.004×Current Ratio); higher scores indicate higher levels of financial distress.
Default probability	The estimated probability of default based on KMV-Merton's (1974) and Bharath and Shumway's (2008) model.
Corporate cost of debt 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 above) 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 (defined above) 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 (defined above) 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).

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 Fama–French–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 Fama–French–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.
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.
ΔROA	Changes in ROA.
ΔTobin's Q	Changes in the ratio of market-to-book value of assets.
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. 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 CEO 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	
Asset volatility	The standard deviation of stock return times the market value of equity divided by the market value of assets (Custódio and Metzger (2014)).
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.
ΔPP&E/Assets	Changes in net property, plant and equipment, normalized by the lagged 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.
Net financing deficit (NFD)	Cash dividends plus net investment plus changes in working capital minus cash flow after interest and taxes, normalized by the lagged total assets.
NOL carryforward (0,1)	An indicator variable that equals one if the firms have 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 logarithm of sales.
ΔLn(Sales)	Changes in the logarithm of sales.
Quick ratio	The ratio of cash, short-term investments, and receivables to the current liabilities.
Current ratio	The ratio of current assets to the 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	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 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). Some 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 are not shown.

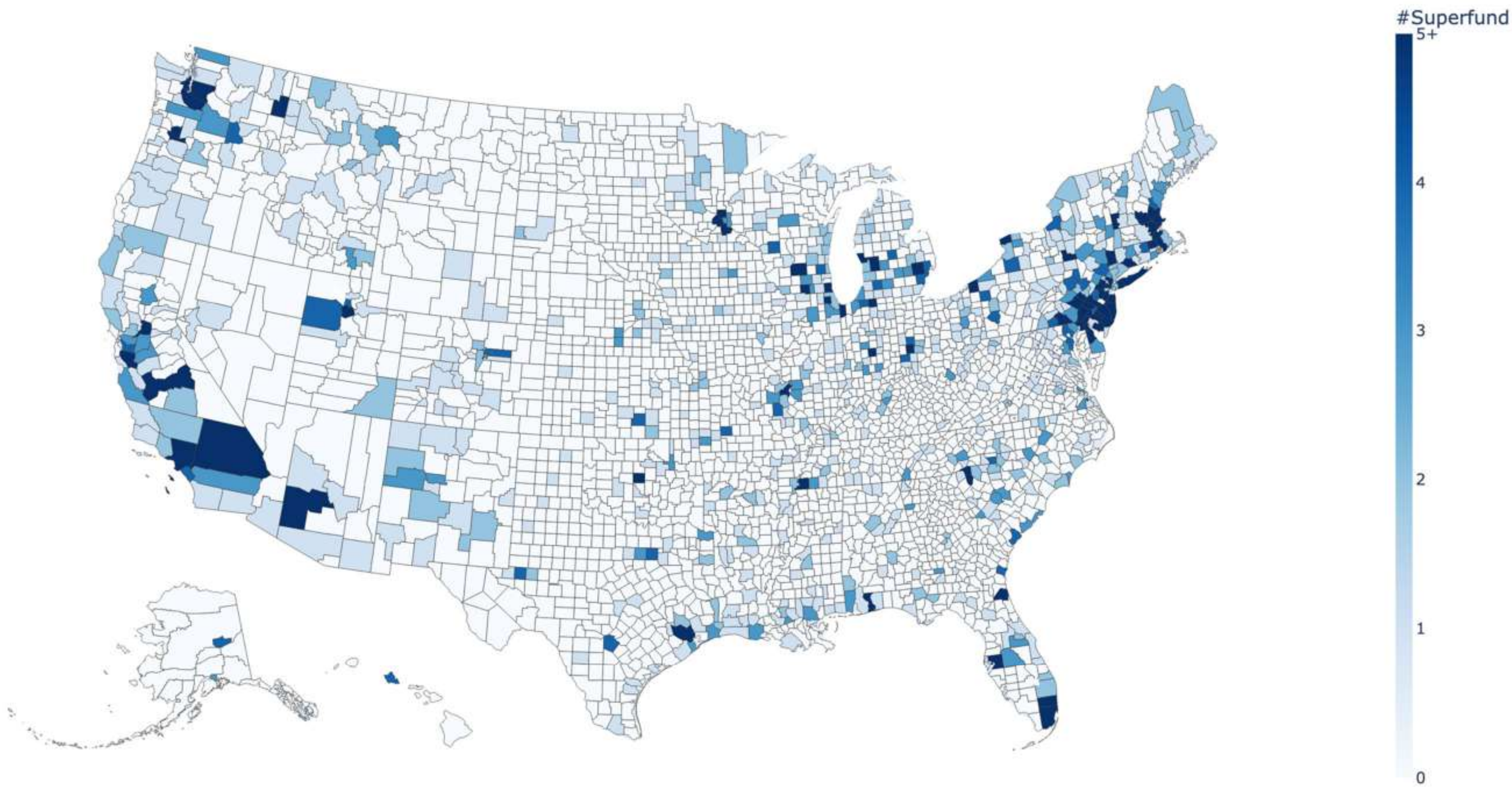

Table 1. Summary statistics for the Superfund program 1981-2018

This Table presents summary statistics on Superfund sites placed on the NPL before December 31, 2018. The duration (in years) of generating 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 sites proposed to NPL	1,803
Formally added to the NPL List during	
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 generating 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 completed 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 in our sample with the percentage of Superfund infants, that were newborns in the counties when the later-designated Superfund sites were generating the U.S. worst hazardous contaminants. Panel B and C compare the infant mortality rates and low birthweight rates of (1) all counties, (2) counties with Superfund sites during the pollutant-generating periods, (3) counties with Superfund sites during periods before or after the pollutant-generating periods, and (4) 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-generating 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%	23.2253% (=638/(638+2,109))

Panel B. Comparison of infant mortality rates

	Infant mortality rate in all counties	Infant mortality rate in counties during pollutant-generating periods	Infant mortality rate in counties during other periods	Infant mortality rate in the remaining counties
Annual mean	1.8571%	2.0477%	1.552%***	1.825%****
Annual median	1.2658%	2.0270%	1.188%***	0.595%****

Panel C. Comparison of low birthweight rates

	Low birthweight rate in all counties	Low birthweight rate in counties during pollutant-generating 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 statistics for the full set of Compustat firms. Columns (7) to (9) report similar statistics for the full set of ExecuComp firms. Panel B reports comparisons between 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 birthdates and birthplaces in U.S. are in the Other 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)	17,895	8.2009	1.9173	240,935	5.1418	2.9240	52,659	7.4037	1.8921	137.77***	48.52***
Ln(Sales)	17,867	7.7613	1.7213	222,449	4.7316	2.8293	52,488	6.9762	1.7641	141.05***	51.70***
Performance											
ROA	17,549	0.1261	0.3205	251,797	-0.1977	1.1896	51,155	0.1126	0.5136	93.72***	2.17**
Tobin's Q	17,664	1.9377	2.4583	226,134	1.9578	2.2489	51,778	1.9853	2.2566	-3.35***	-3.23***
Stock return	15,516	0.1614	0.5875	176,307	0.1367	0.8608	47,644	0.1824	0.6581	7.84***	-0.95
Growth opportunities											
PP&E/Assets	17,624	0.2914	0.2473	236,969	0.2662	0.2761	51,721	0.2587	0.2413	11.80***	15.45***
Capex	16,985	0.0555	0.0591	227,049	0.0581	0.0821	50,797	0.0524	0.0605	-4.09***	5.82***
R&D	17,895	0.0217	0.0895	240,935	0.0562	0.1591	52,659	0.0313	0.1191	-27.13***	-8.02***
Debt risk											
Leverage	17,861	0.2097	0.2036	259,370	0.1837	0.2478	52,836	0.2042	0.2152	15.31***	4.68***
Cash/Assets	17,923	0.1249	0.1539	259,765	0.1907	0.2444	52,994	0.1436	0.1747	-37.92***	-15.73***
Credit rating	12,467	16.2368	3.5247	238,869	14.2963	4.0439	26,915	15.3060	3.4898	49.94***	24.28***
Default probability	13,891	0.0158	0.0558	116,183	0.1621	0.3575	41,477	0.0234	0.0792	-48.17***	-10.45***
Interest expense/Debt	16,196	0.0735	0.1141	204,864	0.1802	0.4639	45,502	0.0986	0.1646	-24.79***	-6.45***
Equity risk											
Dividend (0,1)	17,889	0.6909	0.4621	241,131	0.4199	0.4936	52,415	0.5845	0.4928	75.31***	26.16***
Ln(1+Share repurchase)	16,291	2.6244	2.7437	238,966	0.6583	1.5598	49,239	2.0398	2.4197	90.47***	24.25***
$\sigma_{\text{Stock return}}$	15,533	0.3809	0.2255	178,349	0.4953	0.3605	47,729	0.4120	0.2339	-38.39***	-13.87***
$\sigma_{\text{Specific return}}$	15,373	0.3145	0.1992	162,064	0.4328	0.3191	47,669	0.3297	0.2210	-52.62***	-17.37***
Other risk											
Acquisition (0,1)	17,971	0.3398	0.4736	310,598	0.1193	0.3241	53,398	0.2828	0.4504	61.58***	14.13***

Panel B: Comparison between Superfund CEOs and other CEOs subsamples

	Superfund CEOs (Observations=4,248)				Other CEOs (Observations=13,723)				t-test Superfund vs. Other CEOs	(Kruskal-Wallis H test) Superfund vs. Other CEOs
	N	Mean	Median	Std. Dev.	N	Mean	Median	Std. Dev.		
# of Unique CEOs	638				2,109					
Size										
Ln(Assets)	4,228	8.5347	8.5354	1.8965	13,667	8.0976	8.0269	1.9119	13.07***	(179.88***)
Ln(Sales)	4,227	8.0588	8.1147	1.7450	13,640	7.6691	7.6703	1.7034	12.76***	(166.02***)
Performance										
ROA	4,143	0.1192	0.1156	0.1036	13,406	0.1282	0.1234	0.3622	-5.00***	(31.07***)
Tobin's Q	4,171	1.8901	1.3944	1.9771	13,493	1.9524	1.3991	2.8845	-2.40**	(0.02)
Stock return	3,693	0.1570	0.1023	0.4411	11,823	0.1628	0.1166	0.4432	-1.80*	(12.06***)
Growth opportunities										
PP&E/Assets	4,164	0.2679	0.1908	0.2449	13,460	0.2987	0.2398	0.2475	-7.07***	(60.94***)
Capex	4,054	0.0520	0.0358	0.0567	12,931	0.0566	0.0427	0.0598	-4.53***	(55.90***)
R&D	4,228	0.0247	0.0000	0.0557	13,667	0.0208	0.0000	0.0977	4.62***	(13.97***)
Debt risk										
Leverage	4,225	0.2179	0.1813	0.2030	13,636	0.2071	0.1788	0.2037	3.11***	(2.12)
Cash/Assets	4,239	0.1185	0.0558	0.1520	13,684	0.1269	0.0682	0.1544	-3.13***	(34.60***)
Credit rating	3,094	16.0882	17.000	3.6157	9,373	16.2859	16.000	3.4922	-2.98***	(31.80***)
Default probability	3,329	0.0189	0.0000	0.0607	10,562	0.0148	0.0000	0.0541	3.47***	(9.58***)
Interest expense/Debt	3,826	0.0824	0.0686	0.1086	12,370	0.0708	0.0618	0.1157	6.20***	(149.15***)
Equity risk										
Dividend (0,1)	4,227	0.6638	1.0000	0.4725	13,662	0.6993	1.0000	0.4586	-4.30***	(19.03***)
Ln(1+Share repurchase)	3,919	3.0309	2.7700	2.8756	12,372	2.4956	1.6471	2.6880	10.31***	(94.54***)
$\sigma_{\text{Stock return}}$	3,697	0.3850	0.3281	0.2391	11,836	0.3796	0.3200	0.2101	1.86*	(7.00***)
$\sigma_{\text{Specific return}}$	3,664	0.3211	0.2679	0.2062	11,709	0.3124	0.2570	0.1950	2.70***	(29.80***)
Other risk										
Acquisition (0,1)	4,248	0.3599	0.0000	0.4800	13,723	0.3335	0.0000	0.4715	3.15***	(10.08***)

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

This table reports coefficients from fixed effects OLS regressions of cash, leverage, and payout policy for fiscal year *t*. Specifically, we regress *Cash/Assets*, *Leverage*, and *Ln*(1+*Share repurchase*) on our CEOs' Superfund exposure measure and control variables (of firms, CEOs, and counties characteristics) with fixed effects in columns (1) – (3). Our control variables are similar to those in Bates, Kahle, and Stulz (2009), Custódio and Metzger (2014), and Bernile, Bhagwat, and Rau (2017). County-level variables are measured in the CEO's birth year and the CEO's birth county. Variables are defined in Appendix A. 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' Superfund exposure on corporate debt aggressiveness

This table reports coefficients from censored Tobit (column 1) and fixed effects OLS (column 2) regressions of corporate debt aggressiveness for fiscal year *t*. Specifically, we regress the *Kink* on our CEOs' Superfund exposure measure and control variables (of firms, CEOs, and counties characteristics) with fixed effects. In the Tobit model, observations are left censored at 0 ad right censored at 8. The control variables are comparable to those in Graham (2000) and Malmendier, Tate, and Yan (2011). County-level variables are measured in the CEO's birth year and the CEO's birth county. Variables are defined in Appendix A. 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**	**Kink**
	(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' Superfund exposure on corporate credit risk and default risk

This table reports coefficients from ordered Probit and fixed effects OLS regressions of corporate credit risk and default risk for fiscal year *t*. Specifically, we regress *Credit rating*, *Junk rating*, *Bankruptcy score*, and *Default probability* on our CEOs' Superfund exposure measure and control variables (of firms, CEOs, and counties characteristics) with fixed effects in columns (1) – (4). Our control variables are similar to those reported in the leverage regression in Table 4. County-level variables are measured in the CEO's birth year and the CEO's birth county. Variables are defined in Appendix A. 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' Superfund exposure on cost of debt

This table reports coefficients from fixed effects OLS regressions of debt costs for fiscal year *t*. Specifically, we regress *Interest expense/Debt* on our CEOs' Superfund exposure measure and control variables (of firms, CEOs, and counties characteristics) with fixed effects in column (1). In columns (2) and (3), we regress *Bank loan all-in-spread* and *Bond issue spread* on our CEOs' Superfund exposure measure and control variables (of firms, loans/bonds, and counties characteristics) with fixed effects. Each observation in these two columns corresponds to each loan/bond issue. County-level variables are measured in the CEO's birth year and the CEO's birth county. Variables are defined in Appendix A. 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' Superfund exposure on equity risk

This table reports coefficients from fixed effects OLS regressions of firm stock return risk for fiscal year *t*. Specifically, we regress $\sigma_{Stock\ return}$, $\sigma_{Specific\ return}$, *Negative skewness*, $\sigma_{Down\text{-}to\text{-}up}$, and *Crash risk* on our CEOs' Superfund exposure measure and control variables (of firms, CEOs, and counties characteristics) with fixed effects in columns (1) – (5). Our control variables are comparable to those in Hutton, Marcus, and Tehranian (2009), Kim, Li, and Zhang (2011), and Xu, Xuan, and Zheng (2021). County-level variables are measured in the CEO's birth year and the CEO's birth county. Variables are defined in Appendix A. 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-squared	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 CEOs' Superfund exposure on M&A announcement abnormal returns and the propensity of unrelated acquisitions

This table reports coefficients from fixed effects OLS regressions of acquirers' announcement returns and linear probability models of the propensity of unrelated acquisitions for fiscal year *t+1*. Specifically, we regress *CAR* (-1,1) *Market model* and *CAR* (-1,1) *FF4 model* on the CEOs' Superfund exposure measure of the acquirers and control variables (of acquirers, their CEOs, M&As, and counties characteristics) with two sets of fixed effects in columns (1) and (2). In columns (3) and (4), we use probit and linear probability models respectively to regress the propensity of an unrelated acquisition (i.e., *Unrelated acquisition* (0,1)) on the same set of control variables and fixed effects as columns (1) and (2). County-level variables are measured in the CEO's birth year and the CEO's birth county of the acquirer. Variables are defined in Appendix A. 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-squared	0.1670	0.1645	0.3345	0.4258
Observations	6,798	6,798	6,065	6,798

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

This table reports coefficients from fixed effects OLS regressions of industry-adjusted (labeled *Ind. adj.*) performance for fiscal year *t*. Specifically, we regress *Ind. adj. ROA*, *Ind. adj. Tobin's Q*, and *Ind. adj. Stock return* on our CEOs' Superfund exposure measure and control variables (of the lagged dependent variable, firms, CEOs, and counties characteristics) with fixed effects in columns (1) – (3). County-level variables are measured in the CEO's birth year and the CEO's birth county. Variables are defined in Appendix A. 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-squared	0.6546	0.6898	0.1362
Observations	10,542	10,452	10,519

Table 11. Effects of CEOs' Superfund exposure on turnover

This table presents results from Probit regression predicting whether a CEO turnover occurs in a given year. Specifically, we regress Generic turnover, forced turnover and a severance payment dummy on our CEOs' Superfund exposure measure and control variables (of firms, industries, 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 Appendix A. 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	**Generic CEO turnover (0,1)** (1)	**Forced CEO turnover (0,1)** (2)	**Severance-payment if CEO turnover (0,1)** (3)
Ln(1+CEO #Superfund exposure$_t$)	0.0200	0.2757***	-0.0568
	(0.25)	(3.24)	(-0.51)
Ln(Local peers)$_{t-1}$	0.0082	0.0742**	0.0119
	(0.23)	(1.97)	(0.23)
Non-compete index	-0.2148**	-0.0473	0.0330
	(-2.45)	(-0.46)	(0.24)
Ind. return percentile$_{t-1}$	-0.0007	0.0004	-0.0006
	(-1.09)	(0.51)	(-0.62)
Firm abnormal return percentile$_{t-1}$	-0.0029***	-0.0020**	-0.0021**
	(-3.83)	(-2.36)	(-2.18)
Ind. return risk$_{t-1}$	0.6332	1.3879	2.5771
	(0.39)	(0.74)	(1.17)
Firm abnormal return volatility$_{t-1}$	1.3795**	2.3612***	1.0343
	(2.53)	(4.35)	(1.44)
Ln(Assets)$_{t-1}$	0.0382*	0.0870***	0.0230
	(1.80)	(4.19)	(0.78)
Tobin's Q$_{t-1}$	-0.0028	0.0004	-0.0089*
	(-0.77)	(0.11)	(-1.74)
CEO age≥ 60 (0,1)$_{t-1}$	0.3537***	-0.1437**	0.1612*
	(5.83)	(-2.03)	(1.94)
Ln(1+CEO tenure)$_{t-1}$	0.2221***	-0.0198	0.3026***
	(5.37)	(-0.45)	(5.10)
Outside CEO(0,1)$_{t-1}$	0.0299	-0.0569	-0.0176
	(0.53)	(-0.99)	(-0.24)
Founder CEO(0,1)$_{t-1}$	-0.2036**	0.0358	-0.3695***
	(-2.43)	(0.46)	(-3.15)
CEO duality(0,1)$_{t-1}$	0.0407	-0.1573***	0.0609
	(0.72)	(-2.64)	(0.76)
CEO ownership$_{t-1}$ (%)	-0.0206***	0.0057	-0.0106*
	(-3.75)	(1.44)	(-1.69)
CEO employment contract (0,1)$_{t-1}$	-0.1172**	-0.0782	3.1745***
	(-2.27)	(-1.47)	(9.81)
Inst. ownership$_{t-1}$ (%)	0.0112	-0.0997	-0.1298
	(0.08)	(-0.65)	(-0.69)
Ln(1+Delta)$_{t-1}$	-0.0275	-0.0520***	-0.0416*
	(-1.59)	(-2.88)	(-1.71)
County poverty status	0.0098	-0.0079	0.0202
	(1.17)	(-0.84)	(1.57)
County employment status	-0.0002	0.0001	-0.0036
	(-0.05)	(0.02)	(-0.44)
Ln(County earnings per capita)	-0.1983*	-0.0539	-0.1033
	(-1.84)	(-0.47)	(-0.76)
Industry, Year, Birth Year, Birth County, and HQ State FE	Yes	Yes	Yes
Clustered by CEO-firm and year	Yes	Yes	Yes
Pseudo R^2	0.1550	0.3486	0.2866
Observations	10,085	7,731	8,670

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

This table repeats tests in Tables 4 to 11 focusing on CEOs' Superfund exposure to developmental toxic chemicals. Here, we regress our models with *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 contaminant released by the Superfund sites. In each case, we control for the same set of 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 Appendix A. *, **, 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	$\sigma_{\text{Stock return}}$	$\sigma_{\text{Specific return}}$	**Negative skewness**	$\sigma_{\text{Down-to-up}}$	**Crash risk (0,1)**
	(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
Dependent variable	**Forced CEO turnover (0,1)**
	(23)
Developmental toxic chemical $(0,1)_t$	0.1645***
	(8.76)
Chemical, Industry, Year, Birth Year, Birth County, and HQ State FE	Yes
Pseudo R^2	0.5158
Observations	355,197

Table OA2. Robustness test: Firms' current exposure to pollution

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 pollutant exposure* (0,1) and *Facility current pollutant exposure* (0,1) capture whether the firm's headquarters and its facilities are currently exposed to toxic pollutants, respectively. In each column, we control for the same set of 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 Appendix A. *, **, 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 pollutant exposure (0,1)$_t$	-0.0017	-0.0171***	0.0753	0.2242***
	(-0.37)	(-3.31)	(0.73)	(12.41)
Facility current pollutant 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 pollutant 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 pollutant 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 OA2, 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 (0,1)
	(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 pollutant 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 pollutant 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 pollutant 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 pollutant 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 OA2, continued

Corresponding table	11
Dependent variable	**Forced CEO turnover (0,1)**
	(23)
Ln(1+CEO #Superfund exposure$_t$)	0.2693***
	(3.14)
Firm current polluter? (0,1)$_t$	0.0339
	(0.25)
HQ current pollutant exposure (0,1)$_t$	0.1294*
	(1.66)
Facility current pollutant exposure (0,1)$_t$	-0.4572***
	(-3.39)
Industry, Year, Birth Year, Birth County, and HQ State FE	Yes
Pseudo R^2	0.3545
Observations	7,731

Table OA3. 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 treated CEOs with Superfund pollution exposure matched with CEOs without Superfund pollution exposure. Matched CEO-firm pairs satisfy: (1) their CEOs were born in the same year (if feasible) or in the same decade, and (2) they are in the same FF48 industry. For those satisfying the above requirements, we choose our control CEO as the one born in the nearest neighboring counties to the treated CEO. In each column, we control for the same set of 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 Appendix A. *, **, 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 OA3, continued

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 (0,1)
	(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
Dependent variable	Forced CEO turnover (0,1)
	(23)
Ln(1+CEO #Superfund exposure$_t$)	1.3064***
	(4.84)
Industry, Year, Birth Year, Birth County, and HQ State FE	
Pseudo R^2	0.5142
Observations	2,974

Table OA4. Robustness test: Superfund CEOs versus Non-Superfund CEOs – Nearest firm's 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, and (2) they are in the same FF48 industry. For those satisfying the above requirements, we choose the control firm with headquarters located in the nearest neighboring counties to the treated firm. In each column, we control for the same set of 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 Appendix A. *, **, 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 OA4, continued

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 (0,1)
	(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
Dependent variable	Forced CEO turnover (0,1)
	(23)
Ln(1+CEO #Superfund exposure$_t$)	3.5779***
	(4.67)
Industry, Year, Birth Year, Birth County, and HQ State FE	Yes
Pseudo R^2	0.7171
Observations	1,994

Table OA5. Robustness test: Difference-in-difference analysis on CEOs' sudden deaths

This table repeats tests in Tables 4 to 11 using difference-in-differences focusing on firms that experienced the sudden death of their CEO. We contrast the firm-year observations for the three years before and the three years after the CEO demise using *Post CEO demise period* (0,1) on the treatment of deceased CEOs' prenatal Superfund exposures (i.e., *Ln*(1+*deceased CEO #Superfund exposure*)). In each column, we control for 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 Appendix A. *, **, 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 $(0,1)_t$ × 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 $(0,1)_t$ × 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 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 (0,1)**
	(12)	**(13)**	**(14)**	**(15)**	**(16)**
Post CEO demise $(0,1)_t$ × Ln(1+deceased	-0.2394**	-0.3109***	-2.3685*	-0.6099**	-1.6384***
CEO #Superfund exposure$_t$)	(-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

Table OA6. Placebo test: Random assignment of CEO 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 (i.e., the Superfund exposures 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 only to the counties containing CEOs' birthplaces in our sample). The main regressions are run on this pseudo-sample. This entire process is then 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 entire process is then 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 control for the same set of 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 Appendix A. Bolded values signify cases when the pseudo random procedure results in significant 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 (0,1)	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
Forced CEO turnover (0,1)	11	**0.070**	**0.190**