Every emission you create–every dollar you'll donate: The effect of regulation-induced pollution on corporate philanthropy*

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Abstract

This paper investigates the role of charitable giving as a form of insurance by analyzing donations to nonprofits from philanthropic foundations associated with U.S. corporations that operate polluting facilities. Our empirical setting exploits the close attainment and nonattainment designation status of counties under the Clean Air Act as a source of exogenous variation in a firm's local pollution. Using regression discontinuity, we find that firms operating in close attainment counties pollute more and subsequently donate more to local nonprofits compared to those in close nonattainment counties. Firms maximize the insurance value of donations by using the most salient forms of charitable giving and reallocate donations to areas where they pollute the most. Potential mechanisms that propagate the relation between regulation-induced emissions and donations to local nonprofits include a firm's local media coverage, reputational risk exposure, and history of regulatory noncompliance. Overall, the evidence suggests that insurance-motives are a key determinant of polluting firms' participation in philanthropy.

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1. Introduction

In the United States, there has been an unprecedented surge in corporate philanthropy in the past decade. According to Giving USA 2019,[1] corporate charitable giving increased by 5.4% in 2018, totaling $20.05 billion. Of this amount, corporate foundation grantmaking constituted $6.88 billion, an increase of 6.5% from 2017. In particular, some of the biggest polluting firms such as Chevron and ExxonMobil not only are the largest and most generous donors in corporate philanthropy but also direct their donations to some of the most prolific environmental nonprofit organizations.[2] Despite the active engagement of polluting firms in corporate philanthropy, most studies have focused on the financial benefits and consequences of corporate philanthropy (Brammer & Millington, 2008; Cuypers, Koh, & Wang, 2016; Elfenbein & McManus, 2010; Lev, Petrovits, & Radhakrishnan, 2010; Wang, Choi, & Li, 2008), while there has been relatively less attention on examining why firms engage in corporate philanthropy. Thus, the objective of this paper is to explore the determinants of corporate philanthropy for polluting firms.

While there are many motivations to participate in charitable activities, we argue that polluting firms use corporate philanthropy as a salient form of reputation insurance. In particular, undertaking philanthropy can build reputational capital among various stakeholders (Godfrey, 2005; Godfrey, Merrill, & Hansen, 2009) and improve the firm's public image (Porter & Kramer, 2002), which in turn provides insurance protection by offsetting potential costs associated with the occurrence of future adverse events when emissions increase (Luo, Kaul, & Seo, 2018; Luo & Bhattacharya, 2009). Our argument is grounded in the insurance-based view of corporate social responsibility (CSR), whereby CSR can function as an insurance mechanism (Barnett, Hartmann, & Salomon, 2018; Koh, Qian, & Wang, 2014; Shiu & Yang, 2017) that mitigates the decline in firm value when negative outcomes are realized (Flammer, 2013; Freund, Nguyen, & Phan, 2021; Hong, Kubik, Liskovich, & Scheinkman, 2019). To provide evidence of the insurance-motive, we analyze how changes in firm pollution affect corporate philanthropy.[3] In this regard, we study donations to nonprofit organizations ("nonprofits")

[1] See www.givingusa.org.

[2] For example, both Chevron and ExxonMobil have long-standing partnerships with nonprofit organizations such as Conservation International and the Wildlife Conservation Society. For more details, refer to "25 of the most generous companies in America," *Business Insider*, June 23, 2016 and `https://news.mongabay.com/2016/05/big-donors-corporations-shape-conservation-goals/`.

[3] A considerable body of work has been dedicated to examining the drivers of firm pollution (Akey & Appel, 2021; Bartram, Hou, & Kim, 2022; Kim, Wan, Wang, & Yang, 2019; Levine, Lin, Wang, & Xie, 2018; Shive & Forster, 2020; Xu & Kim, 2022). In contrast, we focus on the effects of firm pollution on firm outcomes such as corporate philanthropy.

made through a firm's corporate foundation, which is arguably the most salient form of donation activity because foundations usually bear the same name as their parent company and often serve as the flagship of a firm's corporate giving strategy.

The main empirical challenge is that a firm's level of pollution and donation to nonprofits are arguably endogenous choices made by the firm. For example, it could be that preexisting differences in unobservable firm characteristics lead firms with different levels of pollution to engage in philanthropy to different extents. From an empirical perspective, the ideal experiment would be to randomly assign firms into a "high polluting group" and a "low polluting group" and compare their donations following this "treatment". If the insurance-motive drives corporate philanthropy, then we expect to see more donations to nonprofits from the high polluting group compared to the low polluting group because the insurance value of donations is greater for the high polluting group. Obviously, such an ideal experiment would be unreasonably difficult to implement in practice.

Our identification strategy uses a quasi-natural experiment that is very close in spirit to this ideal experiment. We rely on a key regulatory component of the Clean Air Act (CAA), namely the yearly designation of counties into attainment or nonattainment status with respect to the National Ambient Air Quality Standards (NAAQS) for ozone. Through the NAAQS, the federal United States Environmental Protection Agency (EPA) sets maximum allowable concentrations of ozone pollution. Counties with ozone pollution levels above the NAAQS threshold are deemed to be noncompliant (i.e., nonattainment), while those with pollution levels below the threshold are considered compliant (i.e., attainment). The designation of a county into attainment or nonattainment status has significant ramifications on a firm's polluting behavior in that county. In particular, firms that operate polluting plants located in nonattainment counties face stringent regulations and emission restrictions compared to those in attainment counties. Due to the differences in regulatory stringency, firms have a greater incentive to pollute in attainment counties (Bento, Freedman, & Lang, 2015; Gibson, 2019; Greenstone, 2002, 2003).

To determine compliance, each year, the EPA calculates a summary statistic for each county based on ozone monitor readings, known as a design value (DV). Counties with DVs above the NAAQS threshold are designated nonattainment, while those with DVs below the threshold are designated attainment. Our empirical strategy exploits the variation in county-level DVs around the NAAQS threshold by using a regression discontinuity design (RDD) approach. Specifically, we compare firms operating polluting plants in counties with

DVs slightly above the NAAQS threshold so that they are marginally in violation ("close nonattainment") with firms operating plants in counties with DVs slightly below the threshold so that they are marginally in compliance ("close attainment"). The outcome variable that we examine is the amount of subsequent donations to nonprofits located in the same county ("local nonprofits") where the firm operates its polluting plants. Since moving from a DV above to below the NAAQS threshold sharply increases the probability of attainment, these close attainment and nonattainment designations provide a source of random variation in a firm's level of pollution that can be used to estimate the causal effect on its donation activities to local nonprofits.

Our RDD approach uses a sample of 1,079 unique firms with corporate foundations, operating polluting plants in 857 unique counties over the period 1999–2018. Consistent with the existing literature, we find that a county's attainment status has a significant impact on local polluting plants' ozone emissions (Greenstone, 2003). Our results indicate that firms operating plants in close attainment counties emit up to 51% more ozone than those in close nonattainment counties. More importantly, we find evidence consistent with the insurance-motive by showing that firms operating polluting plants in close attainment counties subsequently donate significantly more to local nonprofits relative to those operating in close nonattainment counties. Furthermore, the results are primarily driven by firms that operate historically heavy ozone-polluting plants, rather than by those that operate only non-ozone emitting plants, consistent with the fact that the insurance value of donations are greater for the former set of firms because the relaxation in regulation due to close attainment status increases their incentives to continue emitting ozone.

If reputation insurance is a main driver of philanthropy, then we expect firms to use the most salient forms of donations to maximize the insurance value of these donations. In line with this prediction, we find that firms in close attainment counties donate significantly more to local nonprofits in the health, social and human services, community development, and environment categories relative to those in close nonattainment counties. There are no differential effects in donation outcomes for less-relevant categories such as art, religion, sports, etc. We also examine the possibility that the insurance-motive is driven by other characteristics that could potentially mediate the relation between close attainment designation status and donations to local nonprofits. We find, however, that the insurance-motive does not depend on plants' distance to ozone monitors, plants' age, or local competition between polluting plants. Lastly, we ensure that our results are robust to a variety of alternative RDD specifications and placebo tests.

We provide additional evidence of the insurance-motive of philanthropy using a distinct source of variation in our data. Polluting firms may donate to nonprofits located in many counties, but may not necessarily operate plants in all of those counties. Since the probability of an adverse event happening is greater in counties where firms operate polluting plants, the expected insurance value of donations is greater in these counties compared to those where the firm does not operate plants. We find that firms shift donations away from counties where they have historically made donations to but do not operate plants and toward attainment counties where they operate plants. Our results are consistent with the interpretation that firms reallocate donations to areas where they pollute the most and hence maximize the expected insurance value of such donations.

Our next set of analysis focuses on the plausible mechanisms that could propagate the relation between regulation-induced emissions and donations to local nonprofits. We show that local media coverage is a potential channel through which firms use to increase their reputational capital. In particular, we find that the closure of a local newspaper in a close attainment county leads to a decrease of almost 80% in donations to local nonprofits relative to other close attainment counties without any closures. Another channel that influences a firm's donation activities is its reputational risk exposure to media news of their CSR-related incidents. Our results show that firms with a history of high reputational risk exposure donate more to local nonprofits in close attainment counties, consistent with the notion that these firms benefit the most from the insurance value of donations. In a similar channel, we find that firms with a history of publicized regulatory noncompliance also donate more to local nonprofits in close attainment counties, suggesting that such donations may offer insurance against future potential regulatory compliance costs associated with additional emissions.

In our final set of analysis, we expand our focus to society's perspective and examine the implications for social welfare by comparing the social damages associated with the regulation-induced pollution and the social benefits from the corresponding donations. Through this exercise, we are able to provide some insight into whether firms are underpaying or overpaying for the insurance value they receive from their donations and determine whether corporate philanthropy benefits firms at the cost of social welfare. We find that the marginal increase in mortality-related damages associated with the pollution from firms operating plants in close attainment counties exceeds the marginal increase in donations to local nonprofits by these firms. On average, for every ton of ozone emitted by a firm operating plants in close attainment counties, the firm donates \$1,011.99 to local nonprofits while creating damages to society worth \$3,430.59. Therefore, our results indicate that firms benefit from the insurance protection of corporate philanthropy at the cost of social welfare.

Our research contributes to the burgeoning literature on the motivations of firms to engage in corporate philanthropy. Existing studies have documented agency problems as a key determinant of philanthropy (Brown, Helland, & Smith, 2006; Masulis & Reza, 2014; Yermack, 2009), which can arise because corporate giving reflects managers' preferences for using firm resources to increase their own utility through the consumption of private benefits. However, these studies focus on the *inflow* of funds from firms to foundations and the less-visible channel of direct donations from firms to nonprofits, while we focus on the publicly observable *outflow* of funds from foundations to nonprofits.[4] Other studies have documented corporate philanthropy as a means of securing favorable regulatory treatment (Bertrand, Bombardini, Fisman, Hackinen, & Trebbi, 2021; Bertrand, Bombardini, Fisman, & Trebbi, 2020; Wang & Qian, 2011) or to gain competitive advantages (Baron, 2001; Choi, Park, & Xu, 2022; Navarro, 1988). Our paper adds to this literature by showing that the insurance-motive is another distinct factor for participating in corporate philanthropy.

Our research also contributes to the understanding of how changes in a firm's polluting behavior impact on its CSR such as corporate philanthropy. Prior studies have examined the effects of a firm's overall CSR on its valuation (Flammer, 2015; Hendricks & Singhal, 1996; Klassen & McLaughlin, 1996; Lins, Servaes, & Tamayo, 2017; Servaes & Tamayo, 2013) and stock market reactions to a firm's corporate social irresponsibility (Flammer, 2013; Gande & Lewis, 2009; Karpoff, Lott, & Wehrly, 2005; Liu, Cheong, & Zurbruegg, 2020). However, corporate philanthropy is a very nuanced type of CSR because stakeholders often view charitable giving as a short-term cost with no meaningful long-term benefits for the business (Bénabou & Tirole, 2010). By exploiting the granular nature of our donations data, we are able to identify and associate changes in local pollution with changes in local donations. In particular, we find evidence suggesting that firms undertake philanthropy in response to an increase in emissions to accrue reputational capital within their local communities, especially

[4]The nature of our data is also inherently different from those used in the existing literature on agency motives. Specifically, these studies use data on the aggregate amount of *direct* charitable giving at the firm–year level. However, these donations are difficult to track because firms are not required to disclose publicly the recipients of their directed donations. Our study uses more granular data at the nonprofit–firm–year level because we examine donations made through corporate foundations, which are publicly observable via foundation disclosures. Another advantage of the granularity of our data is that we are able to exploit geographic variation in donations since we observe the nonprofit recipients. This geographical distribution is a key component of our identification strategy because it allows us to examine the variation of donations across different counties with varying levels of DVs.

for those with a history of reputational risk exposure and regulatory noncompliance.

Finally, we contribute to the understanding of how environmental regulations affect corporate philanthropic activities. The literature has utilized county-level attainment and nonattainment designation status as an instrument for emissions to study health outcomes (Bishop, Ketcham, & Kuminoff, 2020), industrial activity (Becker & Henderson, 2000; Greenstone, 2002; List, McHone, & Millimet, 2004; List, Millimet, Fredriksson, & McHone, 2003), housing prices (Bento et al., 2015; Chay & Greenstone, 2005; Grainger, 2012), employment (Curtis, 2020; Kahn & Mansur, 2013), labor reallocation (Walker, 2011, 2013), productivity (Greenstone, List, & Syverson, 2012; Shapiro & Walker, 2018), earnings (Isen, Rossin-Slater, & Walker, 2017), and pollution substitution (Gibson, 2019; Greenstone, 2003). To our knowledge, we provide the first empirical analysis that uses attainment designations to examine the effects of regulation-induced pollution on firms' corporate philanthropy.

2. Background

The CAA requires the EPA to set the NAAQS for six pollutants: carbon monoxide, nitrogen dioxide, ozone, sulfur dioxide, particulate matter, and lead. The NAAQS place pollutant-specific limits on the maximum allowable concentration of pollution in a given area to provide protection of human health. We focus on ozone because counties most often fail to meet NAAQS thresholds by exceeding ozone concentration limits, rather than by violating the NAAQS thresholds for the other pollutants (Curtis, 2020). As a result, ozone offers a much larger treatment group of counties for our analyses.[5]

Each year, the EPA, together with state and local jurisdictions, makes a determination as to whether each county in the United States is in attainment with the ozone NAAQS. Attainment determinations rely on daily and hourly readings from ozone monitoring stations across the United States. To assess compliance, the EPA calculates an annual county-level summary statistic using monitor readings across the county, known as a DV. Counties with DVs above the threshold for a given standard are considered to be out of attainment (i.e., nonattainment) with the standard, while counties with DVs below the threshold are in attainment. As shown in Internet Appendix Table IA.1, during our sample period from 1999 to 2018, the EPA implemented four different ozone standards: i) the 1-Hour Ozone (1979) standard from 1999 to 2003; ii) the 8-Hour Ozone (1997) standard from 2004 to 2011; iii) the 8-Hour Ozone (2008)

[5]Another advantage with focusing only on ozone is that the NAAQS specifies only one primary standard for ozone, while there exists both a primary and secondary standard for other pollutants such as particulate matter. The existence of only one standard for ozone allows us to implement a RDD approach to study the effect of ozone emissions on donations.

standard from 2012 to 2017; and iv) the 8-Hour Ozone (2015) standard in 2018. The difference between these standards is the threshold used to determine compliance. Revisions in the NAAQS thresholds over time are exogenous because they are based on new scientific research to reflect the ongoing health effects of air pollution (Gibson, 2019).

For counties that are designated nonattainment, the EPA requires each state to submit state implementation plans (SIP), which are comprehensive plans that outline how a state will bring their counties' emission levels back into compliance (United States Environmental Protection Agency, 2013). Environmental regulations in nonattainment counties are intended to be stringent and involve a multitude of restrictions with the main purpose of curbing emissions.[6] Existing studies show that nonattainment designations are effective at reducing pollution levels, and much of this reduction is a result of increased firm compliance, implying that nonattainment regulations are binding for polluting plants (Chay & Greenstone, 2003; Henderson, 1996).

For a county to be redesignated as attainment, states must develop proper SIPs demonstrating the regulatory actions that will be taken to meet and maintain the NAAQS. In attainment counties, polluting plants face more lax regulatory standards and significantly less emission limits.[7] Due to the regulatory differences in emission limitations, firms with polluting facilities located in attainment counties are allowed to emit substantially more ozone than those located in nonattainment counties (Greenstone, 2003). We exploit the sharp increase in attainment probability when a county's DV moves from above to below the NAAQS threshold and the corresponding change in a firm's polluting behavior stemming from attainment designations to study the impact of increased emissions on a firm's donation activities to local nonprofits.

3. Conceptual framework

In this section, we describe the potential motivations driving charitable activities for polluting firms and derive testable implications.

3.1. Insurance-motives for corporate philanthropy

The motivations for participating in corporate philanthropy depends critically on a firm's operating environment (Ioannou & Serafeim, 2012; Liang & Renneboog, 2017). In this paper, we argue that changes in a firm's polluting behavior stemming from environmental regulations

[6]For example, large pollution sources are required to install the cleanest available technology, regardless of costs. Moreover, any emissions from new or expanding sources must be offset from an existing source located in the same county before commencing operations.

[7]Large-scale investments involve less expensive pollution abatement equipment and pollution offsets are not necessary.

can influence its charitable giving. In particular, we posit that reputation insurance is a key determinant of polluting firms' donation activities when changes in environmental regulation increases their incentives to pollute.

Due to the differences in regulatory stringency, it is well-documented that firms operating facilities in attainment counties pollute significantly more than those operating in nonattainment counties (e.g., Bento et al., 2015; Gibson, 2019; Greenstone, 2002, 2003). Although the lax regulations in attainment counties incentivize firms to pollute more, they could also lead to negative consequences. Institutional investors have started to place considerable attention on the negative externalities of firms' emissions through divestments (Azar, Duro, Kadach, & Ormazabal, 2021; Kim et al., 2019) and activism campaigns (Akey & Appel, 2020; Naaraayanan, Sachdeva, & Sharma, 2021). In addition, an increase in emissions can lead to additional penalties (Xu & Kim, 2022), greater compliance costs (Blundell, Gowrisankaran, & Langer, 2020), and losses in stock price valuations (Karpoff et al., 2005).

Given the potential costs associated with an increase in emissions, we argue that a firm can use corporate philanthropy as a tool to offset such costs (Godfrey, 2005; Godfrey et al., 2009). In particular, philanthropy serves as a salient form of reputation insurance; firms that undertake philanthropy accrue reputational capital within their local community, which pays off when adverse events occur (Luo et al., 2018). More generally, our reasoning is supported by the insurance-based view of CSR, whereby CSR provides protection against negative outcomes by harnessing the goodwill of stakeholder groups (Lev et al., 2010; Wang et al., 2008) and insures the firm against socially irresponsible actions (Barnett et al., 2018; Flammer, 2013; Freund et al., 2021; Hong et al., 2019; Koh et al., 2014; Shiu & Yang, 2017). The insurance-motive for corporate philanthropy has a straightforward testable implication in our setting. Since attainment status is associated with an increase in emissions, firms operating plants in counties with DVs that are marginally in compliance with the NAAQS threshold are predicted to donate more to local nonprofits relative to those operating in counties with DVs that are marginally in violation of the threshold.

3.2. Donations in operating versus non-operating counties

Polluting firms may donate to nonprofits located in two types of counties, namely those where they operate plants and those where they do not operate plants. Since the probability of an adverse event occurring is greater in counties where firms operate polluting plants, the expected value of insurance from every dollar donated is greater in such counties compared to counties where they do not operate plants (Parkin & Wu, 1972). A stylized fact of corporate foundations' grantmaking is that their overall charitable giving across all counties remains relatively stable over time even if there are fluctuations in the firms' contributions to their foundations in a given year (Petrovits, 2006; Sansing & Yetman, 2006; Webb, 1994).[8] In addition, foundation grantmaking is a costly process that involves search, screening, and reputation costs.[9] Thus, if the insurance-motive is a driving factor for donations, then given an exogenous shock in firms' incentives to pollute in a given county due to regulatory changes, firms will maximize the insurance value of their donations by internally reallocating donations from counties where they do not operate plants to counties where they operate plants (Billett & Mauer, 2003; Shin & Stulz, 1998). Therefore, another testable implication of the insurance-motive for corporate philanthropy is that in order to satisfy the increase in donations in close attainment operating counties, firms reallocate donations away from other counties in which they have historically made donations to but do not operate plants there and toward close attainment counties where they operate polluting plants.

3.3. Propagating channels

In this section, we discuss the potential mechanisms that could propagate the relation between regulation-induced emissions and donations to local nonprofits. The local media is a possible channel that firms use to improve their reputational capital because it helps disseminate news of their charitable activities, allowing them to accrue reputational capital by positively shaping the public's perceptions of such donations (Luo & Bhattacharya, 2006). Studies have shown that firms with better CSR performance receive more favorable media coverage (Cahan, Chen, Chen, & Nguyen, 2015), with media coverage of locally-oriented CSR being the most value-enhancing (Byun & Oh, 2018). In turn, local news reporting is an important determinant of firms' reputation (Dyck, Volchkova, & Zingales, 2008; Gurun & Butler, 2012; Miller, 2006), with more positive media coverage leading to an improvement in firms' reputational capital (Liu & McConnell, 2013).

Recent work by Heese, Pérez-Cavazos, and Peter (2022) document that the local media is an effective monitor of corporate misconduct, with local newspaper closures leading to an increase in local facility-level violations. To study the role of local news coverage on propagating the

[8] The literature has documented multiple reasons as to why foundations smooth their distributions over time including earnings management (Petrovits, 2006), tax-induced incentives (Sansing & Yetman, 2006), and to maintain a steady level of corporate goodwill (Webb, 1994).

[9] Search costs include the extensive research required to identify the pool of potential grantees that align with the social goals targeted by the foundation. Screening costs arise due to grant solicitation and increase as the volume of funding applications increases. Finally, firms face potential reputation costs if they fund a dubious nonprofit.

relation between close attainment designation status and donations to local nonprofits, we follow Heese et al. (2022) and study the consequences of local newspaper closures on donation outcomes. If reputation insurance drives firms' philanthropic efforts, then we expect firms to decrease donations to local nonprofits in close attainment counties with a local newspaper closure because the insurance value of such donations decreases given a reduction in local news coverage of their charitable activities.

Another channel that could influence a firm's donations to local nonprofits in close attainment counties is the firm's reputational risk exposure to media news of their CSR-related incidents. Studies have shown that shareholders react negatively to news about CSR incidents (Flammer, 2013; Karpoff et al., 2005; Krueger, 2015), with firms that have higher emissions experiencing a higher frequency of environmental-related incidents covered by the media news (Hsu, Li, & Tsou, 2022). Additionally, Glossner (2021) and Yang (2021) both show that a firm's past history of news-based CSR incidents is the best predictor of future incidents. Therefore, if insurance-motives are driving philanthropy, then we expect firms with a history of high reputational risk exposure to increase their donations to local nonprofits to mitigate the potential costs associated with additional emissions in close attainment counties relative to those with less reputational risk exposure.

In a similar vein, we also examine a firm's history of publicized regulatory noncompliance based on regulatory incidents. Firms with a history of regulatory noncompliance are subject to greater regulatory scrutiny (Blundell et al., 2020), which increases their regulatory compliance costs (Blundell, 2020), especially if such noncompliances are publicly available (Johnson, 2020). Thus, the insurance-motive of philanthropy predicts that firms with a history of regulatory noncompliance should increase donations to local nonprofits to offset future potential regulatory compliance costs associated with additional emissions in close attainment counties relative to firms with less regulatory incidents.

4. Data

4.1. Firms' ozone pollution

We use pollution data from the EPA's Toxics Release Inventory (TRI) database, which contains information on the disposal and release of over 650 toxic chemicals from more than 50,000 plants in the U.S. since 1987. Industrial facilities that fall within a specific industry (e.g., manufacturing, waste management, mining, etc), have ten or more full time employees, and handle amounts of toxic chemicals above specified thresholds must submit detailed annual reports on their releases of toxins to the TRI. The TRI provides self-reported toxic emissions at the plant-level along with identifying information about the facility such as the plant's name, county of location, industry, and parent company's name.[10]

Since we only focus on ozone, we classify a facility's emissions of toxic chemicals into ozone pollutants and non-ozone pollutants.[11] In any given year, we calculate a facility's total amount of ozone emissions as the amount of chemical emissions that are classified as volatile organic compounds or nitrogen oxides, both precursors to ozone formation.[12] Although the TRI data provides information on chemical emissions through the ground, air and water, we only consider emissions through the air because the NAAQS only regulates air emissions. To obtain parent companies' financial and stock price information, we manually match the TRI parent company names to those in Compustat and CRSP. We aggregate a firm's ozone emissions across all facilities in a given county since our analysis is at the firm–county–year level. Internet Appendix Table IA.2 lists the three-digit NAICS industries in TRI that are included in our sample. Similar to Akey and Appel (2021), the most common industries are chemical manufacturing (12.97% of sample), fabricated metal product manufacturing (12.64%), and transportation equipment manufacturing (8.22%). The final TRI sample consists of 89,481 firm–county–year observations from 1999 to 2018.

4.2. Corporate foundations

Data on charitable donations by foundations linked to corporations come from Foundation-Search, which provides funding information based on Internal Revenue Service (IRS) 990-PF forms for more than 120,000 active foundations. The starting point for our sample is the companies in the S&P 1500. We match firms with their foundations using the foundation directory from Candid. Since we only focus on polluting firms, we restrict sample of corporate foundations to those that are owned by parent firms of TRI facilities.

Once we establish a link between a firm and its foundation, the donation record is obtained from FoundationSearch. For each grant, FoundationSearch reports the amount, the recipient's

[10]While the TRI data are self-reported, the EPA regularly conducts quality analyses to identify potential errors and purposefully misreporting emissions can lead to criminal or civil penalties (Xu & Kim, 2022). Additionally, most reporting errors are due to changes in reporting requirements in the early years of TRI data collection (Bui & Mayer, 2003; De Marchi & Hamilton, 2006), which leaves our study unaffected since our sample period begins from 1999.

[11]We use the mapping from TRI chemicals to CAA criteria pollutants from Greenstone (2003). However, additional chemicals have been introduced into the TRI since the creation of the mapping. Thus, we contacted the EPA and also hired a Ph.D. chemist in atmospheric science to classify the remaining chemicals.

[12]Ozone is not directly emitted by plants, but rather formed through chemical reactions in the atmosphere. We refer to emitters of ozone precursors as ozone emitters/polluters.

name, city, and state, as well as a giving category created by the database.[13] For observations that are missing information regarding the city and/or state where the grant recipients are incorporated, we match the recipient name in FoundationSearch to a master list of all nonprofits from the IRS Exempt Organizations Business Master File to obtain the precise address of the recipient. We collect a total of 327,132 grants made to nonprofits in the United States for the sample period from 1999 to 2018.[14] We aggregate a firm's foundation donations across all nonprofits in a given county to form a sample of 101,573 observations at the firm–county–year level.

4.3. Ozone design values

We obtain monitor-level ozone concentrations from the Air Quality System (AQS) database maintained by the EPA. For each ozone monitor, the database includes ozone concentration readings and the county location of the monitor. We use these ozone concentrations to calculate DVs, which are statistics that the EPA uses to determine whether a county is in compliance with the NAAQS each year.[15] From 1999 to 2003, we use the 1-Hour Ozone (1979) standard with a NAAQS threshold of 0.12 ppm. Under this standard, monitor-level DVs are calculated as the annual daily maximum hourly average concentration. From 2004 to 2011, we use the 8-Hour Ozone (1997) standard with a NAAQS threshold of 0.08 ppm. From 2012 to 2017, we use the 8-Hour Ozone (2008) standard with a NAAQS threshold of 0.075 ppm. In 2018, we use the 8-Hour Ozone (2015) standard with a NAAQS threshold of 0.070 ppm. For each of the standards from 2004 onwards, monitor-level DVs are calculated as the three-year rolling average of the annual fourth highest daily maximum 8-hr ozone concentration. The rule used to compute the DVs and the relevant thresholds for each ozone standard are summarized in Table IA.1 of the Internet Appendix. We follow the EPA and aggregate monitor-level ozone DVs to the county-level by taking the maximum DV across all monitors within a county–year. Counties with DVs that are above the relevant threshold are designated nonattainment, while those below the threshold remain in attainment. Our sample of county-level DVs consist of 15,914 county–year observations from 1999 to 2018.

[13]The 10 categories are: Arts & Culture, Community Development, Education, Environment, Health, International Giving, Religion, Social & Human Services, Sports & Recreation, and Miscellaneous Philanthropy.

[14]Following Bertrand et al. (2020), we winsorize the dollar amount of donations at the highest 1 percent of the values to account for extremely large donations.

[15]We only include monitor–year observations that are not affected by "extreme natural events" beyond human influence, occurrences that are noted in the AQS data.

4.4. Plant-level variables

We use a host of plant-level variables obtained from various database which are summarized as follows. We use the EPA's Pollution Prevention (P2) database to create pollution abatement variables. The database provides information on a facility's source reduction activities that limit the amount of toxic chemicals released (e.g., recycling, recovery, and treatment). We also use the production ratio variable in the P2 database, which measures the change in output associated with the release of a chemical in a given year.[16] We use EPA's Integrated Compliance Information System for Air (ICIS-Air) database for information on plant-level ozone violations, operating permits, and stack tests. We obtain data on formal administrative and judicial cases from EPA's Integrated Compliance Information System for Federal Civil Enforcement Case Data (ICIS FE&C). Finally, we collect data on a plant's sales and first year of operation from the National Establishment Time-Series (NETS).

4.5. Control variables

In our analyses, we use a variety of variables related to a firm's polluting activities and financial characteristics. The variables for polluting activities include a dummy variable equal to one if a given firm operates plants in a given county that emit core ozone chemicals as defined by TRI, and zero otherwise (*Core chemical*);[17] a dummy variable equal to one if a given firm operates plants in a given county that hold operating permits for ozone emissions, and zero otherwise (*Permit*); a dummy variable equal to one if a given firm operates plants in a given county that engage in ozone source reduction activities, and zero otherwise (*Source reduction*); and a given firm's average ozone production ratio across all plants in a given county (*Production ratio*). Variables for firm financial characteristics include the natural logarithm of market capitalization (*ln(Size)*); the natural logarithm of book-to-market ratio (*ln(BM)*); return on assets (*ROA*), calculated as net income divided by total assets; debt to assets ratio (*Leverage*), calculated as total liabilities divided by total assets; sales growth (*Sales growth*), defined as the ratio of sales in the current fiscal year to sales in the last year minus one; financial constraints (*KZ*), defined as the Kaplan-Zingales index; cash ratio (*Cash*), calculated as cash divided by total assets; price momentum (*Momentum*), defined as the cumulative 12-month return

[16] For example, if a chemical is used in the manufacturing of refrigerators, the production ratio for year t is given by $\frac{\#\text{Refrigerators produced}_t}{\#\text{Refrigerators produced}_{t-1}}$. If the chemical is used as part of an activity and not directly in the production of goods, then the production ratio represents a change in the activity. For instance, if a chemical is used to clean molds, then the production ratio for year t is given by $\frac{\#\text{Molds cleaned}_t}{\#\text{Molds cleaned}_{t-1}}$

[17] Core chemicals are those that have consistent reporting requirements in TRI.

of a stock, excluding the immediate past month; annual stock returns (*Stock returns*); and bankruptcy risk (*z-score*), defined as Altman's unlevered z-score.

4.6. Descriptive statistics

After taking the intersection of the TRI, FoundationSearch, and DV data, the final sample comprises 1,079 unique firms with corporate foundations that operate polluting plants in 857 unique counties, resulting in 54,524 firm–county–year observations over the period 1999–2018. Figure 1 presents the average DVs (in parts per million) over the sample period in the counties where TRI plants operate and where DV data is available. As can be seen, there is substantial variation in a county's compliance status across the United States.

Table 1 presents summary statistics on the firm variables. A full list of the variables used in this paper and their data sources can be found in Table A.1 in Appendix A. On average, firms donate approximately $14,000 to nonprofits in the counties where they operate polluting plants. However, there is substantial variation in the donation size given the sizable standard deviation in donations. Salient categories such as health, social and human services, and community development have the three highest average donations. In terms of emissions, the average firm emits roughly 15 tons of ozone in a given county–year with a standard deviation of 90 tons. Finally, about 71% of a given firm's polluting plants are operating in counties that are in compliance with the NAAQS threshold.

5. Methodology

In this section, we describe our empirical framework to estimate the impact of firms' local ozone air pollution on their donation activities. A firm's pollution in a given county is potentially endogenous to its donations to local nonprofits because unobserved firm characteristics that are also correlated with pollution likely affect the amount of charitable giving. For example, firms that are more profitable may have more resources to donate to local nonprofits and may also be more likely to emit more pollutants as they produce more. Therefore, we use a RDD approach to estimate the effect of firms' county-level ozone emissions on donations to local nonprofits.

Our identification strategy relies on a county's close attainment designation status based on its DVs. Counties with a DV below the NAAQS threshold are likely to be designated as attainment. Firms with polluting facilities located in these attainment counties are allowed to emit significantly more ozone than those located in nonattainment counties. Ideally, we would want a county's designation status to be a randomly assigned variable with regard to firms' characteristics, especially the firms' donation activities. The RDD framework that exploits a county's DVs helps us to approximate this ideal setup because the designation of attainment status is a random outcome in an arbitrarily small interval around the NAAQS threshold; for example, whether a county is in compliance with a DV slightly below the NAAQS threshold or in violation with a DV slightly above the threshold is arguably random. These close attainment designations, therefore, provide a source of random variation in a firm's county-level ozone emissions that can be used to estimate the impact of its pollution on local donations.

We perform the RDD by using a nonparametric, local linear estimation. Small neighborhoods on the left- and right-hand sides of the NAAQS threshold are used to estimate discontinuities in firms' donations to local nonprofits. We follow Imbens and Kalyanaraman (2012) and Calonico, Cattaneo, and Titiunik (2014) to derive the asymptotically optimal bandwidth under a squared-error loss. The choices of the neighborhood (bandwidth) are data-driven (determined by the data structure) and different across samples and variables. By choosing the optimal bandwidth to the left and right of the threshold, we only include observations in the RDD specification if the absolute difference between the DV for that observation and the threshold is less than the bandwidth. The local linear regression model can therefore be specified as

$$Y_{i,c,t+1} = \alpha + \beta Comply_{c,t} + \phi f(R_{c,t}) + \varepsilon_{i,c,t+1} \tag{1}$$

where, in our main analyses, $Y_{i,c,t+1}$ is the natural logarithm of one plus the total amount of donations of firm i to nonprofits located in county c in year $t+1$. $R_{c,t}$ is the centered DV (i.e., the running variable in RDD parlance), defined as the difference between the NAAQS threshold and the DV of county c in year t.[18] Positive (negative) values indicate that the county is in compliance with (violation of) the NAAQS threshold. Our primary specifications use local linear functions in the running variable with rectangular kernels as represented by $f(R_{c,t})$. $Comply_{c,t}$ is a dummy variable equal to one if county c is in compliance with the NAAQS threshold in year t, and zero otherwise. Since treatment assignment is at the county-level, standard errors are clustered by county and bias-corrected as discussed in Calonico et al. (2014).

The estimate of β captures the discontinuity at the NAAQS threshold—the difference in donation outcomes between the firms operating polluting plants in counties that marginally comply with the NAAQS threshold and the firms operating plants in counties that marginally

[18] Specifically, we define $R_{c,t} = \text{NAAQS}_t - \text{DV}_{c,t}$

violate the NAAQS threshold—and, hence, provides a consistent estimate of the effect of firms' ozone pollution on their charitable activities at the county-level. We consider a host of sensitivity analyses, such as using alternative bandwidths that are either narrower or wider than the optimal bandwidth, using covariate-adjusted bandwidth selection and point estimation, using different kernel functions, using global polynomial regressions, controlling for local quadratic and cubic polynomials in the running variable, and residualizing the outcome variable by different sets of fixed effects before estimating the RDD specification.

5.1. Tests for quasi-randomized assignment

The identifying assumption of the RDD is that, around the NAAQS threshold, a county's designation status is as good as randomly assigned. In this section, we perform two standard tests for the RDD validity that counties cannot precisely manipulate the running variable so that their DVs are right below the NAAQS threshold (Lee & Lemieux, 2010). If this assumption is satisfied, then the variation in a county's attainment designation status should be as good as that from a randomized experiment.

5.1.1. Continuity in the distribution of design values

Having a DV below the NAAQS threshold is a critical factor in determining a county's compliance status. Since being classified as nonattainment imposes costly regulatory actions to curb emissions, counties have a strong incentive to keep pollution levels below the threshold. Thus, one potential concern is that counties just above the threshold might try to manipulate their monitored ozone concentrations in order to be right below the threshold. The first test that we conduct evaluates whether the distribution of DVs is continuous around the NAAQS threshold. Any discontinuity would suggest a nonrandom assignment of attainment versus nonattainment status around the threshold.

In practice, however, it is unlikely that counties could strategically manipulate their DVs. All counties are evaluated on the same standards, so attainment designations are likely to be exogenous to all county-specific characteristics other than local air quality conditions. Additionally, studies show that attainment designations often depend on weather patterns (Cleveland & Graedel, 1979; Cleveland, Kleiner, McRae, & Warner, 1976), suggesting that attainment status is unlikely to be related to differences in tastes, geographic attributes, or underlying economic conditions across counties. Finally, the federal enforcement powers of the EPA generally limits the states' ability to overlook noncompliant counties, implying that a county's political government or collective firm lobbying efforts are unlikely to influence attainment designations.

Figure 2 presents the histogram of county-level DVs from years 1999–2018 in the counties where TRI plants operate and where DV data is available. If counties were manipulating their DVs to strategically avoid nonattainment designations, one would expect to see a bunching of counties just below the NAAQS thresholds. However, the figure shows that the distribution of DVs appears to be smooth and continuous around the NAAQS thresholds. Take, for example, the 8-Hour Ozone (1997) standard with a threshold of 0.08 ppm. The histogram shows that DVs are evenly distributed just below and above this threshold. A more formal approach is provided in Figure 3, which plots the local density of centered DVs on either side of the NAAQS threshold. Observations on the right (left) of the vertical dashed line indicate that the county is in compliance with (violation of) the NAAQS threshold. As is shown, there is no evidence for a discontinuous jump in DVs around the threshold. Using the density break test following Cattaneo, Jansson, and Ma (2020),[19] we fail to reject the null hypothesis that counties are unable to manipulate their pollution levels in order to be right below the threshold specified by the NAAQS (p-value = 0.450).

5.1.2. Preexisting differences

The second testable implication of the randomness assumption is that firms operating plants in counties whose DVs are immediately below or above the NAAQS threshold should be very similar on the basis of ex ante characteristics. In other words, if a county's designation status is as good as randomized, it should be orthogonal to firm characteristics prior to the designation.

In Table 2, we examine whether there are any preexisting differences between firms operating plants in counties that comply and violate NAAQS thresholds. In columns (1) and (2), we examine these characteristics in the year preceding the designation ($t-1$). In columns (3) and (4), we examine the change in these characteristics between years $t-2$ and $t-1$. Columns (1) and (3) report the differences among all firms in the sample, whereas columns (2) and (4) report the differences at the narrow margin (using the optimal bandwidth) around the NAAQS threshold.

As can be seen in columns (1) and (3), the firm's characteristics—size, cash ratio, price momentum, annual stock returns, bankruptcy risk, ozone permits, and ozone source reduction activities—of those operating plants in counties that are in compliance with the NAAQS differ significantly from those operating plants in counties that are in violation. Importantly, however, columns (2) and (4) show that these differences completely disappear when we

[19]The density break test builds upon the more standard density manipulation test by McCrary (2008).

restrict the sample to be within a small window around the threshold. Overall, this evidence suggests that no systematic or significant difference exists between firms operating plants in counties with DVs that are marginally below or above the NAAQS thresholds, which lends support to our identification strategy.

6. Close attainment designation status and donations

6.1. First-stage results

Before presenting our main results, we first validate two basic premises of our RDD framework, namely the sharp increase in attainment probability when moving from a DV above to below the NAAQS threshold and the change in a firm's polluting behavior stemming from attainment designations.

In Panel A of Table 3, we present the effects of a county's attainment status on local polluting plants' ozone emissions. We use the same RDD specification as in Equation (1), except the dependent variable is the natural logarithm of one plus the total amount of ozone air emissions (in pounds) in a given county of a given firm in a given year. Across all columns, we find that firms operating plants in counties with DVs that are marginally in compliance with the NAAQS threshold emit significantly more ozone in those counties relative to the counties that are marginally in violation of the threshold. Economically, moving from a close nonattainment to a close attainment county increases a firm's county-level ozone emissions by 37.03% to 51.13%.

Panel B of Table 3 reports the probability of a county being designated as attainment conditional on its compliance with the NAAQS threshold. Column (1) shows that having a DV below the threshold increases the probability of being designated attainment by roughly 80%. Similarly, in column (2), we follow Curtis (2020) and include additional county-level control variables in the regression. These include a county's level of employment, emissions to employment ratio, change in employment levels, and whether the county is located in a MSA. However, as can be seen, a county's DV compliance with the NAAQS threshold is still the main determinant of its attainment designation status.

6.2. Graphical analysis

Having verified the basic premise of our RDD setting, we now measure the impact of regulation-induced ozone pollution on donation activities. To display the magnitudes of potential discontinuities in our outcome variable, we provide a visualization of the data in Figure 4. Specifically, the figure plots $ln(Donation)_{t+1}$, defined as the natural logarithm of one plus the total dollar amount of donations of a given firm to nonprofits in a given county in year $t+1$, against the centered DVs. Each dot in the figure represents the average of non-zero values of $ln(Donation)_{t+1}$ using integrated mean squared error optimal bins following Calonico et al. (2014). The solid lines on either side of the NAAQS threshold is based on two separate regressions of $ln(Donation)_{t+1}$ on local quadratic polynomials in centered DVs using the rectangular kernel and optimal bandwidth following Calonico et al. (2014). Bins to the left of zero indicate close nonattainment counties and bins to the right of zero indicate close attainment counties.

As can be seen from the figure, the amount of county-level donations appear to be a continuous and smooth function of the centered DVs everywhere except at the NAAQS threshold, where there is a discontinuous jump when crossing from a close nonattainment county to a close attainment county. This evidence suggests that firms operating polluting plants in a given county donate more to nonprofits located in the same county if the county has a DV that is marginally in compliance with the NAAQS threshold relative to firms operating plants in a county that is marginally in violation of the threshold.

6.3. Regression analysis

In this section, we formally quantify the discontinuity illustrated in Figure 4 by estimating the RDD specification in Equation (1). We present the results in Table 4, which reports estimates of the difference in a firm's donation activities in response to a county's close attainment designation status. Column (1) shows that firms operating polluting plants donate significantly more to nonprofits located in close attainment counties relative to close nonattainment counties. In economic terms, firms donate 39.38% more to nonprofits located in counties where they operate polluting plants and the counties are marginally in compliance with the NAAQS threshold relative to those operating plants in counties that are marginally in violation of the threshold. The coefficient on $Comply_{c,t}$ remains positive and statistically significant when we add covariates to the optimal bandwidth selection and point estimation following Calonico et al. (2014), as shown in column (2). Similar results are obtained when we use 50% and 150% of the optimal bandwidth as shown in columns (3) and (4), and when we use the triangular kernel in column (5).[20]

Overall, the results in this section coupled with the findings of the first-stage results imply that firms operating plants in close attainment counties not only pollute more locally relative

[20]According to Imbens and Lemieux (2008), the choice of kernel has little impact on the estimation in practice, although using a rectangular kernel is more common.

to those in close nonattainment counties but also donate more to local nonprofits, possibly as a form of reputation insurance to offset the potential costs associated higher emissions.

6.4. Ozone versus non-ozone facilities

While Equation (1) identifies the effect of close attainment designation status on firms' donation activities to local nonprofits overall, we expect differential effects for ozone-emitting plants versus non-ozone emitting plants. Specifically, some polluting plants may emit more ozone than others because they rely more on ozone chemicals for their production. Thus, firms that operate historically heavy ozone-polluting plants obtain more insurance value from donations because a county's close attainment designation status enables them to continue emitting ozone. To investigate this hypothesis, we alter Equation (1) by including an interaction term as follows:

$$\begin{aligned} &\mathit{ln(Donation)}_{i,c,t+1} = \alpha + \beta_1 \mathit{Comply}_{c,t} + \beta_2 \mathit{ln(Ozone)}_{i,c,t-1} + \beta_3 \mathit{Comply}_{c,t} \\ &\times \mathit{ln(Ozone)}_{i,c,t-1} + \phi f(R_{c,t}) + \varepsilon_{i,c,t+1} \end{aligned} \tag{2}$$

where the notation is identical to Equation (1). Since attainment designations are based on the *amount* of ozone emissions and not ozone emission *intensity* (i.e., ozone emissions per unit of production), we define $\mathit{ln(Ozone)}_{i,c,t-1}$ to be the natural logarithm of one plus the total amount of ozone air emissions (in pounds) in county c of firm i as of year $t-1$. This variable is measured in year $t-1$ to reflect a firm's most recent ozone emissions prior to the designation. The coefficient of interest is β_3, which represents the differential effect of close attainment designations on firms' donations to local nonprofits of firms operating heavy ozone-polluting plants in a given county, relative to those operating plants with less ozone emissions. Since firms that operate heavy ozone-polluting plants are more likely to be affected by a close attainment designation because it allows them to maintain high ozone emissions, we expect such firms to donate more to local nonprofits to offset the potential costs associated with additional ozone emissions, leading to a positive β_3.

We present the results in Table 5. Consistent with our predictions, we see that the coefficients on $\mathit{Comply} \times \mathit{ln(Ozone)}$ are positive and statistically significant across all regression specifications, indicating that firms operating heavy ozone-polluting plants in a close attainment county donate more to local nonprofits than those operating plants with less ozone emissions. Economically, the coefficient estimate in column (2) implies that in a close attainment county, a one standard deviation increase in the (log) amount of ozone emissions leads to a 23%

increase in donations to local nonprofits.

The coefficient on *Comply* represents the impact of close attainment designation status on donations to local nonprofits for firms operating plants that do not emit any ozone in a given county. Across all columns, these coefficients are positive but statistically insignificant (with the exception of column (4)). These results are in line with the fact that the polluting behavior of firms operating only non-ozone plants are effectively unaffected by the regulations of a county's ozone attainment status, which translates into a lack of significance in their donation activities following the designation. In summary, the fact that close attainment designations have differential effects on firms' donations to local nonprofits depending on their historical ozone emissions adds to the evidence in support of the insurance-motives of philanthropy.

6.5. What types of donations matter?

If firms are utilizing corporate philanthropy as a form of reputation insurance, then we expect firms to maximize the insurance value by using the most salient forms of donations to increase the public's awareness of their charitable activities. For example, polluting firms may find it optimal to donate to health-related nonprofits, as opposed to art- or religious-related nonprofits, to mitigate the negative environmental image of their ozone emissions by donating to nonprofits that addresses the negative externalities of pollution. Thus, we decompose a firm's donations into categories based on the type of nonprofits that receive the donations as classified by FoundationSearch. We estimate the same regression specification as in Equation (1), but aggregate the dollar amount of donations based on the category.

Table 6 presents the results. As can be seen across the first four columns, firms that operate plants in close attainment counties donate significantly more to local nonprofits in the health, social and human services, community development, and environment categories relative to those operating plants in close nonattainment counties. The largest economic magnitude on $Comply_{c,t}$ is for the health category, which corresponds to roughly a 38% increase in donations to local nonprofits. These results indicate that firms appear to target nonprofits that maximizes the salience of their donations. On the other hand, the coefficients on $Comply_{c,t}$ are insignificant for the less-salient categories in columns (5) to (9), consistent with the interpretation that these donation categories are less relevant for polluting firms.

6.6. Other characteristics and donation activity

Our theoretical arguments are based on the idea that firms use corporate philanthropy as a form of insurance to mitigate the potential negative consequences of their additional emissions. In this section, we examine the possibility that the insurance-motive is driven by other characteristics that could potentially mediate the relation between close attainment designation status and donations to local nonprofits.

We first consider the average distance between the plants of a given firm and the closest air quality monitor in a given county. Since nonattainment designations are based on a three-year rolling average of pollution concentration, in any given county–year, local air quality managers are incentivized to focus their attention on curbing emissions in nearby areas surrounding monitors that record concentrations in violation of the standards (Auffhammer, Bento, & Lowe, 2009; Bento et al., 2015). Thus, all else equal, firms operating polluting plants located further away from monitors may donate more to local nonprofits because they have a higher incentive to pollute as they are less intensely regulated for their emissions. Consequently, plants' distance to the nearest monitor could mediate the relation between close attainment designation status and donations to local nonprofits.

We examine this possibility in columns (1) and (2) of Table 7, whereby we split the sample based on whether the average distance between the plants of a given firm and the closest monitor in a given county is above ("Far") or below ("Close") the median, respectively. Although the coefficient on *Comply* is larger in magnitude for the "Far" category, the difference between the subsamples is statistically insignificant. More importantly, the coefficients on *Comply* are positive and statistically significant in both subsamples, indicating that donations to local nonprofits do not appear to be driven by heterogeneity in ozone emissions caused by localized regulatory efforts.

Next, we study the average age of polluting plants that a firm operates in a given county. Becker and Henderson (2001) and Becker (2005) find that younger plants face greater regulatory costs of ozone emissions as they are targeted first by regulators, while older and more established plants experience less costs by escaping stringent regulations as they already have well-developed pollution abatement technology installed. Thus, all else equal, firms operating mostly older plants have the capacity to emit more, which could lead to them donating more to local nonprofits for insurance protection. As a result, plants' age could mediate the relation between close attainment designation status and donations to local nonprofits.

In columns (3) and (4) of Table 7, we split the sample based on whether the average age of the plants of a given firm in a given county is below ("Young") or above ("Old") the median, respectively.[21] The coefficient on *Comply* is larger in the Old group, but the difference is

[21]The first year a plant appears in the TRI database is not necessarily its first year of operation since a plant only reports to TRI if it meets the reporting requirements. Thus, to compute the age of a given plant,

statistically insignificant with that of the Young group. In particular, the coefficients are positive and statistically significant in both subsamples, implying that donation decisions are independent of the differences in regulatory treatment based on plants' age.

Lastly, we examine the possibility that the relation between close attainment designation status and donations to local nonprofits is mediated by local competition. Specifically, Choi, Levine, Park, and Xu (2022) find that the less stringent regulations associated with attainment designations reduce barriers to entry, which subsequently leads to an increase in county-level competition between polluting firms. Studies have shown that firms may respond to an increase in competition by donating more to local nonprofits to gain a competitive advantage (Choi, Park, & Xu, 2022; Ding, Levine, Lin, & Xie, 2020). Thus, an alternative explanation for our results may be that firms are donating more to local nonprofits in close attainment counties in response to an increase in local competition, rather than for insurance purposes.

Following Choi, Levine, et al. (2022), we measure competition at the county-level by computing the Herfindahl-Hirschman Index (HHI) based on the dollar amount of sales at the facility-level using data from NETS. In particular, we calculate the sum of the squared facility-level sales of all polluting plants that operate in a given county in a given year. A greater value indicates that the amount of sales across polluting plants in a given county is more concentrated (i.e., less competitive) and hence serves as a measure of competition at the county-level. Columns (5) and (6) of Table 7 report the results for the subsample where the county-level HHI is above ("High") and below ("Low") the median, respectively. Consistent with the findings in the literature, firms operating plants in more competitive counties (Low group) donate more to local nonprofits, although the difference is not statistically significant when compared to less competitive counties (High group). Importantly, the coefficient on *Comply* is positive and statistically significant in both subsamples, implying that close attainment designations lead to an increase in donations to local nonprofits regardless of local competition.

6.7. Robustness

We perform a number of robustness tests to ensure that our baseline results remain qualitatively unchanged. For brevity, we report a concise summary of these tests, while the corresponding tables can be found on the Internet Appendix.

we use the first year of operation of a given facility in the NETS database.

6.7.1. *Global polynomial regression*

In Internet Appendix Table IA.3, we conduct a similar RDD test using a different methodology to capture the discontinuity. Instead of relying only on the observations within the optimal bandwidths, we extend the regression discontinuity analysis with an estimation of a global polynomial series model by including polynomials of order two and three that are different on both sides of the threshold.[22] Although the economic magnitudes are slightly smaller when compared to those of Table 4, the coefficient on *Comply* remains positive and statistically significant, thus further confirming our baseline results.

6.7.2. *Alternative RDD specifications*

We consider a host of alternative RDD specifications. In Internet Appendix Table IA.4, we use the Epanechnikov kernel with the mean squared error optimal bandwidth following Calonico et al. (2014). We also report results across alternative bandwidths, including 50% of optimal bandwidth (narrower bandwidth) and 150% of optimal bandwidth (wider bandwidth). We additionally control for local quadratic and cubic polynomials in centered design values using the rectangular kernel function. The estimates on *Comply* are robust to these permutations to the regression model.

Since not all firms make donations to local nonprofits, Bellemare and Wichman (2020) argue that one should use the inverse hyperbolic sine transformed amount of donations as the dependent variable because this transformation not only resembles the natural log transformation but also retains zero values. Thus, in Internet Appendix Table IA.5, we use $\mathit{arcsinh(Donation)}_{t+1}$ as the dependent variable and replicate the analysis of Table 4. We find very little effect on the coefficient of interest.

We also residualize the dollar amount of donations by various fixed effects in Internet Appendix Table IA.6. Specifically, we first regress $\mathit{ln(Donation)}_{t+1}$ on firm (column (1)), firm and county (column (2)), firm, county, and year (column (3)), firm–year (column (4)), and firm–year and firm–county (column (5)) fixed effects. Then, we use the residuals of these regressions as the dependent variable in Equation (1). Again, our results remain unchanged.

In Internet Appendix Table IA.7, we replicate the analysis in Table 5, except rather than measuring ozone emissions in the year immediately preceding the designation, we calculate the rolling average of ozone emissions in the previous three years. Measuring historical ozone emissions in this manner accounts for cases where a plant may not emit any ozone in year

[22] The global polynomial approach, however, fails to take into consideration RDD's strong locality and weak externality, which are important features of the approach (Bakke & Whited, 2012).

$t-1$ but emits heavily in years $t-2$ and $t-3$. Our results remain largely consistent when using rolling average ozone emissions.

6.7.3. Two-year forward donation activity

A firm may not necessarily implement all of its donation activities in the year immediately following the close attainment designation, but rather continue to make donations in the future. To examine whether a firm extends its donation activities to local nonprofits beyond year $t+1$, we use the two-year forward amount of donations as the dependent variable in the baseline RDD specification. Internet Appendix Table IA.8 shows that firms operating polluting plants located in close attainment counties donate significantly more to nonprofits in the following two years relative to those in close nonattainment counties.

6.7.4. Placebo tests

We conduct two placebo tests on the baseline RDD specification to rule out confounding effects. In the first test, we use placebo NAAQS thresholds whereby the 1-Hour Ozone (1979) standard uses the 8-Hour Ozone (2008) standard's threshold, the 8-Hour Ozone (1997) standard uses the 1-Hour Ozone (1979) standard's threshold, the 8-Hour Ozone (2008) standard uses the 8-Hour Ozone (2015) standard's threshold, and the 8-Hour Ozone (2015) standard uses the 8-Hour Ozone (1997) standard's threshold. If our results are driven by close attainment designations for counties with DVs in a narrow window around the NAAQS threshold, then there should be no such results when using placebo thresholds. As expected, there are no significant effects of a close attainment designation status on firms' donations based on the placebo thresholds (columns (1) and (2) of Internet Appendix Table IA.9).

In the second test, we use a placebo sample of counties whereby we limit the sample to the counties where the firm does not operate any polluting plants. Since firms have no emissions in these counties, their donation decisions in these counties should not be impacted by the counties' close attainment designation status if such donations are indeed mainly driven by insurance-motives. Using this placebo sample, the coefficient on *Comply* becomes statistically insignificant (columns (3) and (4) of Internet Appendix Table IA.9), which is in line with our predictions.

7. Reallocation of donations

So far, our analysis has only utilized one source of variation in our data, namely donations to local nonprofits in the same county where the firm operates polluting plants. In this section, we provide additional evidence in support of the insurance-motives by using another distinct source of variation in the data. We focus on the dynamics of donations to local nonprofits in counties where the firm does not operate any plants ("connected non-operating counties") and relate such dynamics to changes in donations in close attainment counties where the firm operates plants ("close attainment operating counties"). The intuition behind this approach is straightforward. If we observe a decline in donations by firms to nonprofits located in connected non-operating counties that is coincident with an increase in donations in attainment counties where they operate plants then, we argue, the donations in the close attainment counties would plausibly have been motivated by insurance purposes, since firms are incentivized to reallocate donations to areas where they pollute the most and hence maximize the insurance value of such donations.

7.1. Empirical strategy

We highlight our empirical design in Figure 5, which consists of three key steps. The first step encompasses the analysis presented so far in the previous Section 6, whereby we established that close attainment designation status leads to an increase in donations to local nonprofits. In the second step, we expand the set of counties to include those connected counties where firms have historically made donations to but do not operate plants there. In the third step, we relate the changes in donations in both sets of counties and show that in order to satisfy the increase in donations in close attainment operating counties, firms reallocate donations away from connected non-operating counties and toward close attainment operating counties.

To study the reallocation of donations, we construct a panel data set at the firm–county–year level from 1999 to 2018. For each firm–year, we include all of the counties in which that firm donated to nonprofits in the prior calendar year. These counties are assumed to contain the relevant nonprofits for the firms' charitable activities. Once a firm–county enters our data set, we keep it going forward, even if during some years that firm made no donations to nonprofits in that county. We then flag each county in the year in which that county has a DV below the NAAQS threshold and the firm operates plants there (i.e., close attainment operating counties), and leave that flag on during the following two years.[23] Lastly, we drop these flagged county–years from our sample because our aim is to study how close attainment designation status affects donations in connected non-operating counties.

To measure the incremental donations made by each firm in the flagged close attainment

[23]We use two years because of our earlier results in Section 6.7.3 showing that close attainment designation status is associated with differential effects in donations up to two years following the designation.

county–years, we construct the following variable at the firm–year level:

$$\Delta \textit{Comply donation}_{i,t} = \frac{\Delta \textit{Donation in close attainment operating counties}_{i,t}/N_{i,t}}{\sum_c \textit{Donation}_{i,c,t}} \tag{3}$$

where i indexes firm, c indexes county, and t indexes year. The variable Δ*Donation in close attainment operating counties*$_{i,t}$ equals to the change in the dollar value of donations between year t and year $t-1$ for firm i, summed across all operating counties with DVs that are in compliance with the NAAQS threshold in year t. However, since a given firm donates to nonprofits across many different connected non-operating counties, we parcel out the additional increase in donations in close attainment counties equally across the number of connected non-operating counties ($N_{i,t}$). Finally, we normalize by each firm's total donations summed across all counties (both operating and non-operating) so that Δ*Comply donation*$_{i,t}$ is bounded between -1 and 1.

7.2. Estimation and results

Using the constructed data set, we estimate the effect of each firm's additional donations in close attainment operating counties on its donations to nonprofits in connected non-operating counties, as follows:

$$\Delta \textit{Connected donation}_{i,c,t} = \beta_0 + \sum_{k=1}^{2} \beta_k \Delta \textit{Comply donation}_{i,t-k} + \beta_3 X_t + \text{F.E.} + \varepsilon_{i,c,t} \tag{4}$$

for firm i, county c, and year t. The dependent variable is measured at the firm–county–year level and is equal to the change in the total dollar value of donations between year t and year $t-1$ in connected non-operating counties, normalized by the total amount of firm donations in year t across all counties. We control for a variety of firm-level characteristics, as represented by X_t. In the baseline specification, we use firm, county, and year fixed effects. In our most stringent specification, we include firm $\times$ county fixed effects to control for time-invariant effects within a firm–county pair. For example, a firm may prefer to donate to nonprofits located in specific areas where many of its employees are situated. If those areas happen to coincide with the areas where the firm operates its plants, then this could bias the estimate of β_k. We also include county $\times$ year fixed effects to sweep out potentially confounding factors affecting all firms in a given county–year (such as business cycle effects, trends, etc). The coefficients of interest are the two lags on the Δ*Comply donation* variable, which captures the extent to which firms reallocate donations from connected non-operating counties to close attainment operating counties.

We present the estimation results of Equation (4) in Table 8. The specifications in each column are based on different samples of close attainment counties used to define the Δ*Comply donation* variable. For example, columns (1) and (2) use the full sample of attainment counties, whereas columns (3) and (4) restrict the sample of attainment counties to a narrow window around the NAAQS threshold using the mean squared error optimal bandwidth following Calonico et al. (2014). The remaining columns use 50% and 150% of the optimal bandwidth. Across all specifications, the coefficients on the two lags of Δ*Comply donation* are all negative and statistically significant, suggesting that firms reallocate donations away from connected non-operating counties and toward close attainment operating counties. These results are consistent with the interpretation that firms are maximizing the insurance-value of donations by reallocating them to the areas where they pollute the most. Furthermore, the magnitude of the coefficients decreases monotonically as we move from the first lag to the second lag, indicating that the majority of the reallocation occurs in the first year following a close attainment designation, but gradually becomes weaker over time.

The regression in Equation (4) is based on dollar-changes in normalized donations divided equally across connected non-operating counties. Thus, the sum of the coefficients on the lags of Δ*Comply donation* provides a straightforward economic interpretation on the total effect per dollar of increased donation in close attainment operating counties on the changes in donations in connected non-operating counties. Take the coefficient estimates in column (4) of Table 8 as an example. The sum of the two lags is -0.294 and is statistically significant with a F-statistic of 8.69. This result shows that the effect of donation reallocation is economically sizable as it implies that donations fall by roughly 29 cents in connected non-operating counties per dollar of additional donations stimulated by close attainment designations. We obtain qualitatively similar results when using the coefficient estimates in other columns.

8. Mechanisms

In this section, we investigate several plausible mechanisms that could propagate the relation between regulation-induced emissions and donations to local nonprofits. We first examine the role of local media as a channel through which firms use to improve their reputational capital. Then, we examine the impact of a firm's reputational risk exposure to news-related CSR incidents and history of regulatory noncompliance on its donation activities.

8.1. Local newspaper closures

We follow Heese et al. (2022) and study the effect of local newspaper closures on donations to local nonprofits in close attainment counties. We collect data on active local newspapers and their closures and mergers from the UNC Center for Innovation and Sustainability in Local Media (CISLM). This dataset provides snapshots of the name, the owner, and the physical location of all local newspapers in the United States in 2004, 2014, 2016, and 2020. In addition, the dataset contains a list of newspapers that have closed between 2004 and 2019 and identifies whether each closure is due to being merged by another newspaper.[24] Based on the snapshots, we construct an annual time series of the active local newspapers data by forward-filling observations between the report years. We assume that the level of the active local newspapers remains unchanged from the current data collection year to the next data collection year. We only focus on the local newspaper closures and not mergers because mergers do not necessarily reduce local-news availability (Heese et al., 2022). Then, we aggregate the data at the county-level.

The sample of counties that we examine consists of those that have at least one active local newspaper. We identify all of the county–years where there is a local newspaper closure and define $\mathit{Closure}_{c,t-1}$ to be a dummy variable equal to one if a local newspaper closed in county c in the past three years until year $t-1$, and zero otherwise.[25] The sample period is from 2004 to 2018 because this is the period where we have available data on local newspaper closures. We estimate an augmented version of Equation (1) by fully interacting *Closure* with *Comply*:

$$\begin{aligned} \mathit{ln(Donation)}_{i,c,t+1} &= \alpha + \beta_1 \mathit{Comply}_{c,t} + \beta_2 \mathit{Closure}_{c,t-1} + \beta_3 \mathit{Comply}_{c,t} \\ &\times \mathit{Closure}_{c,t-1} + \phi f(R_{c,t}) + \varepsilon_{i,c,t+1} \end{aligned} \tag{5}$$

for firm i, county c, and year t. The coefficient of interest is β_3, which measures the changes in donations to local nonprofits in close attainment counties with a local newspaper closure in the past three years relative to other close attainment counties without any closures.

Table 9 reports the results of estimating Equation (5) using the mean squared error optimal bandwidth following Calonico et al. (2014). Across all specifications, the coefficient on the

[24] For additional information about the database, please refer to `https://www.usnewsdeserts.com`. The list of newspaper closures and mergers from 2004 to 2019 can be found at `https://newspaperownership.com/additional-material/closed-merged-newspapers-map`.

[25] We look back three years because Heese et al. (2022) show that the impact of local newspaper closures on firm behavior lasts up to three years.

interaction term *Comply* × *Closure* is negative and statistically significant. In terms of economic magnitude, the results indicate that the closure of a newspaper in a close attainment county leads to a decrease of almost 80% in donations to local nonprofits (based on column (2)). On the other hand, the coefficient on *Comply* remains positive and statistically significant across all columns, with the coefficient estimate in column (2) implying that close attainment counties without a local newspaper closure leads to an increase in donations to local nonprofits by roughly 57%. Overall, the results indicate that polluting firms respond to local newspaper closures by decreasing donations to local nonprofits, suggesting that local media coverage is an important avenue behind the insurance-motives of philanthropy.

8.2. Reputational risk exposure

In this section, we directly measure the impact of a firm's reputational risk exposure on its donations to local nonprofits in close attainment counties. Specifically, we focus on firms' reputational risk exposure to salient news of their CSR-related incidents using data from RepRisk, which is a data provider that screens over 80,000 media sources for CSR incidents.[26] This database is suitable for our analysis because it is based on an outcome-driven approach that focuses on a firm's adverse CSR events that are actually reported by the media news. Thus, using a news-based measure of CSR incidents allows for an objective assessment of a firm's reputational risk exposure (Houston & Shan, 2022; Li & Wu, 2020).[27]

We measure a firm's reputational risk exposure by using RepRisk's Reputational Risk Index (RRI). The RRI is a score that ranges from 0 to 100, where a higher value denotes a higher CSR incident rate. The RRI of a firm increases whenever it experiences a new CSR incident. How much the index increases depends on the severity and novelty of the incident as well as on the reach and intensity of the news about the incident.[28] We use RepRisk's "Peak RRI" score, which is the two-year maximum value of the RRI capturing the long-term CSR incident history of a firm. The sample period begins from 2007, the first year that RepRisk provides data, until 2018. We estimate Equation (1) by fully interacting a firm's Peak RRI score with *Comply* as follows:

$$\begin{aligned} &\mathit{ln(Donation)}_{i,c,t+1} = \alpha + \beta_1 \mathit{Comply}_{c,t} + \beta_2 \mathit{Peak\ RRI}_{i,t-1} + \beta_3 \mathit{Comply}_{c,t} \\ &\times \mathit{Peak\ RRI}_{i,t-1} + \phi f(R_{c,t}) + \varepsilon_{i,c,t+1} \end{aligned} \tag{6}$$

[26]RepRisk is not a rating agency as its main business is about the archival of news about negative CSR events.

[27]In contrast, many other databases primarily assign ratings based on whether the firm "claims" to enact certain policies that are more discretionary and subject to green-washing bias (Yang, 2021).

[28]For more information, see `https://www.reprisk.com/news-research/resources/methodology`.

for firm i, county c, and year t. *Peak* $RRI_{i,t-1}$ is a given firm's two-year maximum value of the RRI measured in year $t-1$. The coefficient of interest is β_3, which measures the difference in donations to local nonprofits in close attainment counties for firms with a high reputational risk exposure relative to other firms with a lower exposure.

We present the results in Table 10 using the mean squared error optimal bandwidth following Calonico et al. (2014). Across all regression specifications, the coefficient on the interaction term *Comply* $\times$ *Peak RRI* is positive and statistically significant, indicating that firms with a historically high reputational risk exposure to CSR incident news donate more to local nonprofits in close attainment counties. The economic magnitude is sizable. For example, the coefficient estimate in column (2) implies that a one standard deviation increase in a firm's Peak RRI leads to an increase of roughly 75% in donations to local nonprofits. It is also worthwhile to note that although the coefficient estimates on *Comply* in Table 10 are positive, they are all statistically insignificant. This result is consistent with the interpretation that the insurance value of donations is lower for firms with no reputational risk exposure, implying that such firms have fewer incentives to significantly increase their donations to local nonprofits in close attainment counties. To ensure that our results in this section are robust, in Internet Appendix Table IA.10, we replicate the analysis in Table 10 but use a firm's "Current RRI" to measure a firm's short-term exposure to reputational risks. Our results remain qualitatively unchanged.

8.3. Past regulatory noncompliance

To provide further evidence of the insurance-motives of philanthropy, we study a firm's history of publicized regulatory noncompliance based on regulatory incidents. Specifically, we examine a firm's facility-level high priority violations (HPV), stack tests, and enforcement cases, all of which are made available to the public by the EPA through their Enforcement and Compliance History Online (ECHO) system.

The first type of regulatory noncompliance that we examine is a facility's HPV. The EPA can label a facility with particularly serious or repeated violations as a HPV.[29] Once a facility enters HPV status, it triggers a period of intense oversight by the EPA that could lead to higher fines and additional reporting requirements, which are very costly for the firm (Blundell, 2020; Blundell et al., 2020). Next, we consider stack tests, which are plant-level evaluation tests conducted for the purposes of determining and demonstrating compliance with CAA

[29]HPVs cover a broad range of issues including excess emissions, failure to install plant modifications, and violating an operating parameter, among others.

regulations.[30] Failing stack tests is costly because it could lead to firms being labeled as a HPV (Choi, Levine, et al., 2022). Lastly, we examine enforcement cases, which consists of judicial and administrative cases brought forth by the EPA against facilities that violate various environmental statutes. These enforcement cases are particularly costly for firms because they could lead to legal penalties (Heitz, Wang, & Wang, 2021; Shive & Forster, 2020; Xu & Kim, 2022).

To capture a firm's history of regulatory noncompliance, we define *ln(HPV)*, *ln(Stack)*, and *ln(Case)* as the natural logarithm of one plus the number of HPVs, stack tests, and enforcement cases, respectively, across all facilities in a given county of a given firm in the past three years. We look back three years because ECHO tracks facility-level compliance status using the last three years of available data. Then, we estimate Equation (1) by fully interacting the aforementioned measures with *Comply* as follows:

$$\begin{aligned} &\mathit{ln(Donation)}_{i,c,t+1} = \alpha + \beta_1 \mathit{Comply}_{c,t} + \beta_2 \mathit{Noncompliance}_{i,c,t-1} + \beta_3 \mathit{Comply}_{c,t} \\ &\times \mathit{Noncompliance}_{i,c,t-1} + \phi f(R_{c,t}) + \varepsilon_{i,c,t+1} \end{aligned} \tag{7}$$

for firm i, county c, and year t. $\mathit{Noncompliance}_{i,c,t-1}$ is one of the three regulatory noncompliance variables defined above. The coefficient of interest is β_3, which measures the difference in donations to local nonprofits in close attainment counties for firms with a history of a high frequency of regulatory noncompliance relative to other firms with less noncompliance.

Table 11 presents the results. Across all specifications, we find that the coefficients on *Comply* and the *Comply* × *Noncompliance* are both positive and statistically significant. For example, in column (2) the coefficient on *Comply* implies that firms operating facilities without any regulatory noncompliance in the past three years in close attainment counties donate 34.58% more to local nonprofits. However, given a one standard deviation increase in the (log) number of HPVs, firms donate an extra 35.28% more to local nonprofits. Similar results are obtained in the other columns when using the number of stack tests and enforcement cases. Overall, the findings suggest that firms with a history of regulatory noncompliance donate more to local nonprofits, presumably to insure against future regulatory compliance costs associated with additional emissions.

[30] These tests involve evaluating a facility based on its emissions, condition of control equipment, and results of monitoring data.

9. Social welfare

Thus far, we have focused on the firm's perspective and shown that firms that pollute more locally also donate more to local nonprofits as a form of reputation insurance against the potential costs of increased emissions. In this section, we expand our focus and examine the social welfare implications of such donations and pollution. Specifically, we ask the question "is more damage being done through pollution than social good through donations?" To answer this, we consider only the counties where TRI plants operate and compare the additional damages ("marginal damages") with the additional donations ("marginal donations") associated with a one-ton increase in ozone emissions from TRI plants. This exercise is economically important because if marginal damages are greater than marginal donations, then firms are paying too low of a price for the insurance value they receive for their charitable activities, implying that corporate philanthropy may benefit firms at the cost of social welfare. In contrast, if marginal damages are less than marginal donations, then firms are overpaying for the coverage they receive from corporate philanthropy, with the insurance benefits when negative events happen being offset by the cost of philanthropy when they do not.

9.1. Calculating marginal donations and marginal damages of pollution

We calculate marginal donations by using the RDD estimates obtained from Tables 3 and 4 to compute the change in the average donations in a given county by all TRI firms operating in that county divided by the change in average total ozone emissions by those TRI firms. To illustrate, consider the RDD estimate of 0.413 in column (2), panel A of Table 3. The average ozone air emissions at the firm–county–year level in the sample of counties within the optimal bandwidth is 27,162.85 pounds (unreported). Thus, moving from a close nonattaiment to close attainment county increases ozone emissions by roughly 13,889.59 pounds (= 6.94 tons) on average. Similarly, combining the corresponding RDD estimate of 0.382 in column (2) of Table 4 and the average donation amount of $15,107.27 (unreported) in the sample of counties within the optimal bandwidth implies that donations increase by $7,028.09 on average, given a close attainment designation. Taken together, these estimates result in a marginal donation of $7,028.09/6.94 = \$1,012$ per ton of yearly emissions in the sample of counties within the optimal bandwidth.

We compute marginal damages using the AP3 model, which is a leading "integrated assessment" model that has been widely used in influential economics and policy research (Holland, Mansur, Muller, & Yates, 2016, 2020; Muller & Mendelsohn, 2009; Muller, Mendelsohn, &

Nordhaus, 2011).[31] The AP3 model includes four main components. First, it uses ozone emissions from all sources in every county across the United States. Second, it uses an air quality model translating emissions from each source county into ambient air quality in all counties. Third, it uses published elasticities linking air quality to outcomes such as mortality. Fourth, it monetizes the value of these outcomes using an estimate of the value of a statistical life (VSL). The marginal damages computed using the AP3 model can be interpreted as the additional dollar value of damages associated with a one-ton increase in ozone emissions from TRI facilities in a given county. More details on the calibration and estimation of the AP3 model can be found in Appendix B.

A few caveats are in order when comparing marginal donations and marginal damages in our setting. First, our measure of marginal donations is only an estimate of the true social benefits of corporate philanthropy, which may be greater or lower than the raw dollar value of donations. This is because the social benefits of donations depend on the social impact of the nonprofit that receives the donation. For example, a nonprofit that allocates $10,000 of donated funds towards the successful development of a piece of green technology may create social benefits that well exceeds the $10,000 of donations it received. Second, estimates of the marginal damages of ozone emissions may understate true marginal willingness to pay, since people may value clean air for reasons not captured in the mortality-damage function approach (e.g., pure amenity value) that AP3 follows. In practice, hedonic models have been economists' primary approach to estimating marginal willingness to pay for clean air. However, comparing hedonic estimates with those from integrated assessment models' damage functions does not suggest the latter substantially understates marginal willingness to pay; if anything, the hedonic estimates are smaller than the damage function estimates (Bajari, Fruehwirth, Kim, & Timmins, 2012; Chay & Greenstone, 2005; Smith & Huang, 1995). Nonetheless, our analysis is still an important exercise in providing a glimpse into the costs and benefits of regulation-induced pollution from society's perspective.

9.2. Comparison results

Table 12 compares the mean marginal damages with the mean marginal donations across all counties where TRI plants operate. The differences across each column is in the sample of counties used to estimate the marginal donations and marginal damages. Column (1) uses the full sample of counties, whereas column (2) uses the sample of counties located in the narrow window around the NAAQS threshold by computing the mean squared error optimal

[31]We thank Nick Muller for generously providing the raw AP3 code.

bandwidth following Calonico et al. (2014). In columns (3) and (4), we report results across alternative bandwidths, including 50% of optimal bandwidth (narrower bandwidth) and 150% of optimal bandwidth (wider bandwidth). The sample period in all specifications is from 2002 to 2017 because these are the years where data on marginal damages are available. We consider two types of marginal damages, namely within-county marginal damages refer to the damages restricted to the same county as where the emissions are produced, whereas all counties marginal damages refer to the damages caused by the emissions produced in a given county that spread across all counties.

Comparing the estimate of marginal donations in column (2) of Table 12 with the within-county marginal damages using the baseline AP3 model parameters shows that marginal damages are, on average, 3.39 times larger than marginal donations in a given county. Economically, these estimates imply that on average, a firm donates $1,011.99 to local nonprofits per ton of additional emissions given a close attainment designation. At the same time, the firm creates $3,430.59 per ton in welfare damages within the same county. These results suggest that firms are underpaying for the insurance value of philanthropy at the cost of social welfare. The gap between marginal damages and marginal donations increases considerably when we consider damages across all contiguous counties, as mean marginal damages are now 10.45 times larger than mean marginal donations.

We report several sensitivity analyses based on different models used to compute marginal damages. The baseline estimates use the EPA's preferred VSL of $8.6 million (2015 dollars) (United States Environmental Protection Agency, 2010). We use one alternative estimate of $4.5 million from the Organization for Economic Cooperation and Development (OECD, 2012). We also use alternative parameters for the pollution concentration mortality response function from the 5th and 95th percentile, respectively, of Krewski et al.'s (2009) study. These results are also presented in Table 12 and reaffirm the baseline results that marginal damages exceed marginal donations.

Finally, we plot the yearly mean within-county marginal damages and yearly mean marginal donations based on the sample of counties within the optimal bandwidth in Internet Appendix Figure IA.1. Our objective is to see whether there are any particular years where marginal damages do not exceed marginal donations and to observe the time trends between the two measures. The estimates of marginal damages vary year-by-year due to changes in population density, differences in mortality rates, and differences in the baseline levels of emissions. Likewise, estimates of marginal donations also vary year-by-year because of changes in the yearly average donations and emissions in each county. Table 12 essentially shows the mean value of this plot during the period 2002 to 2017, while the figure shows the underlying year-by-year averages, for all years. A glance at the two time series in Internet Appendix Figure IA.1 reveals that marginal damages are much higher than marginal donations in every year, although the gap appears to be smaller in more recent years. In summary, the results in this section suggest that polluting firms benefit from the insurance protection of corporate philanthropy at the cost of social welfare.

10. Conclusion

Despite the fact that many polluting companies actively engage in corporate philanthropy, relatively little is known about their motivations for participating in philanthropy. Using a sample of U.S. firms that have active corporate foundations and operate polluting plants over the period 1999–2018, we examine the role of charitable giving as a form of insurance protection.

Our identification strategy relies on a county's close attainment and nonattainment designation status based on its DVs as a source of locally exogenous variation in firm pollution. We find strong evidence for the insurance-motives of corporate philanthropy, with firms operating polluting plants in close attainment counties emitting more but also subsequently donating more to local nonprofits relative to those operating in close nonattainment counties. Firms appear to maximize the insurance value of donations by reallocating donations to the areas where they pollute the most. Furthermore, we find that a firm's local media coverage, reputational risk exposure to news-based CSR incidents, and history of regulatory noncompliance are potential mechanisms that could propagate the relation between regulation-induced emissions and donations to local nonprofits. From society's perspective, firms underpay for the insurance value of donations, suggesting that corporate philanthropy may benefit firms at the cost of social welfare.

Collectively, our findings suggest that corporate philanthropy could be a particularly nuanced form of business strategy. Given the special merits associated with charitable foundations such as tax-exempt status, corporate giving can potentially serve as a less costly insurance mechanism compared to more traditional practices.

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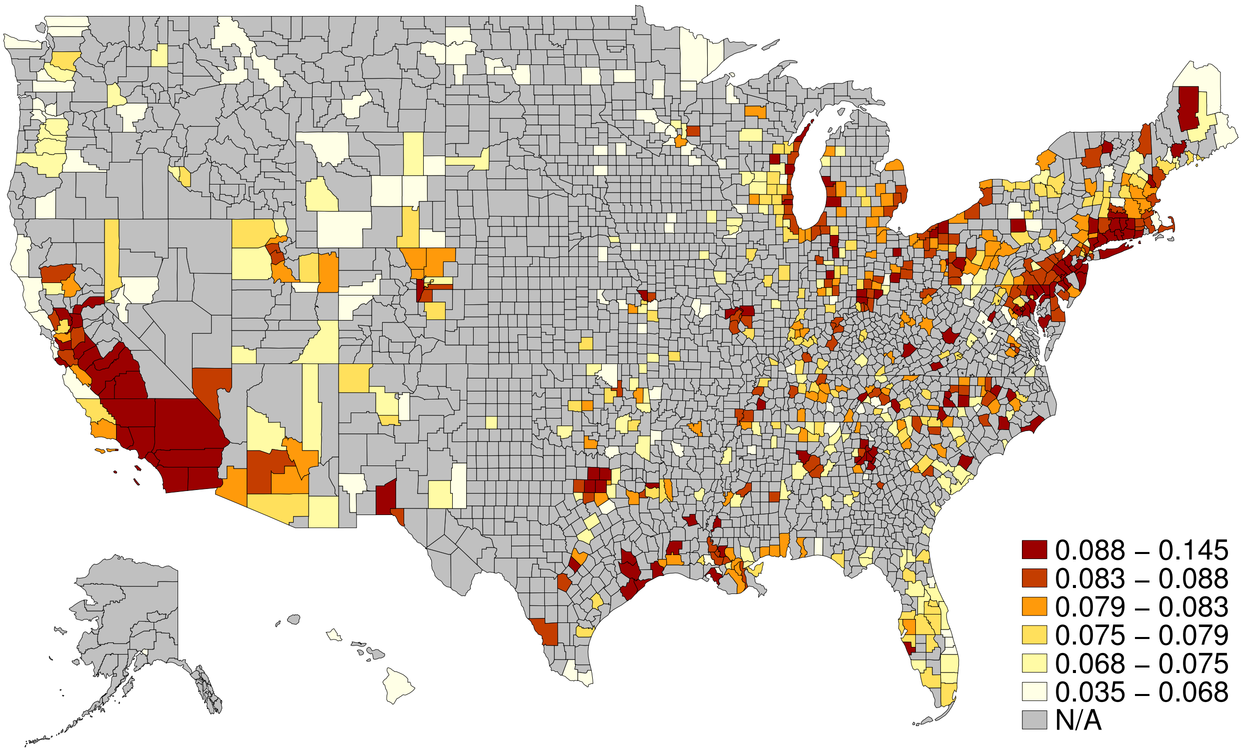
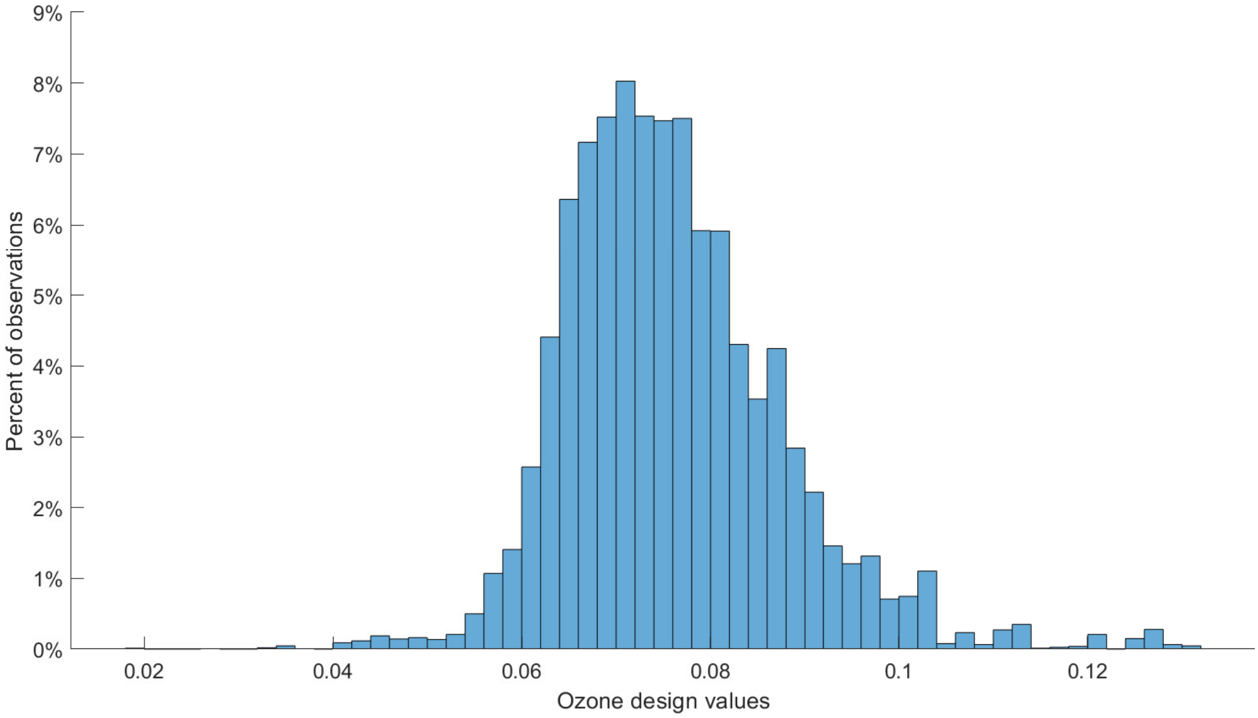
Figure 1
County-level design values.



This figure presents the average DVs (in parts per million) from years 1999–2018 in the counties where TRI plants operate and where DV data is available. Counties with higher DVs (indicated by darker shades) correspond to those with greater concentrations of ozone pollution and are more likely to be designated nonattainment with respect to the ozone NAAQS.

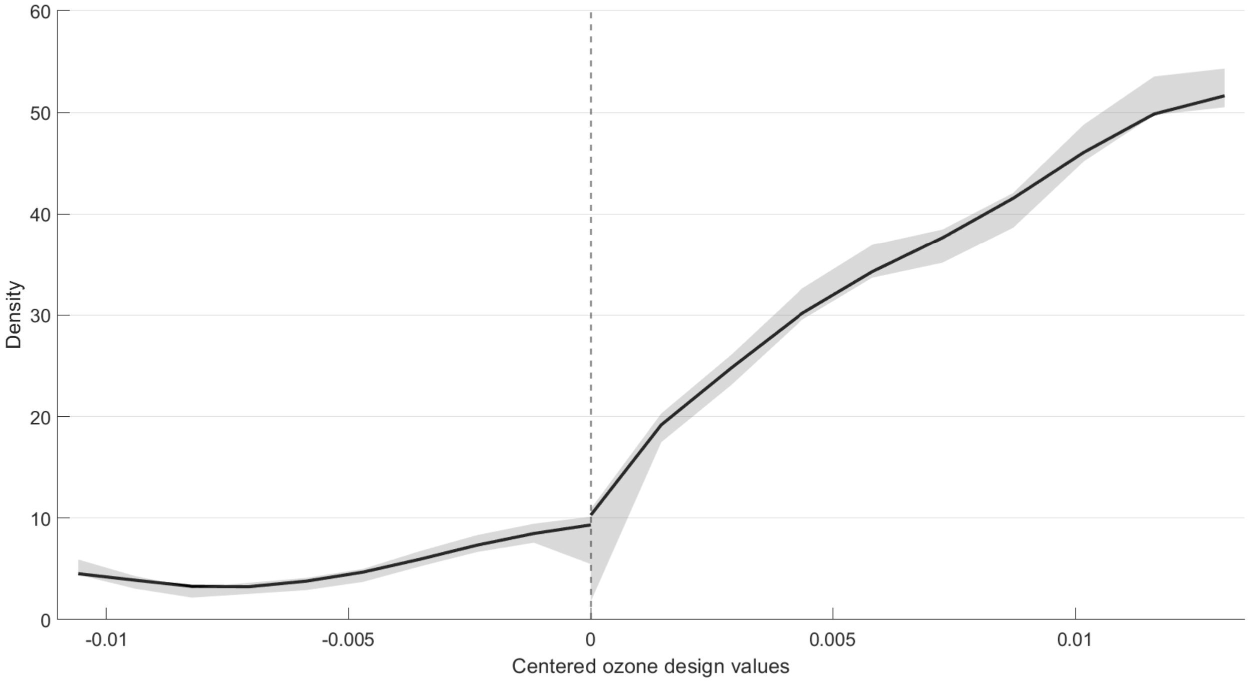
Figure 2
Distribution of county-level design values.



This figure presents the histogram of the county-level DVs (in parts per million) from years 1999–2018 in the counties where TRI plants operate and where DV data is available. The horizontal axis indicates the DV in 0.2% intervals. The vertical axis indicates the percentage of counties in our sample per DV interval.

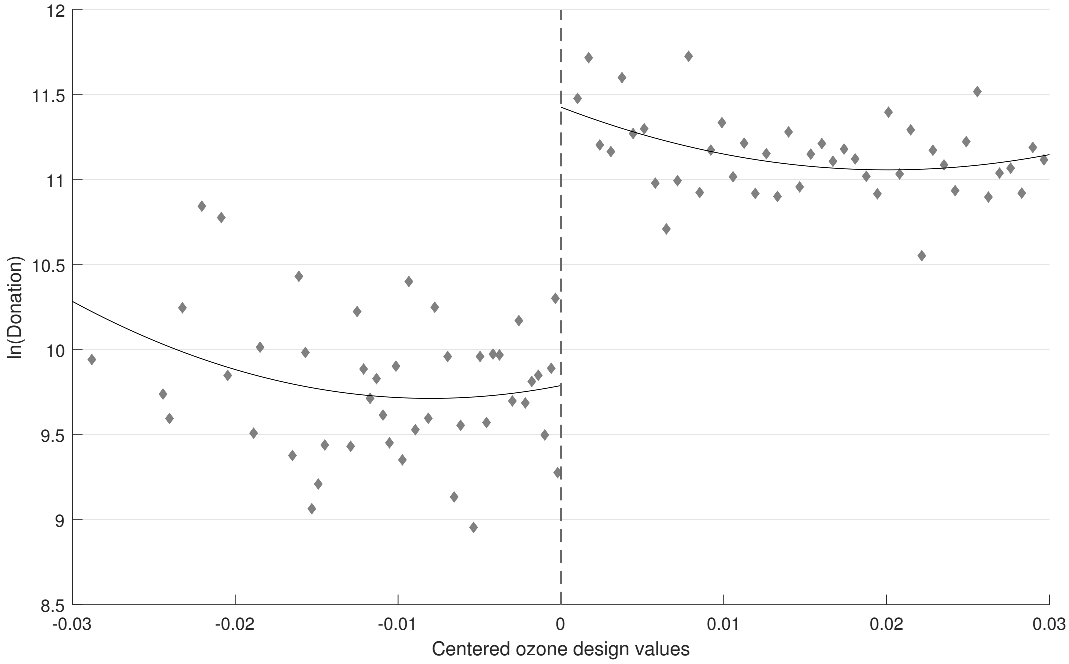
Figure 3

Density break test of the number of counties around NAAQS thresholds.



This figure presents the density of observations by the distance to the ozone NAAQS threshold. The unit of observation underlying the estimation of this density is at the county–year level, considering only the counties where TRI plants operate and where DV data is available from years 1999–2018. The horizontal axis shows the centered DVs around zero by subtracting them from the NAAQS threshold. The dashed vertical line at zero represents the NAAQS threshold for ozone attainment status. Observations on the right (left) of the line indicate that the county is in compliance with (violation of) the NAAQS threshold. The solid black lines represent the local density on either side of the NAAQS threshold and the shaded gray area corresponds to the 95% confidence interval bounds, calculated using the plug-in estimator proposed by Cattaneo et al. (2020). We fail to reject the null hypothesis that there is no break in density around the threshold, with a p-value of 0.450.

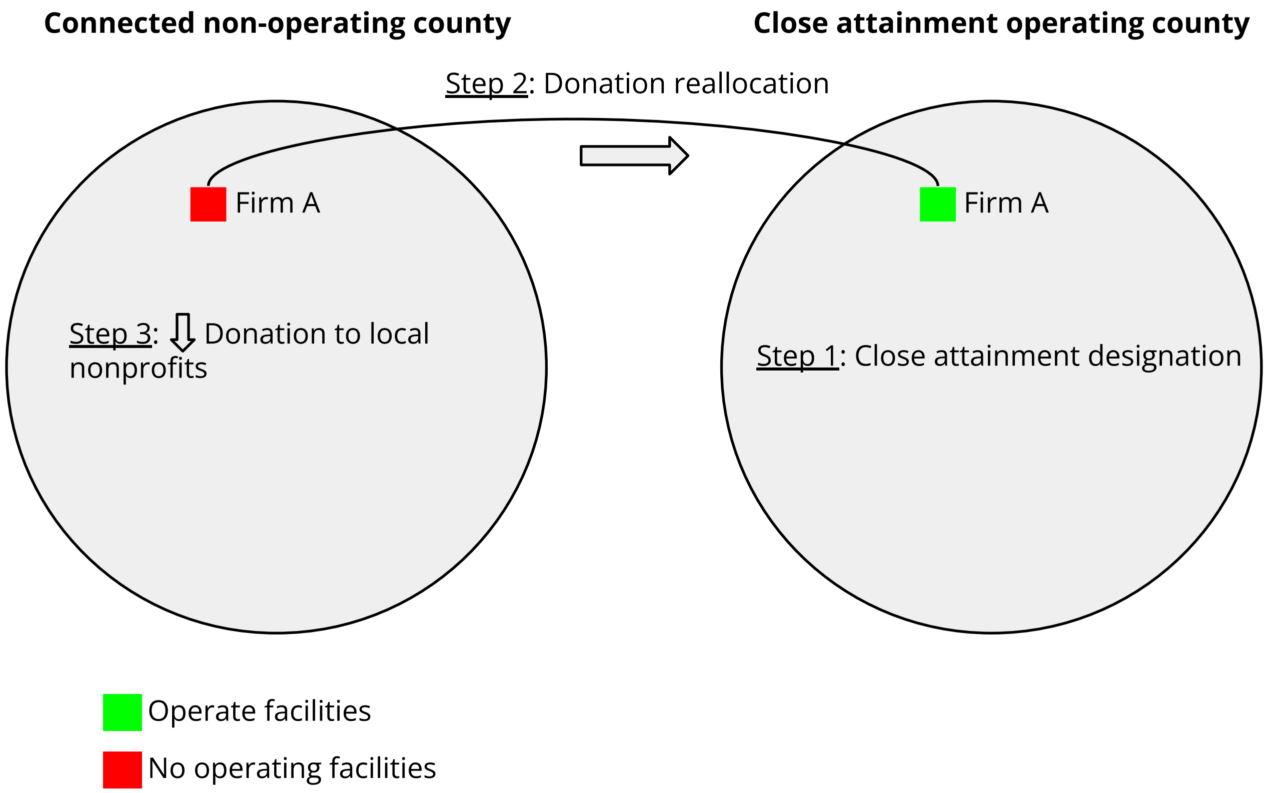
Figure 4
Donation activity around ozone NAAQS thresholds.



This figure presents the regression discontinuity relating centered DVs to the amount of donations at the firm–county level from years 1999–2018. The variable on the vertical axis is $ln(Donation)_{t+1}$, defined as the natural logarithm of one plus the total dollar amount of donations of a given firm to nonprofits in a given county in year $t+1$. The horizontal axis shows the centered DVs around zero by subtracting DVs from the NAAQS threshold. The dashed vertical line at zero represents the NAAQS threshold for ozone attainment status. Observations on the right (left) of the line indicate that the county is in compliance with (violation of) the NAAQS threshold. Each dot in the figure represents the average of non-zero values of $ln(Donation)_{t+1}$ using integrated mean squared error optimal bins following Calonico et al. (2014). The solid lines on either side of the NAAQS threshold is based on two separate regressions of $ln(Donation)_{t+1}$ on local quadratic polynomials in centered DVs using the rectangular kernel and mean squared error optimal bandwidth following Calonico et al. (2014).

Figure 5

Empirical design for the reallocation of donations.



This figure illustrates the three key steps behind the empirical strategy examining the reallocation of donations. First, firms that operate polluting facilities in close attainment counties increase their donations to local nonprofits. Second, firms reallocate donations away from connected counties where they historically have made donations but do not operate facilities and toward close attainment counties. Third, the reallocation of donations leads to a decrease in the donations to local nonprofits in connected counties.

Table 1
Summary statistics.

Variables	Mean	Median	Standard deviation	Observations
Donation ($ ’000s)	14.007	0.000	99.043	54,524
Health ($ ’000s)	3.515	0.000	119.106	54,524
Social & Human Services ($ ’000s)	2.113	0.000	13.715	54,524
Community Development ($ ’000s)	3.398	0.000	112.385	54,524
Environment ($ ’000s)	1.162	0.000	30.579	54,524
Education ($ ’000s)	1.473	0.000	10.447	54,524
Art ($ ’000s)	0.250	0.000	2.433	54,524
Religion ($ ’000s)	0.599	0.000	11.637	54,524
Sports ($ ’000s)	0.178	0.000	5.305	54,524
Miscellaneous ($ ’000s)	0.448	0.000	3.675	54,524
Comply donation ($ ’000s)	89.134	0.000	450.772	10,606
Connected donation ($ ’000s)	13.186	0.000	53.014	130,751
Ozone (ton)	14.990	0.000	90.405	54,524
Comply	0.705	1.000	0.456	54,524
ln(Size)	8.335	8.301	2.132	51,080
ln(BM)	0.516	0.522	0.135	51,075
ROA	0.032	0.032	0.023	50,223
Leverage	0.278	0.224	0.204	50,841
Sales growth	0.094	0.058	1.009	51,929
KZ	1.130	1.023	6.122	49,891
Cash	0.080	0.055	0.089	53,077
Momentum	1.138	1.103	0.441	49,848
Stock returns	0.139	0.104	0.459	49,269
z-score	0.869	0.937	0.845	48,433
Core chemical	0.379	0.000	0.485	54,524
Permit	0.506	1.000	0.500	54,524
Source reduction	0.069	0.000	0.254	54,524
Production ratio	0.910	0.984	0.394	28,683
Monitor distance (km)	11.206	9.004	8.817	54,514
Age (years)	23.748	19.000	20.775	54,524
Concentration	0.425	0.358	0.259	53,711
Closure	0.019	0.000	0.137	38,361
ln(HPV)	0.065	0.000	0.271	54,524
ln(Stack)	0.271	0.000	0.742	54,524
ln(Case)	0.044	0.000	0.188	54,524
Peak RRI	22.071	25.250	20.057	32,262
Current RRI	13.115	9.917	14.528	32,262

This table reports the summary statistics for the variables used in this study. The sample consists of 1,079 unique firms with corporate foundations that operate polluting plants in 857 unique counties, resulting in 54,524 firm–county–year observations over the period 1999–2018. Variable definitions are presented in Table A.1 in Appendix A.

Table 2
Preexisting differences in firm characteristics.

	Year ($t-1$)		Δ from year ($t-2$) to ($t-1$)	
	(1)	(2)	(3)	(4)
ln(Size)	0.203**	0.064	0.022*	0.005
	(0.082)	(0.194)	(0.012)	(0.033)
ln(BM)	0.006	-0.001	0.003	-0.016
	(0.005)	(0.011)	(0.002)	(0.012)
ROA	-0.002	-0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Leverage	0.005	-0.017	0.004	0.005
	(0.007)	(0.018)	(0.002)	(0.006)
Sales growth	-0.022	-0.023	0.001	-0.001
	(0.018)	(0.060)	(0.007)	(0.035)
KZ	0.041	-0.087	-0.011	-0.029
	(0.043)	(0.093)	(0.017)	(0.078)
Cash	0.013***	0.003	-0.001**	-0.001
	(0.003)	(0.007)	(0.001)	(0.003)
Momentum	0.029**	-0.002	0.023**	-0.022
	(0.012)	(0.034)	(0.010)	(0.037)
Stock returns	-0.028**	-0.005	0.013	0.007
	(0.011)	(0.040)	(0.009)	(0.038)
z-score	-0.065***	-0.003	0.005	0.001
	(0.024)	(0.051)	(0.007)	(0.024)
Core chemical	-0.008	0.042	0.003	0.012
	(0.016)	(0.032)	(0.003)	(0.009)
Permit	0.109**	-0.069	0.003	-0.008
	(0.049)	(0.046)	(0.004)	(0.008)
Source reduction	-0.019***	-0.018	0.006**	-0.001
	(0.007)	(0.015)	(0.003)	(0.006)
Production ratio	0.007	0.009	-0.005	-0.026
	(0.009)	(0.033)	(0.007)	(0.022)
Sample:	Full	Opt.	Full	Opt.

This table examines the differences in observable firm characteristics between firms that operate polluting plants in counties that are in compliance with NAAQS thresholds and those operating in counties that are in violation. In columns (1) and (2), these characteristics are measured in the year preceding the designation ($t-1$). Columns (3) and (4) consider the change in these characteristics between years $t-2$ and $t-1$. Columns (1) and (3) report the differences using the full sample of firms, whereas columns (2) and (4) report the differences using a narrow window around the NAAQS threshold by computing the mean squared error optimal bandwidth following Calonico et al. (2014). For all specifications, standard errors are clustered by county, bias-corrected following Calonico et al. (2014), and reported in the parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table 3
Effect of close attainment designation status on ozone emissions and attainment probability.

Panel A: Ozone emissions					
Dep. variable: *ln(Ozone)*$_t$	(1)	(2)	(3)	(4)	(5)
$Comply_{c,t}$	0.315**	0.413**	0.394**	0.318***	0.318**
	(2.20)	(2.17)	(2.24)	(2.87)	(2.23)
Kernel	Rec.	Rec.	Rec.	Rec.	Tri.
Bandwidth type	Opt.	Opt.	50% Opt.	150% Opt.	Opt.
Bandwidth estimate	0.015	0.020	0.010	0.030	0.012
Covariates	No	Yes	Yes	Yes	Yes
Observations	25,539	32,318	11,773	41,299	16,289

Panel B: Probability of attainment		
Dep. variable: $A_{c,t}$	(1)	(2)
$Comply_{c,t}$	0.795***	0.753***
	(24.63)	(10.81)
County controls	No	Yes
Year F.E.	Yes	Yes
County F.E.	Yes	Yes
Observations	16,707	15,143

Panel A reports the impact of a county's close attainment designation status on polluting plants' local ozone emissions. We estimate a local linear regression using the mean squared error optimal bandwidth following Calonico et al. (2014). We also report results across alternative bandwidths, including 50% of optimal bandwidth (narrower bandwidth) and 150% of optimal bandwidth (wider bandwidth). Results using both rectangular and triangular kernels are reported. $Comply_{c,t}$ is a dummy variable equal to one if county c is in compliance with the NAAQS threshold in year t, and zero otherwise. *ln(Ozone)*$_t$ equals to the natural logarithm of one plus the total amount of ozone air emissions (in pounds) in a given county of a given firm in year t. Covariates include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *KZ*, *Cash*, *Momentum*, *Stock returns*, *z-score*, *Core chemical*, *Permit*, *Source reduction*, and *Production ratio*. Panel B presents the probability of actual attainment designation status given a county's compliance with the NAAQS threshold. $A_{c,t}$ is a dummy variable equal to one if county c is actually designated attainment in year t, and zero otherwise. County controls include the natural logarithm of one plus the employment levels in a given county, a given county's NO_x emissions to employment ratio, the change in a given county's employment levels, and a dummy variable equal to one if the county is located in a MSA. For all specifications, standard errors are clustered by county and bias-corrected following Calonico et al. (2014); t-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table 4
Donation activity in response to close attainment designation status.

Dep. variable: *ln(Donation)*$_{t+1}$	(1)	(2)	(3)	(4)	(5)
Comply$_{c,t}$	0.332***	0.382***	0.359**	0.390***	0.371***
	(2.64)	(2.90)	(2.00)	(3.64)	(2.69)
Kernel	Rec.	Rec.	Rec.	Rec.	Tri.
Bandwidth type	Opt.	Opt.	50% Opt.	150% Opt.	Opt.
Bandwidth estimate	0.010	0.011	0.006	0.017	0.012
Covariates	No	Yes	Yes	Yes	Yes
Observations	13,505	13,826	5,963	26,246	15,753

This table presents a firm's donation activities in response to a county's close attainment designation status. We estimate the local linear regression specification given in Equation (1) using the mean squared error optimal bandwidth following Calonico et al. (2014). We also report results across alternative bandwidths, including 50% of optimal bandwidth (narrower bandwidth) and 150% of optimal bandwidth (wider bandwidth). Results using both rectangular and triangular kernels are reported. *ln(Donation)*$_{t+1}$ equals to the natural logarithm of one plus the total dollar amount of donations of a given firm to nonprofits in a given county in year $t + 1$. *Comply*$_{c,t}$ is a dummy variable equal to one if county c is in compliance with the NAAQS threshold in year t, and zero otherwise. Covariates include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *KZ*, *Cash*, *Momentum*, *Stock returns*, *z-score*, *Core chemical*, *Permit*, *Source reduction*, and *Production ratio*. For all specifications, standard errors are clustered by county and bias-corrected following Calonico et al. (2014); t-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table 5
Donation activity in response to close attainment designation status conditional on past ozone emissions.

Dep. variable: $ln(Donation)_{t+1}$	(1)	(2)	(3)	(4)	(5)
$Comply_{c,t}$	0.112	0.139	0.040	0.193**	0.135
	(1.12)	(1.38)	(0.32)	(2.47)	(1.16)
$ln(Ozone)_{t-1}$	0.014	0.014	0.003	0.019	0.005
	(0.88)	(0.81)	(0.13)	(1.14)	(0.30)
$Comply_{c,t} \times ln(Ozone)_{t-1}$	0.055**	0.049***	0.075**	0.042**	0.063***
	(2.31)	(2.70)	(2.10)	(2.02)	(2.74)
Kernel	Rec.	Rec.	Rec.	Rec.	Tri.
Bandwidth type	Opt.	Opt.	50% Opt.	150% Opt.	Opt.
Bandwidth estimate	0.010	0.011	0.006	0.017	0.012
Covariates	No	Yes	Yes	Yes	Yes
Observations	13,505	13,826	5,963	26,246	15,753

This table presents a firm's donation activities in response to a county's close attainment designation status conditional on past ozone emissions. We estimate the local linear regression specification given in Equation (2) using the mean squared error optimal bandwidth following Calonico et al. (2014). We also report results across alternative bandwidths, including 50% of optimal bandwidth (narrower bandwidth) and 150% of optimal bandwidth (wider bandwidth). Results using both rectangular and triangular kernels are reported. $ln(Donation)_{t+1}$ equals to the natural logarithm of one plus the total dollar amount of donations of a given firm to nonprofits in a given county in year $t+1$. $ln(Ozone)_{t-1}$ equals to the natural logarithm of one plus the total amount of ozone air emissions (in pounds) in a given county of a given firm in year $t-1$. $Comply_{c,t}$ is a dummy variable equal to one if county c is in compliance with the NAAQS threshold in year t, and zero otherwise. Covariates include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *KZ*, *Cash*, *Momentum*, *Stock returns*, *z-score*, *Core chemical*, *Permit*, *Source reduction*, and *Production ratio*. For all specifications, standard errors are clustered by county and bias-corrected following Calonico et al. (2014); t-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table 6
Donation activity in response to close attainment designation status by donation type.

Donation type:	Health	Social & Human Services	Community Development	Environment	Education	Art	Religion	Sports	Miscellaneous
Dep. variable: $ln(Donation)_{t+1}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Comply_{c,t}$	0.325***	0.319***	0.213***	0.164***	0.079	0.066	0.037	0.029	0.046
	(4.67)	(2.89)	(3.56)	(4.17)	(0.84)	(1.47)	(0.85)	(1.17)	(1.17)
Kernel	Rec.	Rec.	Rec.	Rec.	Rec.	Rec.	Rec.	Rec.	Rec.
Bandwidth type	Opt.	Opt.	Opt.	Opt.	Opt.	Opt.	Opt.	Opt.	Opt.
Bandwidth estimate	0.009	0.010	0.012	0.011	0.011	0.011	0.016	0.012	0.016
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,522	12,260	15,753	12,260	14,882	12,098	29,354	18,903	27,700

This table presents a firm's donation activities in response to a county's close attainment designation status split by the donation type. We estimate the local linear regression specification given in Equation (1) using rectangular kernels and the mean squared error optimal bandwidth following Calonico et al. (2014). $ln(Donation)_{t+1}$ equals to the natural logarithm of one plus the total dollar amount of a given type of donation of a given firm to nonprofits in a given county in year $t+1$. $Comply_{c,t}$ is a dummy variable equal to one if county c is in compliance with the NAAQS threshold in year t, and zero otherwise. Covariates include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *KZ*, *Cash*, *Momentum*, *Stock returns*, *z-score*, *Core chemical*, *Permit*, *Source reduction*, and *Production ratio*. For all specifications, standard errors are clustered by county and bias-corrected following Calonico et al. (2014); t-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table 7
Other characteristics and donation activity in response to close attainment designation status.

	Monitor distance		Age		Concentration	
	Far	Close	Young	Old	Low	High
Dep. variable: *ln(Donation)*$_{t+1}$	(1)	(2)	(3)	(4)	(5)	(6)
Comply$_{c,t}$	0.361***	0.277**	0.257**	0.457***	0.498***	0.253**
	(2.85)	(2.00)	(2.04)	(3.16)	(4.65)	(2.05)
Coefficient difference	0.084		-0.200		0.245	
p-value	0.656		0.297		0.211	
Kernel	Rec.	Rec.	Rec.	Rec.	Rec.	Rec.
Bandwidth type	Opt.	Opt.	Opt.	Opt.	Opt.	Opt.
Bandwidth estimate	0.010	0.008	0.014	0.011	0.008	0.007
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,657	5,033	9,714	6,077	4,899	2,921

This table presents a firm's donation activities in response to a county's close attainment designation status for subsamples based on other characteristics. We estimate the local linear regression specification given in Equation (1) using rectangular kernels and the mean squared error optimal bandwidth following Calonico et al. (2014). Columns (1) and (2) report the results for the subsample where the average distance between the plants of a given firm and the closest monitor in a given county is above ("Far") and below ("Close") the median, respectively. Columns (3) and (4) report the results for the subsample where the average age of the plants of a given firm in a given county is above ("Old") and below ("Young") the median, respectively. Columns (5) and (6) report the results for the subsample where the county-level HHI based on facility-level sales is above ("High") and below ("Low") the median, respectively. *ln(Donation)*$_{t+1}$ equals to the natural logarithm of one plus the total dollar amount of donations of a given firm to nonprofits in a given county in year $t+1$. *Comply*$_{c,t}$ is a dummy variable equal to one if county c is in compliance with the NAAQS threshold in year t, and zero otherwise. Coefficient difference represents the difference in the coefficient estimates of *Comply*$_{c,t}$ between the two subsamples. Covariates include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *KZ*, *Cash*, *Momentum*, *Stock returns*, *z-score*, *Core chemical*, *Permit*, *Source reduction*, and *Production ratio*. For all specifications, standard errors are clustered by county and bias-corrected following Calonico et al. (2014); t-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table 8
Reallocation of donations from connected non-operating counties to attainment operating counties.

Dep. variable: $\Delta\textit{Connected donation}_{i,c,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta\textit{Comply donation}_{i,t-1}$	-0.111***	-0.134***	-0.220***	-0.201**	-0.648**	-0.676**	-0.159***	-0.148**
	(-3.34)	(-3.39)	(-2.65)	(-2.29)	(-2.40)	(-2.37)	(-2.97)	(-2.50)
$\Delta\textit{Comply donation}_{i,t-2}$	-0.021**	-0.025**	-0.073***	-0.093***	-0.046***	-0.049***	-0.091***	-0.113***
	(-2.30)	(-2.13)	(-3.15)	(-3.27)	(-3.20)	(-2.96)	(-3.51)	(-3.54)
Sample	Full	Full	Opt.	Opt.	50% Opt.	50% Opt.	150% Opt.	150% Opt.
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Coefficient sum	-0.132	-0.159	-0.293	-0.294	-0.694	-0.724	-0.250	-0.261
F(sum of lags)	11.17	11.24	10.22	8.69	6.87	6.85	12.64	10.43
p-Value	0.001	0.001	0.001	0.003	0.009	0.009	0.001	0.001
Firm F.E.	Yes	No	Yes	No	Yes	No	Yes	No
County F.E.	Yes	No	Yes	No	Yes	No	Yes	No
Year F.E.	Yes	No	Yes	No	Yes	No	Yes	No
Firm × County F.E.	No	Yes	No	Yes	No	Yes	No	Yes
County × Year F.E.	No	Yes	No	Yes	No	Yes	No	Yes
Observations	102,139	91,772	89,782	79,077	69,067	58,869	98,937	88,313

This table presents the reallocation of donations away from connected counties where firms historically have made donations but do not operate facilities and toward close attainment counties. We estimate the regression specification given in Equation (4). The dependent variable, $\Delta\textit{Connected donation}_{i,c,t}$, is measured at the firm–county–year level and is equal to the change in the total dollar value of donations between year t and year $t-1$ in connected counties where the firm does not operate any plants, normalized by the total amount of donations of the given firm in year t across all counties. The independent variables, $\Delta\textit{Comply donation}_{i,t}$, are measured at the firm–year level and is equal to the change in the total dollar value of donations between year t and year $t-1$, summed across all counties where the firm operates plants and have DVs that are in compliance with the NAAQS threshold, normalized by the total amount of donations of the given firm in year t across all counties; we divide this by the number of connected non-operating counties associated with the firm in year t. Columns (1) and (2) use the full sample of attainment counties where the firm operates plants, while columns (3) and (4) restrict the sample of attainment counties to a narrow window around the NAAQS threshold using the mean squared error optimal bandwidth following Calonico et al. (2014). We also report results across alternative bandwidths, including 50% of optimal bandwidth (narrower bandwidth) in columns (5) and (6), and 150% of optimal bandwidth (wider bandwidth) in columns (7) and (8). Control variables include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *KZ*, *Cash*, *Momentum*, *Stock returns*, *z-score*, *Core chemical*, *Permit*, *Source reduction*, and *Production ratio*. For all specifications, standard errors are robust to heteroskedasticity and clustered by county; t-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table 9

Effect of local newspaper closures on donation activity in response to close attainment designation status.

Dep. variable: *ln(Donation)*$_{t+1}$	(1)	(2)	(3)	(4)	(5)
$Comply_{c,t}$	0.342***	0.449***	0.298*	0.388***	0.362***
	(3.52)	(4.13)	(1.89)	(4.17)	(3.09)
$Closure_{t-1}$	-0.100	-0.213	-0.004	-0.488	-0.221
	(-0.19)	(-0.31)	(-0.01)	(-0.54)	(-0.35)
$Comply_{c,t} \times Closure_{t-1}$	-1.487**	-1.588***	-1.703***	-1.380***	-1.649***
	(-2.16)	(-3.61)	(-3.32)	(-3.38)	(-3.26)
Kernel	Rec.	Rec.	Rec.	Rec.	Tri.
Bandwidth type	Opt.	Opt.	50% Opt.	150% Opt.	Opt.
Bandwidth estimate	0.012	0.013	0.007	0.020	0.014
Covariates	No	Yes	Yes	Yes	Yes
Observations	11,584	11,148	4,511	23,048	12,845

This table presents a firm's donation activities in response to a county's close attainment designation status given local newspaper closures. We estimate the local linear regression specification given in Equation (5) using the mean squared error optimal bandwidth following Calonico et al. (2014). We also report results across alternative bandwidths, including 50% of optimal bandwidth (narrower bandwidth) and 150% of optimal bandwidth (wider bandwidth). Results using both rectangular and triangular kernels are reported. *ln(Donation)*$_{t+1}$ equals to the natural logarithm of one plus the total dollar amount of donations of a given firm to nonprofits in a given county in year $t+1$. $Closure_{t-1}$ is a dummy variable equal to one if a local newspaper closed in a given county in the past three years until year $t-1$, and zero otherwise. $Comply_{c,t}$ is a dummy variable equal to one if county c is in compliance with the NAAQS threshold in year t, and zero otherwise. Covariates include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *KZ*, *Cash*, *Momentum*, *Stock returns*, *z-score*, *Core chemical*, *Permit*, *Source reduction*, and *Production ratio*. For all specifications, standard errors are clustered by county and bias-corrected following Calonico et al. (2014); t-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table 10
Donation activity in response to close attainment designation status conditional on firms' peak reputational risk.

Dep. variable: *ln(Donation)*$_{t+1}$	(1)	(2)	(3)	(4)	(5)
$Comply_{c,t}$	0.007	0.043	0.049	0.126	0.006
	(0.04)	(0.26)	(0.20)	(1.32)	(0.03)
$Peak\ RRI_{t-1}$	0.003	0.002	0.008	0.005	0.003
	(0.44)	(0.32)	(1.04)	(0.93)	(0.53)
$Comply_{c,t} \times Peak\ RRI_{t-1}$	0.029^{***}	0.028^{***}	0.024^{**}	0.019^{***}	0.030^{***}
	(3.45)	(3.72)	(2.12)	(2.89)	(2.90)
Kernel	Rec.	Rec.	Rec.	Rec.	Tri.
Bandwidth type	Opt.	Opt.	50% Opt.	150% Opt.	Opt.
Bandwidth estimate	0.010	0.011	0.006	0.017	0.012
Covariates	No	Yes	Yes	Yes	Yes
Observations	6,696	7,671	2,733	16,700	9,204

This table presents a firm's donation activities in response to a county's close attainment designation status conditional on the firm's peak reputational risk. We estimate the local linear regression specification given in Equation (6) using the mean squared error optimal bandwidth following Calonico et al. (2014). We also report results across alternative bandwidths, including 50% of optimal bandwidth (narrower bandwidth) and 150% of optimal bandwidth (wider bandwidth). Results using both rectangular and triangular kernels are reported. *ln(Donation)*$_{t+1}$ equals to the natural logarithm of one plus the total dollar amount of donations of a given firm to nonprofits in a given county in year $t+1$. $Peak\ RRI_{t-1}$ is a given firm's two-year maximum value of the RRI measured in year $t-1$. The peak RRI is obtained from RepRisk and is a news-based measure of CSR-related incidents that captures a firm's long-term exposure to reputational risks. The RRI ranges from zero (lowest) to 100 (highest), with a higher value indicating higher reputational risk exposure. $Comply_{c,t}$ is a dummy variable equal to one if county c is in compliance with the NAAQS threshold in year t, and zero otherwise. Covariates include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *KZ*, *Cash*, *Momentum*, *Stock returns*, *z-score*, *Core chemical*, *Permit*, *Source reduction*, and *Production ratio*. For all specifications, standard errors are clustered by county and bias-corrected following Calonico et al. (2014); t-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table 11
Donation activity in response to close attainment designation status conditional on past incidents.

Dep. variable: *ln(Donation)*$_{t+1}$	(1)	(2)	(3)	(4)	(5)	(6)
$Comply_{c,t}$	0.258**	0.297**	0.252**	0.318**	0.251**	0.307**
	(2.06)	(2.19)	(2.06)	(2.02)	(1.97)	(2.28)
$ln(HPV)_{t-1}$	0.122	0.227				
	(0.37)	(0.64)				
$Comply_{c,t} \times ln(HPV)_{t-1}$	1.120**	1.115**				
	(2.23)	(2.05)				
$ln(Stack)_{t-1}$			-0.008	-0.049		
			(-0.03)	(-0.18)		
$Comply_{c,t} \times ln(Stack)_{t-1}$			0.738**	0.619**		
			(2.02)	(2.02)		
$ln(Case)_{t-1}$					-0.149	0.032
					(-0.26)	(0.06)
$Comply_{c,t} \times ln(Case)_{t-1}$					1.641**	1.629**
					(2.11)	(2.09)
Kernel	Rec.	Rec.	Rec.	Rec.	Rec.	Rec.
Bandwidth type	Opt.	Opt.	Opt.	Opt.	Opt.	Opt.
Bandwidth estimate	0.010	0.011	0.010	0.011	0.010	0.011
Covariates	No	Yes	No	Yes	No	Yes
Observations	13,505	13,826	13,505	13,826	13,505	13,826

This table presents a firm's donation activities in response to a county's close attainment designation status conditional on past incidents such as HPVs, stack tests, and enforcement cases. We estimate the local linear regression specification given in Equation (7) using rectangular kernels and the mean squared error optimal bandwidth following Calonico et al. (2014). *ln(Donation)*$_{t+1}$ equals to the natural logarithm of one plus the total dollar amount of donations of a given firm to nonprofits in a given county in year $t+1$. *ln(HPV)*$_{t-1}$ equals to the natural logarithm of one plus the number of high priority violations across all facilities in a given county of a given firm in the past three years until year $t-1$. *ln(Stack)*$_{t-1}$ equals to the natural logarithm of one plus the number of stack tests across all facilities in a given county of a given firm in the past three years until year $t-1$. *ln(Case)*$_{t-1}$ equals to the natural logarithm of one plus the number of enforcement cases across all facilities in a given county of a given firm in the past three years until year $t-1$. Covariates include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *KZ*, *Cash*, *Momentum*, *Stock returns*, *z-score*, *Core chemical*, *Permit*, *Source reduction*, and *Production ratio*. For all specifications, standard errors are clustered by county and bias-corrected following Calonico et al. (2014); t-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table 12
Mean marginal donations and marginal damages of ozone pollution.

	(1)	(2)	(3)	(4)
Marginal donations ($ / tpy)	696.75	1,011.99	1,019.18	1,261.22
Baseline AP3 model				
Within-county marginal damages ($ / tpy)	2,182.09	3,430.59	4,020.88	2,765.17
All counties marginal damages ($ / tpy)	7,658.91	10,578.94	11,664.28	9,198.50
VSL OECD model				
Within-county marginal damages ($ / tpy)	1,130.60	1,777.47	2,083.32	1,432.70
All counties marginal damages ($ / tpy)	3,968.27	5,481.22	6,043.56	4,765.97
Krewski 5th *pctile*				
Within-county marginal damages ($ / tpy)	1,451.43	2,285.27	2,678.94	1,840.41
All counties marginal damages ($ / tpy)	5,109.73	7,067.84	7,793.28	6,149.77
Krewski 95th *pctile*				
Within-county marginal damages ($ / tpy)	2,844.68	4,447.64	5,197.93	3,595.33
All counties marginal damages ($ / tpy)	9,955.42	13,685.19	15,043.79	11,943.77
Sample	Full	Opt.	50% Opt.	150% Opt.
Number of counties	618	355	231	494

This table compares the mean marginal donations of pollution with the marginal damages of pollution. We only consider counties where TRI plants operate, and data exists for both DVs and marginal damages. The sample period is from 2002 to 2017. Marginal donations are computed as the change in the average donations in a given county by all TRI firms operating in that county divided by the change in average total ozone emissions by those TRI firms using the RDD estimates from Tables 3 and 4. We use four different models to compute marginal damages: i) baseline parameters using the AP3 model; ii) alternative VSL estimates following OECD (2012); and iii) alternative parameters for the pollution concentration mortality response function from the 5th and 95th percentile, respectively, of Krewski et al.'s (2009) study. Data on marginal damages are available for years 2002, 2005, 2008, 2011, 2014, 2017, and linearly interpolated between years. Within-county marginal damages refer to the damages restricted to the same county as where the emissions are produced. All counties marginal damages refer to the damages caused by the emissions produced in a given county that spread across all counties. In column (1), we report mean marginal donations and marginal damages using the full sample of counties. Column (2) uses the sample of counties located in the narrow window around the NAAQS threshold by computing the mean squared error optimal bandwidth following Calonico et al. (2014). In columns (3) and (4), we report results across alternative bandwidths, including 50% of optimal bandwidth (narrower bandwidth) and 150% of optimal bandwidth (wider bandwidth). Both marginal damages and marginal donations are in $ per ton of yearly emissions. All currency are in 2015 dollars, deflated using the GDP deflator.

Appendix A: Variable definitions

Table A.1

Variable definitions.

Variable	Definitions	Data source
ln(Donation)	The natural logarithm of one plus the total dollar amount of donations of a given firm to nonprofits in a given county.	FoundationSearch
Δ*Connected donation*	The change in the total dollar value of donations between year t and year $t-1$ in connected counties where the firm does not operate any plants, normalized by the total amount of donations of the given firm in year t across all counties.	FoundationSearch; TRI
Δ*Comply donation*	The change in the total dollar value of donations between year t and year $t-1$, summed across all counties where the firm operates plants and have DVs that are in compliance with the NAAQS threshold, normalized by the total amount of donations of the given firm in year t across all counties; we divide this by the number of connected non-operating counties associated with the firm in year t.	FoundationSearch; TRI
ln(Ozone)	The natural logarithm of one plus the total amount of ozone air emissions (in pounds) in a given county of a given firm.	TRI
Comply	A dummy variable equal to one if a given county is in compliance with the NAAQS threshold in a given year, and zero otherwise.	AQS
Monitor distance (km)	The average distance between the plants of a given firm and the closest monitor in a given county.	TRI; AQS
Age (years)	The average age of polluting plants that a given firm operates in a given county.	NETS
Concentration	County-level HHI based on facility-level sales, calculated as the sum of the squared facility-level sales of all polluting plants that operate in a given county in a given year.	NETS
Closure	A dummy variable equal to one if a local newspaper closed in a given county in the past three years until year $t-1$, and zero otherwise.	UNC CISLM
ln(Size)	The natural logarithm of market equity.	Compustat
ln(BM)	The natural logarithm of one plus the book-to-market ratio.	Compustat
ROA	Net income divided by total assets.	Compustat
Leverage	Total liabilities divided by total assets.	Compustat
Sales growth	Ratio of sales in the current fiscal year to sales in the last year minus one.	Compustat
KZ	Kaplan-Zingales index.	Compustat
Cash	Cash divided by total assets.	Compustat
Momentum	Cumulative 12-month return of a stock, excluding the immediate past month.	CRSP
Stock returns	Firm-level annual stock returns.	CRSP
z-score	Altman's unlevered z-score for a given firm.	Compustat
Core chemical	A dummy variable equal to one if a given firm operates plants in a given county that emit core ozone chemicals as defined by TRI, and zero otherwise.	TRI
Production ratio	A given firm's average ozone production ratio across all plants in a given county.	P2
Permit	A dummy variable equal to one if a given firm operates plants in a given county that hold operating permits for ozone emissions, and zero otherwise.	ICIS-Air
Source reduction	A dummy variable equal to one if a given firm operates plants in a given county that engage in ozone source reduction activities, and zero otherwise.	P2
ln(HPV)	The natural logarithm of one plus the number of high priority violations across all facilities in a given county of a given firm in the past three years until year $t-1$.	ICIS-Air
ln(Stack)	The natural logarithm of one plus the number of stack tests across all facilities in a given county of a given firm in the past three years until year $t-1$.	ICIS-Air
ln(Case)	The natural logarithm of one plus the number of enforcement cases across all facilities in a given county of a given firm in the past three years until year $t-1$.	ICIS FE&C
Peak RRI	A given firm's two-year maximum value of the RRI that captures a firm's long-term exposure to reputational risks.	RepRisk
Current RRI	A given firm's current value of the RRI that captures a firm's short-term exposure to reputational risks.	RepRisk

Appendix B: AP3 model

B.1. AP3 model overview

We calculate county-level marginal damages of ozone emissions from the AP3 model (Holland et al., 2020). AP3 is an integrated assessment model developed to estimate monetary damages from emissions in the continental United States. Since previous research has found that mortality accounts for approximately 95% of the total monetized health damages (Jaramillo & Muller, 2016), the AP3 model does not include morbidity or other environmental damages. The model uses air quality modeling to translate emissions into ambient concentrations, and then to compute population exposure, health effects, and finally the valuation of those effects; each of these steps is described in detail below.

The AP3 air quality model uses annual emissions of all criteria pollutants from all sources within a county, measured from the National Emissions Inventory (NEI). AP3 then inputs these emission rates into the Climatological Regional Dispersion Model, an air pollution transport model, to calculate ambient concentrations of each pollutant in each county. The AP3 model distinguishes among emissions released at four different effective stack height categories: ground-level emissions, point sources (stationary sources) under 250 meters, point sources between 250 meters and 500 meters, and point sources over 500 meters. AP3 then applies concentration-response functions for each outcome it considers. AP3 calculates mortality in each of 19 different age groups used in the U.S. census (0 years old, 1-4 years old, 5-9 years old, ..., 80-84 years old, 85+ years old). AP3 uses separate adult and infant concentration-response functions. AP3 then monetizes the change in mortality using an estimate of the value of a statistical life (VSL).

B.2. Data sources

Data on emissions is taken from the EPA's NEI, which is a comprehensive accounting of emissions from all sectors. Data is available every three years from 2002 to 2017. The stack height of emissions plays an important role in the AP3 model because the altitude at which a pollutant is emitted influences the pollutant's ambient level and spatial distribution. However, since we only focus on TRI facilities and the mean height of emissions of volatile organic compounds (VOCs) from these facilities is only 14.2 meters with a standard deviation of 14.6 meters (United States Environmental Protection Agency, 1999), we apply AP3 assuming stack heights are lower than 250 meters. Population data for each of the 19 different age groups come from the U.S. Census American Community Survey. We use mortality data from the CDC National Vital Statistics System Multiple Cause of Death dataset. The data includes all-cause mortality rates by county for each of the 19 age groups.

B.3. Model calibration and application

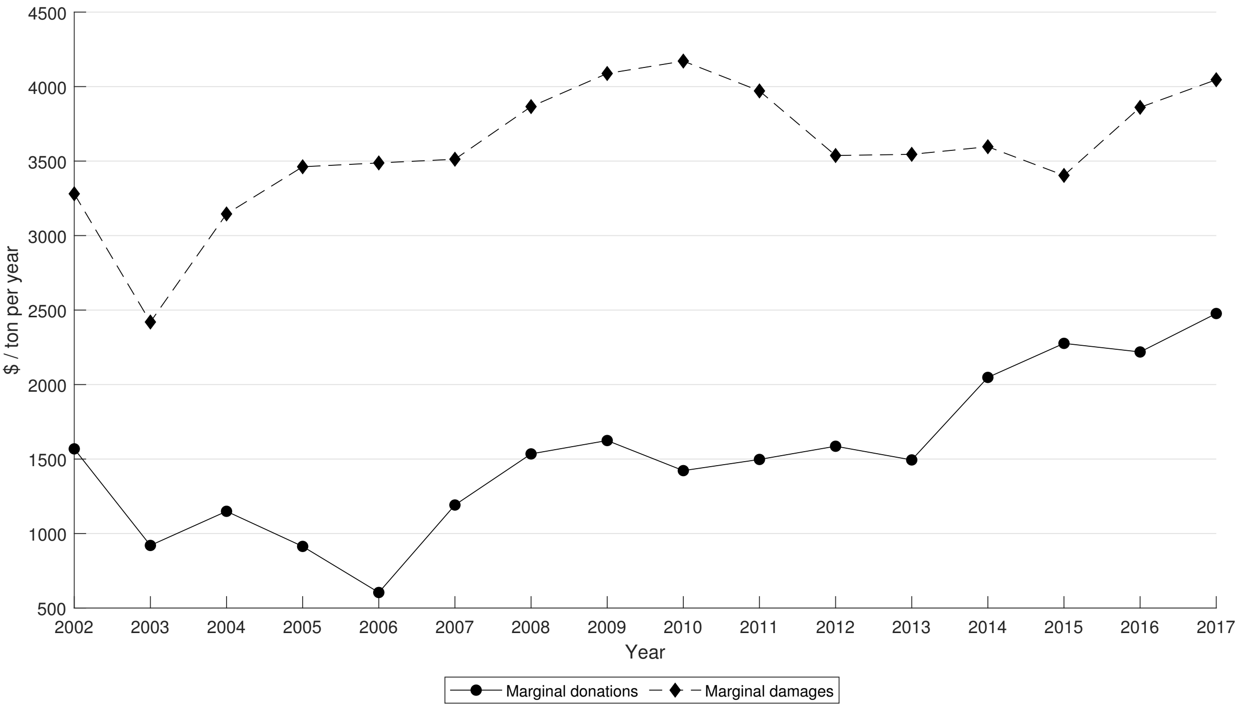
To calculate the marginal damages of ozone emissions using AP3, we start from the raw data files and programs that constitute AP3, which Nick Muller generously shared. The original AP3 uses all VOC emissions in a given county as inputs. However, since we are only interested in the marginal damages of ozone emissions from TRI facilities, we sum together the total VOC emissions from all TRI facilities in a given county and use this value instead. We consider two types of damages: i) within-county damages, which are damages limited to the same county as the source county of VOC emissions; and ii) all county damages, which are damages summed across all counties attributable to the VOC emissions in the source county. To calculate marginal damages, we increase VOC emissions by one ton in a given source county and calculate the change in monetized damages. Since emissions data is only available every three years, we linearly interpolate the marginal damages between years.

The baseline AP3 model use the EPA's preferred VSL of $8.6 million (2015 dollars) (United States Environmental Protection Agency, 2010). This estimate primarily reflects hedonic models of the labor market which assess how a worker's wage increases as the worker's occupational fatality risk increases. An alternative specification is a VSL of $4.5 million, which reflects a similar study covering all countries in the Organization for Economic Cooperation and Development (OECD, 2012). The OECD includes many countries with lower GDP per capita than the U.S., such as Mexico and Turkey, so it is perhaps unsurprising that a VSL estimate for the OECD is lower than a VSL estimate for the U.S.

For the adult and infant concentration-response functions, the baseline AP3 model uses the estimate of 0.0058 from Krewski et al. (2009) and 0.0068 from Woodruff, Parker, and Schoendorf (2006), respectively. For sensitivity analyses, we report estimates based on the 5th percentile of Krewski et al. (2009) and Woodruff et al. (2006), which are 0.0039 and -0.0073, respectively. We also report estimates based on the 95th percentile of Krewski et al. (2009) and Woodruff et al. (2006), which are 0.0077 and 0.0215, respectively.

Internet Appendix For Online Publication Only

Figure IA.1
Mean marginal donations and marginal damages of ozone pollution by year.



This figure compares the yearly mean marginal donations of pollution with the marginal damages of pollution from years 2002 to 2017. We only consider counties where TRI plants operate, and data exists for both DVs and marginal damages. Marginal donations are computed as the change in the yearly average donations in a given county by all TRI firms operating in that county divided by the change in yearly average total ozone emissions by those TRI firms using the RDD estimates from Tables 3 and 4. Marginal damages represent within-county damages and are computed using the baseline parameters using the AP3 model. Data on marginal damages are available for years 2002, 2005, 2008, 2011, 2014, 2017, and linearly interpolated between years. We use the sample of counties located in the narrow window around the NAAQS threshold by computing the mean squared error optimal bandwidth following Calonico et al. (2014). Both marginal damages and marginal donations are in $ per ton of yearly emissions. All currency are in 2015 dollars, deflated using the GDP deflator.

Table IA.1
Ozone NAAQS.

Standard	Effective date	Averaging time	Threshold (ppm)	Form
1-Hour Ozone (1979)	January 6, 1992	1 hour	0.12	Attainment is defined when the expected number of days per calendar year, with maximum hourly average concentration greater than 0.12 ppm, is equal to or less than 1
8-Hour Ozone (1997)	June 15, 2004	8 hours	0.08	Annual fourth-highest daily maximum 8-hr concentration, averaged over 3 years
8-Hour Ozone (2008)	July 20, 2012	8 hours	0.075	Annual fourth-highest daily maximum 8-hr concentration, averaged over 3 years
8-Hour Ozone (2015)	August 3, 2018	8 hours	0.070	Annual fourth-highest daily maximum 8-hr concentration, averaged over 3 years

This table provides basic descriptions of the ozone NAAQS used in our study. Standard refers to the name of the ozone NAAQS. Effective date is the date on which the standard is effectively implemented as stated in the Federal Register. Averaging time is the sampling frequency of the ozone concentration used to calculate DVs. Threshold refers to the DV value which if exceeded, then the county is considered to be in nonattainment. This value is measured in parts per million (ppm). Form is the rule used to compute the DVs for the relevant ozone standard. Our sample period is from 1999–2018. From 1999 to 2003, we use the 1-Hour Ozone (1979) standard. From 2004 to 2011, we use the 8-Hour Ozone (1997) standard. From 2012 to 2017, we use the 8-Hour Ozone (2008) standard. In 2018, we use the 8-Hour Ozone (2015) standard. This table is adapted from `https://www.epa.gov/ground-level-ozone-pollution/timeline-ozone-national-ambient-air-quality-standards-naaqs`.

Table IA.2
TRI industry composition.

NAICS	Description	Proportion (%)
325	Chemical Manufacturing	12.970
332	Fabricated Metal Product Manufacturing	12.644
336	Transportation Equipment Manufacturing	8.222
311	Food Manufacturing	7.942
333	Machinery Manufacturing	7.252
331	Primary Metal Manufacturing	6.733
334	Computer and Electronic Product Manufacturing	5.665
221	Utilities	4.958
327	Nonmetallic Mineral Product Manufacturing	4.709
326	Plastics and Rubber Products Manufacturing	4.430
424	Merchant Wholesalers, Nondurable Goods	3.531
321	Wood Product Manufacturing	3.144
322	Paper Manufacturing	3.128
335	Electrical Equipment, Appliance, and Component Manufacturing	3.044
324	Petroleum and Coal Products Manufacturing	2.740
562	Waste Management and Remediation Services	2.020
339	Miscellaneous Manufacturing	1.739
337	Furniture and Related Product Manufacturing	1.407
212	Mining (except Oil and Gas)	0.819
323	Printing and Related Support Activities	0.814
313	Textile Mills	0.614
312	Beverage and Tobacco Product Manufacturing	0.585
314	Textile Product Mills	0.299
316	Leather and Allied Product Manufacturing	0.110
811	Repair and Maintenance	0.090
454	Nonstore Retailers	0.079
315	Apparel Manufacturing	0.052
541	Professional, Scientific, and Technical Services	0.052
213	Support Activities for Mining	0.029
488	Support Activities for Transportation	0.027
113	Forestry and Logging	0.025
112	Animal Production and Aquaculture	0.024
493	Warehousing and Storage	0.020
486	Pipeline Transportation	0.013
532	Rental and Leasing Services	0.013
551	Management of Companies and Enterprises	0.009
481	Air Transportation	0.008
237	Heavy and Civil Engineering Construction	0.005
423	Merchant Wholesalers, Durable Goods	0.005
425	Wholesale Electronic Markets and Agents and Brokers	0.005
444	Building Material and Garden Equipment and Supplies Dealers	0.004
445	Food and Beverage Stores	0.004
561	Administrative and Support Services	0.004
531	Real Estate	0.003
211	Oil and Gas Extraction	0.002
442	Furniture and Home Furnishings Stores	0.002
484	Truck Transportation	0.002
511	Publishing Industries (except Internet)	0.002
812	Personal and Laundry Services	0.002
115	Support Activities for Agriculture and Forestry	0.002

This table reports the three-digit NAICS industries in TRI that are included in our sample. Proportion refers to the fraction that is represented in our sample.

Table IA.3
Donation activity in response to close attainment designation status using global polynomial regression.

Dep. variable: *ln(Donation)*$_{t+1}$	(1)	(2)	(3)	(4)
$Comply_{c,t}$	0.200***	0.299***	0.198**	0.298***
	(2.59)	(3.46)	(2.13)	(2.79)
Polynomial order	2	2	3	3
Controls	No	Yes	No	Yes
Observations	54,524	45,264	54,524	45,264

This table presents the RDD estimates using global polynomial regression. We use flexible polynomials of order two and three that are different for observations on the left- and right-hand side of the NAAQS threshold. *ln(Donation)*$_{t+1}$ equals to the natural logarithm of one plus the total dollar amount of donations of a given firm to nonprofits in a given county in year $t+1$. $Comply_{c,t}$ is a dummy variable equal to one if county c is in compliance with the NAAQS threshold in year t, and zero otherwise. Control variables include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *KZ*, *Cash*, *Momentum*, *Stock returns*, *z-score*, *Core chemical*, *Permit*, *Source reduction*, and *Production ratio*. For all specifications, standard errors are clustered by county; t-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table IA.4

Alternative RDD specifications for donation activity in response to close attainment designation status.

Dep. variable: *ln(Donation)*$_{t+1}$	(1)	(2)	(3)	(4)	(5)	(6)
$Comply_{c,t}$	0.297**	0.338**	0.455**	0.368***	0.378***	0.339**
	(2.36)	(2.35)	(2.37)	(3.23)	(3.01)	(2.17)
Kernel	Epan.	Epan.	Epan.	Epan.	Rec.	Rec.
Bandwidth type	Opt.	Opt.	50% Opt.	150% Opt.	Opt.	Opt.
Bandwidth estimate	0.011	0.011	0.006	0.017	0.011	0.012
Polynomial order	1	1	1	1	2	3
Covariates	No	Yes	Yes	Yes	Yes	Yes
Observations	15,051	12,977	5,963	26,246	13,700	15,479

This table presents alternative RDD specifications to estimate a firm's donation activities in response to a county's close attainment designation status. In columns (1) to (4), we estimate the local linear regression specification given in Equation (1) using the Epanechnikov kernel function and the mean squared error optimal bandwidth following Calonico et al. (2014). We also report results across alternative bandwidths, including 50% of optimal bandwidth (narrower bandwidth) and 150% of optimal bandwidth (wider bandwidth). In columns (5) and (6), we control for local quadratic and cubic polynomials, respectively, in centered design values using the rectangular kernel function. *ln(Donation)*$_{t+1}$ equals to the natural logarithm of one plus the total dollar amount of donations of a given firm to nonprofits in a given county in year $t+1$. $Comply_{c,t}$ is a dummy variable equal to one if county c is in compliance with the NAAQS threshold in year t, and zero otherwise. Covariates include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *KZ*, *Cash*, *Momentum*, *Stock returns*, *z-score*, *Core chemical*, *Permit*, *Source reduction*, and *Production ratio*. For all specifications, standard errors are clustered by county and bias-corrected following Calonico et al. (2014); t-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table IA.5

Donation activity in response to close attainment designation status using the inverse hyperbolic sine transformed donations.

Dep. variable: *arcsinh(Donation)*$_{t+1}$	(1)	(2)	(3)	(4)	(5)
Comply$_{c,t}$	0.350***	0.402***	0.378**	0.409***	0.392***
	(2.62)	(2.88)	(1.98)	(3.60)	(2.68)
Kernel	Rec.	Rec.	Rec.	Rec.	Tri.
Bandwidth type	Opt.	Opt.	50% Opt.	150% Opt.	Opt.
Bandwidth estimate	0.010	0.011	0.006	0.017	0.012
Covariates	No	Yes	Yes	Yes	Yes
Observations	13,505	13,826	5,963	26,246	15,753

This table presents a firm's donation activities in response to a county's close attainment designation status using the inverse hyperbolic sine transformed donations as the dependent variable. We estimate the local linear regression specification given in Equation (1) using the mean squared error optimal bandwidth following Calonico et al. (2014). We also report results across alternative bandwidths, including 50% of optimal bandwidth (narrower bandwidth) and 150% of optimal bandwidth (wider bandwidth). Results using both rectangular and triangular kernels are reported. *arcsinh(Donation)*$_{t+1}$ equals to the inverse hyperbolic sine (arcsinh) transformed total dollar amount of donations of a given firm to nonprofits in a given county in year $t+1$. *Comply*$_{c,t}$ is a dummy variable equal to one if county c is in compliance with the NAAQS threshold in year t, and zero otherwise. Covariates include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *KZ*, *Cash*, *Momentum*, *Stock returns*, *z-score*, *Core chemical*, *Permit*, *Source reduction*, and *Production ratio*. For all specifications, standard errors are clustered by county and bias-corrected following Calonico et al. (2014); t-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table IA.6

Residualized donation activity in response to close attainment designation status.

Dep. variable: Residualized *ln(Donation)*$_{t+1}$	(1)	(2)	(3)	(4)	(5)
$Comply_{c,t}$	0.363***	0.184**	0.147**	0.292***	0.122**
	(2.95)	(2.34)	(2.11)	(2.59)	(2.04)
Residualize by firm	Yes	Yes	Yes	No	No
Residualize by county	No	Yes	Yes	No	No
Residualize by year	No	No	Yes	No	No
Residualize by firm–year	No	No	No	Yes	Yes
Residualize by firm–county	No	No	No	No	Yes
Kernel	Rec.	Rec.	Rec.	Rec.	Rec.
Bandwidth type	Opt.	Opt.	Opt.	Opt.	Opt.
Bandwidth estimate	0.010	0.011	0.011	0.011	0.013
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	10,512	12,967	14,378	11,503	16,567

This table presents a firm's donation activities in response to a county's close attainment designation status using residualized donation outcomes by various fixed effects. We estimate the local linear regression specification given in Equation (1) using rectangular kernels and the mean squared error optimal bandwidth following Calonico et al. (2014). We residualize *ln(Donation)*$_{t+1}$ by regressing it on various fixed effects and then using the residuals as the dependent variable. *ln(Donation)*$_{t+1}$ equals to the natural logarithm of one plus the total dollar amount of donations of a given firm to nonprofits in a given county in year $t+1$. $Comply_{c,t}$ is a dummy variable equal to one if county c is in compliance with the NAAQS threshold in year t, and zero otherwise. Covariates include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *KZ*, *Cash*, *Momentum*, *Stock returns*, *z-score*, *Core chemical*, *Permit*, *Source reduction*, and *Production ratio*. For all specifications, standard errors are clustered by county and bias-corrected following Calonico et al. (2014); t-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table IA.7
Donation activity in response to close attainment designation status conditional on the rolling average of ozone emissions in the previous three years.

Dep. variable: $ln(Donation)_{t+1}$	(1)	(2)	(3)	(4)	(5)
$Comply_{c,t}$	0.068	0.172	0.063	0.138	0.163
	(0.49)	(1.53)	(0.57)	(1.06)	(1.28)
$ln(\overline{Ozone})_{t-1}$	0.003	0.023	0.008	0.005	0.012
	(0.11)	(1.28)	(0.37)	(0.19)	(0.68)
$Comply_{c,t} \times ln(\overline{Ozone})_{t-1}$	0.059**	0.036**	0.061**	0.048**	0.049**
	(2.00)	(2.14)	(2.10)	(1.97)	(2.30)
Kernel	Rec.	Rec.	Rec.	Rec.	Tri.
Bandwidth type	Opt.	Opt.	50% Opt.	150% Opt.	Opt.
Bandwidth estimate	0.010	0.011	0.006	0.017	0.012
Covariates	No	Yes	Yes	Yes	Yes
Observations	13,505	13,826	7,329	26,246	15,973

This table presents a firm's donation activities in response to a county's close attainment designation status conditional on the rolling average of ozone emissions in the previous three years. We estimate the local linear regression specification given in Equation (2) using the mean squared error optimal bandwidth following Calonico et al. (2014). We also report results across alternative bandwidths, including 50% of optimal bandwidth (narrower bandwidth) and 150% of optimal bandwidth (wider bandwidth). Results using both rectangular and triangular kernels are reported. $ln(Donation)_{t+1}$ equals to the natural logarithm of one plus the total dollar amount of donations of a given firm to nonprofits in a given county in year $t+1$. $ln(\overline{Ozone})_{t-1}$ equals to the natural logarithm of one plus the average of the total amount of ozone air emissions (in pounds) in a given county of a given firm in the previous three years until year $t-1$. $Comply_{c,t}$ is a dummy variable equal to one if county c is in compliance with the NAAQS threshold in year t, and zero otherwise. Covariates include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *KZ*, *Cash*, *Momentum*, *Stock returns*, *z-score*, *Core chemical*, *Permit*, *Source reduction*, and *Production ratio*. For all specifications, standard errors are clustered by county and bias-corrected following Calonico et al. (2014); t-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table IA.8

Two-year forward donation activity in response to close attainment designation status.

Dep. variable: $ln(Donation)_{t+2}$	(1)	(2)	(3)	(4)	(5)
$Comply_{c,t}$	0.343***	0.381***	0.222**	0.176**	0.314***
	(3.27)	(3.41)	(2.36)	(1.97)	(2.61)
Kernel	Rec.	Rec.	Rec.	Rec.	Tri.
Bandwidth type	Opt.	Opt.	50% Opt.	150% Opt.	Opt.
Bandwidth estimate	0.013	0.015	0.008	0.023	0.015
Covariates	No	Yes	Yes	Yes	Yes
Observations	20,419	21,047	8,339	36,421	21,047

This table presents a firm's two-year forward donation activities in response to a county's close attainment designation status. We estimate the local linear regression specification given in Equation (1) using the mean squared error optimal bandwidth following Calonico et al. (2014). We also report results across alternative bandwidths, including 50% of optimal bandwidth (narrower bandwidth) and 150% of optimal bandwidth (wider bandwidth). Results using both rectangular and triangular kernels are reported. $ln(Donation)_{t+2}$ equals to the natural logarithm of one plus the total dollar amount of donations of a given firm to nonprofits in a given county in year $t+2$. $Comply_{c,t}$ is a dummy variable equal to one if county c is in compliance with the NAAQS threshold in year t, and zero otherwise. Covariates include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *KZ*, *Cash*, *Momentum*, *Stock returns*, *z-score*, *Core chemical*, *Permit*, *Source reduction*, and *Production ratio*. For all specifications, standard errors are clustered by county and bias-corrected following Calonico et al. (2014); t-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table IA.9
Placebo RDD specifications.

Dep. variable: *ln(Donation)*$_{t+1}$	Placebo thresholds (1)	Placebo thresholds (2)	Non-operating counties (3)	Non-operating counties (4)
$Comply_{c,t}$	-0.042	-0.139	-0.005	-0.020
	(-0.15)	(-0.52)	(-0.01)	(-0.06)
Kernel	Rec.	Rec.	Rec.	Rec.
Bandwidth type	Opt.	Opt.	Opt.	Opt.
Bandwidth estimate	0.018	0.021	0.017	0.018
Covariates	No	Yes	No	Yes
Observations	18,292	18,045	35,820	36,434

This table presents placebo tests for a firm's donation activities in response to a county's close attainment designation status. In columns (1) and (2), we use placebo NAAQS thresholds whereby the 1-Hour Ozone (1979) standard uses the 8-Hour Ozone (2008) standard's threshold, the 8-Hour Ozone (1997) standard uses the 1-Hour Ozone (1979) standard's threshold, the 8-Hour Ozone (2008) standard uses the 8-Hour Ozone (2015) standard's threshold, and the 8-Hour Ozone (2015) standard uses the 8-Hour Ozone (1997) standard's threshold. In columns (3) and (4), we limit the sample to the counties where the firm does not operate any polluting plants. *ln(Donation)*$_{t+1}$ equals to the natural logarithm of one plus the total dollar amount of donations of a given firm to nonprofits in a given county in year $t+1$. $Comply_{c,t}$ is a dummy variable equal to one if county c is in compliance with the NAAQS threshold in year t, and zero otherwise. Covariates include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *KZ*, *Cash*, *Momentum*, *Stock returns*, *z-score*, *Core chemical*, *Permit*, *Source reduction*, and *Production ratio*. For all specifications, standard errors are clustered by county and bias-corrected following Calonico et al. (2014); t-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table IA.10

Donation activity in response to close attainment designation status conditional on firms' current reputational risk.

Dep. variable: $ln(Donation)_{t+1}$	(1)	(2)	(3)	(4)	(5)
$Comply_{c,t}$	0.052	0.113	0.087	0.151	0.069
	(0.28)	(0.67)	(0.33)	(1.63)	(0.28)
$Current\ RRI_{t-1}$	0.002	0.001	0.005	0.004	0.004
	(0.21)	(0.12)	(0.41)	(0.43)	(0.36)
$Comply_{c,t} \times Current\ RRI_{t-1}$	0.042***	0.039***	0.035**	0.030***	0.042***
	(2.87)	(3.06)	(1.96)	(2.76)	(2.72)
Kernel	Rec.	Rec.	Rec.	Rec.	Tri.
Bandwidth type	Opt.	Opt.	50% Opt.	150% Opt.	Opt.
Bandwidth estimate	0.010	0.011	0.006	0.017	0.012
Covariates	No	Yes	Yes	Yes	Yes
Observations	6,696	7,671	2,733	16,700	9,204

This table presents a firm's donation activities in response to a county's close attainment designation status conditional on the firm's current reputational risk. We estimate the local linear regression specification given in Equation (6) using the mean squared error optimal bandwidth following Calonico et al. (2014). We also report results across alternative bandwidths, including 50% of optimal bandwidth (narrower bandwidth) and 150% of optimal bandwidth (wider bandwidth). Results using both rectangular and triangular kernels are reported. $ln(Donation)_{t+1}$ equals to the natural logarithm of one plus the total dollar amount of donations of a given firm to nonprofits in a given county in year $t+1$. $Current\ RRI_{t-1}$ is a given firm's current value of the RRI measured in year $t-1$. The current RRI is obtained from RepRisk and is a news-based measure of CSR-related incidents that captures a firm's short-term exposure to reputational risks. The RRI ranges from zero (lowest) to 100 (highest), with a higher value indicating higher reputational risk exposure. $Comply_{c,t}$ is a dummy variable equal to one if county c is in compliance with the NAAQS threshold in year t, and zero otherwise. Covariates include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *KZ*, *Cash*, *Momentum*, *Stock returns*, *z-score*, *Core chemical*, *Permit*, *Source reduction*, and *Production ratio*. For all specifications, standard errors are clustered by county and bias-corrected following Calonico et al. (2014); t-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.