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

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Abstract

We investigate the insurance-motives of polluting firms' charitable giving by analyzing donations from philanthropic foundations to nonprofit organizations in the local community. Our empirical setting exploits the National Ambient Air Quality Standards as localized exogenous shocks to pollution. Using regression discontinuity, we find that firms with more pollution subsequently donate more to local nonprofits. Firms maximize the insurance value of donations by reallocating donations to areas where they pollute the most. Potential mechanisms include firms' local media coverage, reputational risk exposure, and history of regulatory noncompliance. Welfare analysis indicates that firms underpay for the insurance value of corporate philanthropy at the cost of society. Overall, the evidence suggests that firms leverage their reputation in local communities through corporate philanthropy as a form of insurance.

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1. Introduction

Polluting firms impose significant negative externalities on the local community because air emissions are primarily restricted to areas where plants are operated (Bento, Freedman, & Lang, 2015; Bishop, Ketcham, & Kuminoff, 2022; Chay & Greenstone, 2005; Currie, Davis, Greenstone, & Walker, 2015). However, polluting firms are also one of the most active participants in corporate philanthropy in the United States.[1] Many of the biggest polluters such as Chevron and ExxonMobil make substantial charitable donations to nonprofit organizations that tackle issues in the local community.[2] This naturally raises the question of whether polluting firms engage in corporate philanthropy to manage the potential costs of negative externalities by accruing reputational capital and improving their public image in the local community as a form of reputation insurance (Flammer, 2013; Porter & Kramer, 2002).[3] In this paper, we link exogenous changes in firms' local air emissions to their charitable activities in the local community to study how firms' donation behavior changes in response to changes in emissions that could plausibly be driven by insurance *motives*.

Theory offers differing perspectives about the insurance value of corporate donations. On the one hand, studies have shown that corporate philanthropy does not enhance value but is simply a manifestation of agency issues used by CEOs to secure private benefits of control (Cai, Xu, & Yang, 2021; Masulis & Reza, 2015). Other studies, however, show that politically-motivated donations can influence government decision-makers by distorting policies and resource allocations to favor donating firms (Bertrand, Bombardini, Fisman, Hackinen, & Trebbi, 2021; Bertrand, Bombardini, Fisman, & Trebbi, 2020). More broadly, there is ample evidence on how insurance-like protection from engaging in corporate social responsibility (CSR) contributes to shareholder value (Fernando, Sharfman, & Uysal, 2017; Flammer, 2015; Freund, Nguyen, & Phan, 2021; Krueger, 2015; Luo, Kaul, & Seo, 2018). However, there is limited evidence on the mechanisms through which firms build positive reputational capital among local stakeholders. Thus, the key focus of this paper is not on the value implications

[1] Corporate philanthropy has grown substantially over the past decade. According to Giving USA, corporate charitable giving grew from \$14.55 billion in 2011 to \$21.08 billion in 2021, an increase of approximately 45% over the 10 years.

[2] Both Chevron and ExxonMobil have long-standing partnerships with nonprofit organizations such as Conservation International and the Wildlife Conservation Society. These nonprofits work closely with local governments and communities to resolve environmentally-related issues. 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] One obvious explanation of why firms engage in corporate philanthropy is due to donations being tax-deductible. However, the cash flows generated through tax shields are typically much lower than the donated amount. Hence, tax motivations cannot fully explain why firms support charitable activities beyond the tax benefits that they receive (Navarro, 1988).

of corporate donations, but rather on the changes in a firm's donation activities in local communities driven by localized changes in emissions.[4]

We provide empirical evidence which robustly suggests that firms leverage their reputation in local communities through corporate philanthropy as a form of insurance. Our results imply that the local community is a particularly important group of stakeholders for polluting firms when managing the potential costs of negative externalities. To provide evidence of the insurance-motive, we assemble a comprehensive dataset that links donations made through a firm's corporate foundation to the recipient nonprofit organizations that are located in the same county where the firm operates its polluting plants ("local nonprofits").[5]

If the insurance-motive drives corporate philanthropy, then we expect firms that operate plants with a high level of pollution in a given area to make more donations to local nonprofits relative to those with less pollution because the insurance value of donations is greater for the former.[6] Empirically, however, examining the causal effect of local pollution on local donation activities is a challenging exercise because a firm's level of pollution and donation to nonprofits are arguably endogenous choices made by the firm. The decision to donate is not a random choice since preexisting differences in unobservable firm characteristics may lead to firms with different levels of pollution engaging in philanthropy to different extents. The local nature of pollution and donations further complicates the matter since a credible identification strategy would need to use localized exogenous shocks to pollution to study the causal effect on local donation activities. The ideal experiment would be to randomly assign firms in areas where they operate plants into a "high polluting group" and a "low polluting group" and compare their local donations following this "treatment". 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 ground-level ozone.[7] Under these

[4]The *type* of air pollutant examined in this paper is also inherently local. Specifically, we only focus on "ground-level" ozone pollution, which is a localized type of man-made air pollutant produced by the reaction between various chemicals emitted from facilities. As a result, ground-level ozone pollution is found in close proximity to the surrounding areas where plants operate.

[5]Donations made through corporate foundations are arguably the most salient form of corporate philanthropy because foundations usually bear the same name as their parent company and often serve as the flagship of a firm's corporate giving strategy.

[6]For example, an increase in emissions has been shown to lead to additional penalties (Xu & Kim, 2022), greater compliance costs (Blundell, Gowrisankaran, & Langer, 2020), and losses in stock price valuations (Karpoff, Lott, & Wehrly, 2005).

[7]Henceforth, we refer to ground-level ozone as simply ozone.

standards, the federal United States Environmental Protection Agency (EPA) sets maximum allowable concentrations of ozone pollution, known as the NAAQS threshold. 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 threshold are deemed to be noncompliant (i.e., designated nonattainment), while those with DVs below the threshold are considered compliant (i.e., designated attainment).

The key implication for firms is that those operating ozone-polluting facilities in nonattainment counties face stringent regulations and mandatory pollution abatement requirements compared to those in attainment counties (Becker, 2005; Becker & Henderson, 2000, 2001; Greenstone, 2002). Importantly, nonattainment designations are federally-enforced legally binding regulations that impose significant emission limits on *all* firms operating ozone-polluting facilities in the nonattainment county regardless of the firms' existing characteristics such as their record of environmental performance. As a result of the mandatory compliance with costly emissions reduction in nonattainment counties, prior research has shown that facilities emit more ozone in attainment counties relative to nonattainment counties (Greenstone, 2003; Henderson, 1996). This differential emissions behavior due to the differences in regulatory stringency between nonattainment and attainment counties forms the basis of our identification strategy.

Our empirical strategy exploits the variation in county-level DVs around the NAAQS threshold by using a regression discontinuity design (RDD). The intuition behind our approach is that we wish to compare the donation activities of firms that operate otherwise similar facilities but differ only in their emissions behavior. Specifically, we *compare* the amount of donations to local nonprofits of firms operating polluting plants in counties with DVs slightly below the threshold so that they are marginally in compliance ("close attainment") with firms operating polluting plants in counties with DVs slightly above the threshold so that they are marginally in violation ("close nonattainment"). Since a county's designation status is a random outcome in a narrow window around the threshold, these close attainment and nonattainment designations provide a source of random variation in a firm's level of local 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, operating polluting plants in 857 unique counties over the period 1999–2018. We first validate the basic identifying assumptions of the RDD by showing that counties cannot manipulate DVs to be just below the threshold and there are no preexisting differences between facilities in the narrow window around the threshold. Consistent with the existing literature, we find that a county's attainment status has a significant impact on local polluting plants' ozone emissions, with facilities in close attainment counties emitting up to 42% more ozone than those in close nonattainment counties. Our main results show that firms operating polluting plants in close attainment counties subsequently donate significantly more to local nonprofits relative to those operating in close nonattainment counties. Specifically, the amount of donations increases by 39%, or equivalently $51,000 on average. We corroborate our main findings by performing a number of robustness checks such as alternative RDD specifications and placebo tests.

We conduct cross-sectional tests examining whether variation in insurance incentives affects local donation decisions. We focus on two aspects: a firm's intensity of ozone emissions in a given county and (ii) a county's level of social capital. We find that our results are primarily driven by firms that operate 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 is greater for the former set of firms. Differences in the level of mutual trust, as measured by social capital, across communities also moderate the effect of regulation-induced emissions on local donations. We show that firms donate more to local nonprofits in close attainment counties with lower social capital because such communities are less likely to forgive them given an adverse event (Hasan, Hoi, Wu, & Zhang, 2017; Jha & Chen, 2015).

We provide additional evidence of the insurance-motive of philanthropy by using another 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, in response to localized regulatory changes, 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 roughly 42% 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 CSR-related incidents. Our results show that firms with 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 another similar channel, we find that firms with a history of publicized regulatory noncompliance also donate more to local nonprofits in close attainment counties, in line with the view that firms with more regulatory noncompliance risk derive more insurance value from donations.

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 $1,290.36 to local nonprofits while creating damages to society worth $3,430.59. Therefore, our results indicate that firms benefit from the insurance value of corporate philanthropy at the cost of social welfare.

Our research contributes to the understanding of how firms strategically leverage their reputation in *local* communities through corporate philanthropy. Existing studies have examined various firm-level reasons for strategic engagements in CSR. For example, Flammer and Luo (2017) show that firms mitigate employees' adverse behavior by investing in CSR to improve employee governance. Firms also adopt CSR as a strategic response to competitive threats (Cao, Liang, & Zhan, 2019) and knowledge spillovers (Flammer & Kacperczyk, 2019). In terms of corporate philanthropy, studies have demonstrated that charitable donations can be used to divert public attention from environmental misconduct as a form of window-dressing (Du, 2015) or mitigate negative effects on corporate reputation when involved in legal violations (Williams & Barrett, 2000). Our study differs in that we highlight the role of local communities by linking firms' pollution sources to their local donation recipients. By showing that firms make more donations and also reallocate donations to areas where they pollute the most, our results suggest that firms actively build reputational capital in local communities to maximize the insurance value of donations.

Our research also contributes to the burgeoning literature on the motivations of firms to engage in corporate philanthropy. One strand of literature shows that corporate philanthropy can reflect agency problems because it can be used to enhance CEOs' personal utility through the consumption of private benefits of control (Brown, Helland, & Smith, 2006; Masulis & Reza, 2015; Yermack, 2009). Cai et al. (2021) find evidence in support of the agency motive by showing that CEO compensation is higher at firms making affiliated donations. Other studies have documented corporate philanthropy as a political tool to obtain favorable regulatory treatment (Bertrand et al., 2021, 2020; Wang & Qian, 2011) or to gain competitive advantages (Choi, Park, & Xu, 2023). Our paper adds to the literature on the determinants of corporate philanthropy by providing evidence of the insurance-motives for participating in corporate philanthropy.

Finally, our study documents how environmental regulations affect corporate philanthropic activities. The environmental economics literature has utilized county-level attainment and nonattainment designation status as an instrument for emissions to study various economic outcomes (e.g., Becker & Henderson, 2000; Curtis, 2020; Greenstone, 2002, among others). We contribute to this literature by documenting that while these environmental regulations have been very successful at achieving the first order objectives of reducing emissions to protect human health, they can also have unintended consequences on firms' corporate philanthropy through regulation-induced changes in pollution behavior.

2. Background

In this section, we discuss the regulatory framework that forms the basis of our identification strategy. The CAA requires the EPA to set NAAQS for six pollutants: carbon monoxide, nitrogen dioxide, ozone, sulfur dioxide, particulate matter, and lead. We focus on ozone because counties most often fail to meet NAAQS standards by exceeding ozone limits, rather than by violating the NAAQS for the other pollutants (Curtis, 2020). As a result, ozone offers a much larger treatment group of counties for our analyses.[8]

[8]Focusing on ozone is also important economically because the largest health benefits from the CAA are derived from ozone regulations (Muller, Mendelsohn, & Nordhaus, 2011). Unlike other pollutants such as particulate matter whose negative health effects may not become apparent until decades later (Bishop et al., 2022), relatively short-term exposure to ozone could lead to severe health effects. 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

Each year, the CAA also requires the EPA to designate each county either as being in attainment or out of attainment (nonattainment) with the NAAQS threshold. 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,[9] during our sample period from 1999 to 2018, the EPA implemented four different ozone standards: i) the 1-Hour Ozone (1979) standard with a threshold of 0.12 ppm from 1999 to 2003; ii) the 8-Hour Ozone (1997) standard with a threshold of 0.08 ppm from 2004 to 2011; iii) the 8-Hour Ozone (2008) standard with a threshold of 0.075 ppm from 2012 to 2017; and iv) the 8-Hour Ozone (2015) standard with a threshold of 0.070 ppm in 2018.[10]

When a county is designated nonattainment, the EPA requires the state to submit a SIP (state implementation plan), which indicates how the state will bring nonattainment counties back into compliance with the NAAQS. While SIPs may vary from state to state, they must follow EPA's guidelines and be approved by the EPA. Failure to submit and execute an acceptable SIP can result in federal sanctions, including withholding federal grants, penalties, and construction bans on new polluting establishments. Most importantly for our purposes, the SIP is federally-enforced and legally binding for *all* firms that operate polluting plants in the nonattainment county regardless of, for example, whether the firm has a record of good environmental performance prior to the designation (Greenstone, 2002).

Environmental regulations under the SIP in nonattainment counties are intended to be stringent and involve regulatory actions to curb emissions. Large pollution sources are required to satisfy the standard of "lowest achievable emission rate", which involve the installation of the cleanest available technology, regardless of economic costs. Moreover, any additional emissions from one pollution source must be offset by paying another source in the same county to reduce its emissions (Nelson, Tietenberg, & Donihue, 1993). Shapiro and Walker (2020) show that expenditures on these emission offsets are one of the largest environmental

one standard for ozone allows us to implement a RDD approach to study the effect of ozone emissions on donations.

[9] In this table, the name of each ozone standard is based on the year in which the new NAAQS was proposed. The effective date is when the EPA actually implemented that standard.

[10] The thresholds used to determine compliance usually decrease over time because they are based on exogenous revisions that reflect new scientific research on the ongoing health effects of air pollution at that point in time.

expenditures for polluting plants in nonattainment areas. Beyond capital expenditures, SIPs in nonattainment counties also impose costly regulatory burdens such as requirements to use certain raw materials and alter operating and maintenance procedures in ways that reduce emissions (Becker, 2005; Becker & Henderson, 2000).

In attainment counties, plants face significantly less expensive environmental standards and less emission limits relative to those in nonattainment counties. Polluting plants are subject to the installation of the "best available control technology", whereby the EPA considers the technology's economic burden on the plant as the foremost priority in determining an acceptable emissions technology. As a result, large-scale investments in attainment counties typically involve less expensive pollution abatement equipment and the EPA does not require emissions offsets.

The differences in the stringency of regulatory compliance between attainment and nonattainment counties generate variation in emissions behavior that is central to our identification strategy. Prior research shows that ozone pollution reduces significantly in nonattainment counties because of increased firm compliance with costly emission limitations. For example, Henderson (1996) and Greenstone (2003) document that ozone emissions decline by roughly 3 to 8 percent in nonattainment counties relative to attainment counties. We exploit differences in emissions behavior between facilities in attainment and nonattainment counties to study the impact of firms' local ozone emissions on their donation activities to local nonprofits.

3. Data and variables

3.1. 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.[11]

Since we only focus on ozone, we classify a facility's emissions of toxic chemicals into

[11] 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, which leaves our study unaffected since our sample period begins from 1999.

ozone pollutants and non-ozone pollutants.[12] 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.[13] 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. Internet Appendix Table IA.2 lists the three-digit NAICS industries in TRI that are included in our sample. The final TRI sample consists of 89,481 firm–county–year observations from 1999 to 2018.

3.2. 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 name, city, and state, as well as a giving category created by the database.[14] 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. 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. 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.

[12] 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.

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

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

3.3. 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 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 threshold of 0.08 ppm. From 2012 to 2017, we use the 8-Hour Ozone (2008) standard with a threshold of 0.075 ppm. In 2018, we use the 8-Hour Ozone (2015) standard with a 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 consists of 15,914 county–year observations from 1999 to 2018.

3.4. Variables

3.4.1. Plant-level

We use a host of plant-level variables (which we then aggregate at the firm–county level) obtained from various databases. From the TRI data, *Core chemical* is a dummy variable equal to one if a given firm operates plants in a given county that emit core ozone chemicals (i.e., those that have consistent reporting requirements), and zero otherwise. We use the EPA's Pollution Prevention (P2) database to obtain information on a facility's source reduction activities that limit the amount of toxic chemicals released (e.g., recycling, recovery, and treatment). *Source reduction* is 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. We also use the production ratio variable in the P2 database, which measures the change in output

[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.

associated with the release of a chemical in a given year.[16] *Production ratio* is a given firm's average ozone production ratio across all plants in a given county.

We use EPA's Integrated Compliance Information System for Air (ICIS-Air) database for information on plant-level ozone high priority violations (HPV), operating permits, and stack tests. Data on formal administrative and judicial enforcement cases are obtained from EPA's Integrated Compliance Information System for Federal Civil Enforcement Case Data (ICIS FE&C). *Permit* is 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. *ln(HPV)*, *ln(Stack)*, and *ln(Case)* are 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.

Finally, we collect data on a plant's number of employees, dollar amount of sales, and solvency risk from the National Establishment Time-Series (NETS). *ln(Employees)* and *ln(Sales)* are the natural logarithm of one plus a given firm's average number of employees and dollar amount of sales, respectively, across all plants in a given county. *Paydex* is a given firm's average paydex score across all plants in a given county. The paydex score ranges from 0 to 100 and is a business credit score based on a facility's trade credit performance. Higher values indicate lower solvency risk.

3.4.2. Firm-level

We control for a variety of firm financial characteristics including 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 of a stock, excluding the immediate past month; and annual stock returns (*Stock returns*).

[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 $\frac{\#\text{Molds cleaned}_t}{\#\text{Molds cleaned}_{t-1}}$.

3.5. Descriptive statistics

After taking the intersection of the TRI, FoundationSearch, and DV data, the final sample comprises 1,079 unique firms 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.[17]

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. Across all non-zero grants, the average donation at the firm–county–year level is $130,196. However, there is substantial variation in the donation size given the sizable standard deviation of approximately $280,000. 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. The average facility emits around 9.8 tons of ozone with a standard deviation of 60 tons. Finally, about 71% of a given firm's polluting plants are operating in counties that are in compliance.

4. 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 to generate locally exogenous variation in pollution. Counties with a DV below the threshold are designated as attainment, resulting in firms with polluting facilities located in these attainment counties 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

[17] There is substantial variation in the length of time that a county remains in nonattainment; some counties are redesignated to attainment after one or two years, while others (e.g., counties in Southern California) have been in nonattainment for over a decade. Furthermore, it is very rare for a county to be designated as nonattainment for a second time once it has been redesignated to attainment.

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 threshold; for example, whether a county is in compliance with a DV slightly below the 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 threshold are used to estimate discontinuities in firms' donations to local nonprofits. We follow 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 $t+1$. $R_{c,t}$ $(= \text{NAAQS}_t - \text{DV}_{c,t})$ is the centered DV (i.e., the running variable in RDD parlance), defined as the difference between the threshold and the DV of county c in year t. Positive (negative) values indicate that the county is in compliance with (violation of) the 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 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 threshold—the difference in donation outcomes between the firms operating polluting plants in counties that marginally comply with the threshold and the firms operating plants in counties that marginally violate it—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.

4.1. Tests for quasi-randomized assignment

The identifying assumption of the RDD is that, around the 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 threshold. If this assumption is satisfied, then the variation in a county's attainment designation should be as good as that from a randomized experiment.

4.1.1. Continuity in the distribution of design values

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 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 nonattainment designations are likely to be exogenous to all county-specific characteristics other than local air quality conditions. Additionally, nonattainment designations often depend on weather patterns (Cleveland & Graedel, 1979). Combined with the fact that ozone emissions are a result of complex chemical reactions in the atomsphere between pollutants such as volatile organic compounds and nitrogen oxides, it is extremely difficult for counties to manipulate their ozone concentration levels precisely. Lastly, ozone emissions that contribute to a county's DV not only originate from stationary sources such as the facilities examined in this paper, but also from mobile pollution sources (such as those from vehicles). Thus, even if there were a coordinated effort to manipulate ozone emissions by a group of facilities, it would still be unlikely to influence the DV of the entire county given other non-stationary emission sources.

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 thresholds. However, the figure shows that the distribution of DVs appears to be smooth and continuous around the 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.

However, since the thresholds change throughout time, a more formal approach is provided in Figure 3, which plots the local density of centered DVs estimated separately on either side of the threshold, using the plug-in estimator proposed by Cattaneo, Jansson, and Ma (2020). Observations on the right (left) of the vertical dashed line indicate that the county is in compliance with (violation of) the threshold. As is shown, there is no evidence for a discontinuous jump in DVs around the threshold. Using the density break test following Cattaneo et al. (2020),[18] 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).

4.1.2. Preexisting differences

The second testable implication of the randomness assumption is that the polluting facilities in counties whose DVs are immediately below or above the 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 facility characteristics prior to the designation.

In Table 2, we examine whether there are any preexisting differences between plants operating in counties that comply and violate 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 facilities in the sample, whereas columns (2) and (4) report the differences at the narrow margin (using the optimal bandwidth) around the threshold.

As can be seen in columns (1) and (3), the facility's characteristics—ozone permits, number of employees, dollar amount of sales, solvency risk, and number of HPVs and stack tests—of those operating in counties that are in compliance differ significantly from those in counties that are in violation. Importantly, however, columns (2) and (4) show that these differences completely disappear when we restrict the sample to be within a small window around the threshold. Overall, this evidence suggests that no systematic or significant differences exist

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

between facilities in close attainment and close nonattainment counties, which lends support to our identification strategy.

5. Close attainment designation status and donations

5.1. First-stage results

Before presenting our main results, we first validate two basic premises of our RDD framework, namely a county's DV determines its designation status and the change in a facility's polluting behavior stemming from attainment designations.

Figure 4 reports a county's probability of nonattainment conditional on the distance of its DV from the threshold. Here the horizontal axis subtracts the threshold from the DV in year t so that observations on the right (left) of the threshold indicate that the county is in violation (compliance). Each dot in the figure represents the average of a dummy variable equal to one if a given county is designated nonattainment in year $t+1$, and zero otherwise, using integrated mean squared error optimal bins following Calonico et al. (2014). We also control for a county's level of employment, emissions to employment ratio, change in employment levels, and whether the county is located in a MSA (Curtis, 2020). The figure shows that a county's probability of being designated nonattainment increases by a staggering 80% if its DV violates the threshold, which lends support the assumption that a county's designation status is as good as randomized in a narrow window around the threshold.

In Table 3, we present the effects of a county's attainment status on local polluting plants' ozone emissions. We estimate a similar RDD specification to Equation (1), except the unit of observation is at the facility–county–year level and 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 facility in year t. Across all columns, we find that facilities operating in counties with DVs that are marginally in compliance emit significantly more ozone relative to those in counties that are marginally in violation. Economically, facilities in close attainment counties emit 21% to 42% more ozone than those in close nonattainment counties.

5.2. Baseline results

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 potential discontinuities in our outcome variable, we provide a visualization of the data in Figure 5. 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 zero 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.

As can be seen from the figure, the amount of county-level donations appears to be a continuous and smooth function of the centered DVs everywhere except at the threshold, where there is a discontinuous jump. This graphical evidence suggests that firms operating polluting plants in close attainment counties donate more to local nonprofits relative to those operating plants in close nonattainment counties.

We formally quantify the discontinuity illustrated in Figure 5 by estimating the RDD specification in Equation (1). We present the results in Table 4. Column (1) shows that firms operating polluting plants donate roughly 39% more to nonprofits located in close attainment counties relative to close nonattainment counties. In dollar terms, donations to local nonprofits increase by around $51,000 on average. The coefficient on $Comply_{c,t}$ remains positive and statistically significant when we add covariates to the optimal bandwidth selection and point estimation, 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), respectively, and when we use the triangular kernel in column (5). 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 to those in close nonattainment counties but also donate more to local nonprofits, possibly as a form of reputation insurance given the potential costs associated higher emissions.

5.3. Cross-sectional tests

In this section, we study cross-sectional predictions examining how variation in incentives to insure against higher emissions affects local donation decisions. We focus on two aspects that likely affect the strength of insurance incentives: (i) the intensity of ozone emissions in a given county and (ii) a county's level of social capital.

5.3.1. Intensity of ozone emissions

Some polluting plants may emit more ozone than others because they rely more on ozone chemicals for their production. Thus, firms that operate heavy ozone-polluting plants in close attainment counties plausibly obtain more insurance value from donations. To investigate this hypothesis, we alter Equation (1) by including an interaction term that measures the intensity of a firm's ozone emissions in a given county as follows:

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

where the notation is identical to Equation (1). We define $\mathit{ln(Firm\ ozone)}_{i,c,t-1}$ 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 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 continue to rely on ozone emissions for their production, we expect such firms to donate more to local nonprofits given 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 *Comply* × *ln(Firm 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 27% 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. These results are in line with the fact that the polluting behavior of firms operating only non-ozone plants are effectively unaffected by a county's attainment status, which does not significantly alter 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 the intensity of their ozone emissions adds to the evidence in support of the insurance-motives of philanthropy.

5.3.2. *Social capital*

We explore whether differences in the level of mutual trust, as measured by social capital, across communities moderate the effect of regulation-induced emissions on local donations. Prior research shows that firms located in communities with higher levels of social capital are perceived as more trustworthy (Guiso, Sapienza, & Zingales, 2004). For example, banks demand lower loan spreads when lending to firms located in higher social capital communities (Hasan et al., 2017). Firms headquartered in U.S. counties with high social capital pay lower audit fees because auditors trust them more (Jha & Chen, 2015). Thus, firms that operate ozone-polluting plants in close attainment counties with higher social capital may have lower incentives to insure against increased emissions because the community is more likely to forgive and be more lenient towards them when negative events occur.

We measure social capital across U.S. counties using the data from the Northeast Regional Center for Rural Development (NRCRD) at Pennsylvania State University. Rupasingha, Goetz, and Freshwater (2006) describe these data in detail. The key variables provide information on voter turnouts in presidential elections (*Pvote*), response rates in US census surveys (*Respn*), total numbers of ten types of social organizations (*Assn*), and total numbers of nonprofit organizations (*Nccs*). Following Rupasingha et al. (2006) and Hasan et al. (2017), we measure social capital as the first principal component from a factor analysis based on *Pvote*, *Respn*, *Assn*, and *Nccs*. We then define the negative of this social capital measure as *Distrust* so that higher values represent lower social capital. We can only directly estimate *Distrust* in years 1997, 2005, 2009, and 2014. Accordingly, we follow Hasan et al. (2017) to backfill data for the missing years using estimates of *Distrust* in the preceding year in which data are available. For example, we fill in missing data from 1999 to 2004 using *Distrust* in 1997.

Table 6 presents the results when we interact *Comply* with *Distrust*. Across all specifications, the coefficients on the interaction term are positive and statistically significant. For example, column (2) implies that in a close attainment county, a one standard deviation increase in *Distrust* leads to a 35% increase in donations to local nonprofits. These results are in line with the insurance-motives of philanthropy because they show that firms operating polluting plants in close attainment counties with lower social capital increase local donations more than those operating in counties with higher social capital.

5.4. Robustness

We perform a number of robustness tests to corroborate our main results. For brevity, we report a concise summary of these tests, while the corresponding tables can be found on the Internet Appendix.

5.4.1. 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 by estimating a global polynomial series model using polynomials of order two and three that are different on both sides of the threshold. 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 main results.

5.4.2. Alternative RDD specifications

We consider a host of alternative RDD specifications. In Internet Appendix Table IA.4, we use the Epanechnikov kernel and the mean squared error optimal bandwidth. 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 qualitatively unchanged.

To ensure that our results are not driven by a small set of firms that have unusually high charitable donations, we estimate Equation (1) after winsorizing the highest two, three, four, and five percent of the dollar amount of donations. Internet Appendix Table IA.7 shows that our results are not driven by extremely large donation amounts in the right tail of the distribution.

Lastly, we account for multiple designations where a county may be in compliance in one year but not in the next. Although multiple designations are unlikely to pose a problem to our empirical analysis since about 70% of all county–years in our sample maintain the same designation status for at least the subsequent three years, we conduct a robustness check by estimating Equation (1) after restricting the sample to counties where there are no changes in designation status in following one to three years. Internet Appendix Table IA.8 shows that our results remain intact.

5.4.3. Long term donation activity

A potential concern is that firms operating in close attainment counties may appear to donate more relative to those in close nonattainment counties because charitable activities and pollution abatement effort could be substitutes. Specifically, firms in close nonattainment counties may donate less to local nonprofits because they invest more in pollution abatement technology. Although this concern is partially mitigated by our empirical design since facilities operating in the optimal bandwidth are very similar to each other in terms of pollution abatement efforts (see Table 2) and source reduction is explicitly included as a control variable in our RDD specifications, we conduct further tests to account for any substitution effects.

Prior studies have shown that pollution abatement costs associated with nonattainment status primarily consist of capital expenditures, which are usually fixed in nature and therefore do not affect marginal production decisions (Becker, 2005). For those variable costs that are tied to current production, e.g., change in the raw materials processed, incumbent plants are generally shielded from these costs because they can escape stringent regulations on pollution abatement until they undergo large expansions (Becker & Henderson, 2000, 2001). Thus, while the fixed costs of pollution abatement activities may reduce donations in the immediate short term, they should not affect donations in the long term.

Rather than studying a firm's donation activities in the year immediately following the close attainment designation, we examine whether a firm extends its donation activities to local nonprofits beyond year $t + 1$ by using the two-year and three-year forward amount of donations as the dependent variable in the baseline RDD specification. The intuition is that any substitution between pollution abatement efforts and donation activities should mainly exist in the short term, while the extent to which donations are used for insurance should persist in the long term. Internet Appendix Table IA.9 shows that firms operating polluting plants located in close attainment counties donate significantly more to nonprofits in the following two and three years relative to those in close nonattainment counties, indicating that substitution effects are unlikely to be driving our results.

5.4.4. Placebo tests

We conduct three placebo tests on the baseline RDD specification to rule out confounding effects. First, one may worry that ozone precursors such as volatile organic compounds or nitrogen oxides may serve as substitutes for other pollutants such as particulate matter (PM). If this were the case, then firms could potentially reduce emissions of ozone precursors in close nonattainment counties but increase PM emissions, leading to an omitted variable in our analysis. However, in practice, it is difficult for firms to substitute between ozone precursors and PM for production because they are drastically different pollutants. Indeed, the correlation between ozone emissions and PM emissions at the firm–county–year level in our sample is only 0.07. To confirm that the insurance-motives we document are driven by ozone emissions and not PM emissions, we interact *Comply* with $\mathit{ln(Firm\ PM)}_{t-1}$, which equals to the natural logarithm of one plus the total amount of PM air emissions (in pounds) in a given county of a given firm in year $t-1$. Internet Appendix Table IA.10 shows that none of the coefficients of this interaction term is significant, while those of *Comply* remain positive and statistically significant. This placebo test confirms that PM emissions do not impact on donation decisions.

Next, we use placebo 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 threshold, then there should be no such results when using placebo thresholds to define compliance. 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.11).

Finally, we use a placebo sample of counties by limiting 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 driven by insurance-motives. Using this placebo sample, the coefficient on *Comply* becomes statistically insignificant (columns (3) and (4) of Internet Appendix Table IA.11), which is in line with our predictions.

6. 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.

6.1. Empirical strategy

We highlight our empirical design in Figure 6, which consists of three key steps. The first step encompasses the analysis presented so far in the previous Section 5, 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 threshold and the firm operates plants there (i.e., close attainment operating counties), and leave that flag on during the following two years.[19] 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 county–years, we construct the following variable at the firm–year level:

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

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 that are in compliance 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 $\Delta \textit{Comply donation}_{i,t}$ is bounded between -1 and 1.

6.2. 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:

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

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.[20] We also include county $\times$ year fixed effects

[19] We use two years because of our earlier results in Section 5.4.3 showing that close attainment designation status is associated with differential effects in long term donations following the designation.

[20] 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.

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 7. 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 threshold using the mean squared error optimal bandwidth. 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 7 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.

7. 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.

7.1. Local newspaper closures

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 local community's perceptions of such donations (Cahan, Chen, Chen, & Nguyen, 2015). Studies have shown that firms with better CSR performance receive more favorable media coverage, 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 (Gurun & Butler, 2012; Miller, 2006), with more positive media coverage leading to an improvement in firms' reputational capital among the local community (Liu & McConnell, 2013). Additionally, 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 because firms face less scrutiny from the public.

To study the role of local news coverage on propagating the 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.

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.[21] 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

[21]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`.

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 $Closure_{c,t-1}$ 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.[22] 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*:

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

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 8 reports the results of estimating Equation (5) using the mean squared error optimal bandwidth. Across all specifications, the coefficient on the interaction term *Comply* $\times$ *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 42% decrease 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 44%. 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.

7.2. Reputational risk exposure

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. Firms that have higher emissions tend to experience a higher frequency of environmental-related incidents covered by the media news (Hsu, Li, & Tsou, 2022). Prior research shows that shareholders react negatively to news about CSR incidents (Flammer, 2013; Karpoff et al.,

[22] 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.

2005; Krueger, 2015). 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 high reputational risk exposure to CSR incidents to increase their donations to local nonprofits, relative to those with less reputational risk exposure.

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.[23] 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).[24]

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. We use two RRI measures, namely, the "Peak RRI" score, which is the two-year maximum value of the RRI capturing the long-term CSR incident history of a firm, and the "Current RRI" score, which measures a firm's short-term exposure to reputational risks. 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 RRI score with *Comply* as follows:

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

for firm i, county c, and year t. *RRI* refers to either *Peak* $\mathit{RRI}_{i,t-1}$, defined as a given firm's two-year maximum value of the RRI measured in year $t-1$, or *Current* $\mathit{RRI}_{i,t-1}$, defined as a given firm's current 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 9 using the mean squared error optimal bandwidth. In the

[23]RepRisk is not a rating agency as its main business is about the archival of news about negative CSR events. For more information, see `https://www.reprisk.com/news-research/resources/methodology`.

[24]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).

first three columns, the coefficient on the interaction term *Comply* $\times$ *Peak RRI* is positive and statistically significant, indicating that firms with long-term 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 (1) 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. Columns (4) to (6) present qualitatively similar results when using a firm's Current RRI. It is also worthwhile to note that although the coefficient estimates on *Comply* 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.

7.3. Past regulatory noncompliance

We also examine a firm's history of publicized regulatory noncompliance based on regulatory incidents. Specifically, we examine a firm's facility-level HPVs, 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. Firms with a history of regulatory noncompliance are subject to greater regulatory scrutiny, which increases their regulatory compliance costs (Blundell et al., 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, relative to firms with less regulatory incidents.

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.[25] 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 et al., 2020). Stack tests are plant-level evaluation tests conducted for the purposes of determining and demonstrating compliance with CAA regulations.[26] Failing stack tests is costly because it could lead to firms being labeled as a HPV. Enforcement cases consist 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

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

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

because they could lead to legal penalties (Heitz, Wang, & Wang, 2021; Shive & Forster, 2020; Xu & Kim, 2022).

We estimate Equation (1) by fully interacting *Comply* with measures of a firm's history of regulatory noncompliance 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. $\mathit{Noncompliance}_{i,c,t-1}$ refers to either *ln(HPV)*, *ln(Stack)*, or *ln(Case)*, which are all defined in Section 3.4.1. Note that all three variables are based on data in the past three years because because ECHO makes available facility-level compliance status to the public only for the past three years. 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 regulatory noncompliance relative to other firms with less noncompliance.

Table 10 presents the results. Across all specifications, we find that the coefficients on *Comply* and *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, consistent with the interpretation that such firms derive more insurance value from donations given their regulatory noncompliance risks.

8. 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 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.

8.1. Calculating marginal donations and marginal damages of pollution

We calculate marginal donations 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 obtained from Tables 3 and 4. To illustrate, consider the RDD estimate of 0.265 in column (2) of Table 3. The average ozone air emissions of a given facility in the sample of counties within the optimal bandwidth is 21,674.47 pounds (unreported). Thus, a close attainment designation increases the ozone emissions of an average facility by roughly 6,576.71 pounds (= 3.29 tons). There are on average 7 TRI facilities in a given county, implying that county-level ozone emissions increase by 23.02 tons. Similarly, combining the corresponding RDD estimate of 0.382 in column (2) of Table 4 and the average donation amount of \$63,846.34 (unreported) in the sample of counties within the optimal bandwidth implies that donations increase by \$29,702.09 on average, given a close attainment designation. Taken together, these estimates result in a marginal donation of $29,702.09/23.02 = \$1,290.36$ per ton of yearly emissions.

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 (Muller et al., 2011).[27] 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

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

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 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 (Chay & Greenstone, 2005). 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.

8.2. Comparison results

Table 11 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 sample of counties located in the narrow window around the threshold by computing the mean squared error optimal bandwidth following Calonico et al. (2014). In columns (2) and (3), 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 (1) of Table 11 with the within-county marginal damages using the baseline AP3 model parameters shows that marginal damages are, on average, 2.66 times larger than marginal donations in a given county. Economically, these estimates imply that on average, a firm donates $1,290.36 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 8.20 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) (US EPA, 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 11 and reaffirm the baseline results that marginal damages exceed marginal donations.

9. 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 reputation insurance.

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.

A potential caveat of our findings is that the causal effect is identified by the subset of counties whose DV is close to the threshold, a limitation that is inherent to any RDD. However, we believe that two aspects of the institutional setting ameliorates some of the concerns regarding the external validity of our results. First, the number of close attainment and close nonattainment county–years that are within the optimal bandwidth represents roughly 30% of the total number of observations, implying that quite a sizable portion of county–years is used to identify the effect at work. Second, since our sample period includes four revisions to the threshold that defines compliance, our results are robust around four discrete levels of pollution rather than at just one level. Nonetheless, extending the external validity of this study by identifying natural experiments that apply to a broader universe of firms and donation activities is an exciting and challenging avenue for future research.

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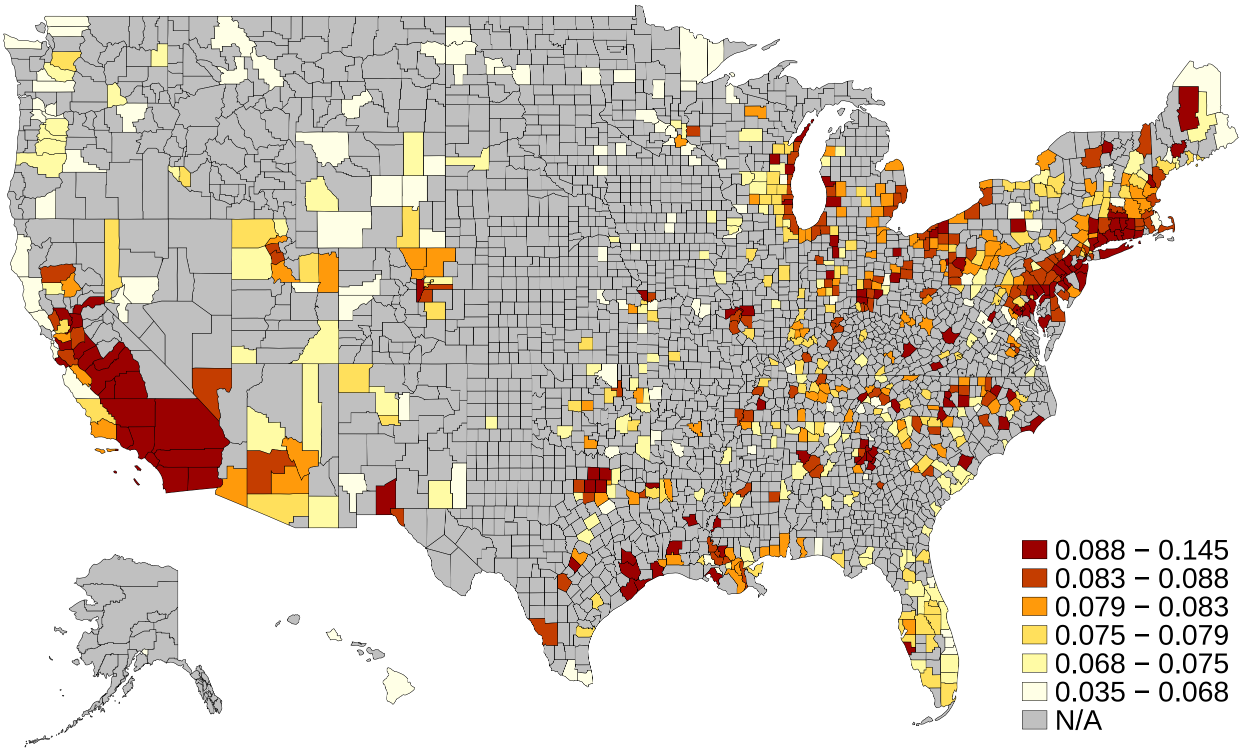
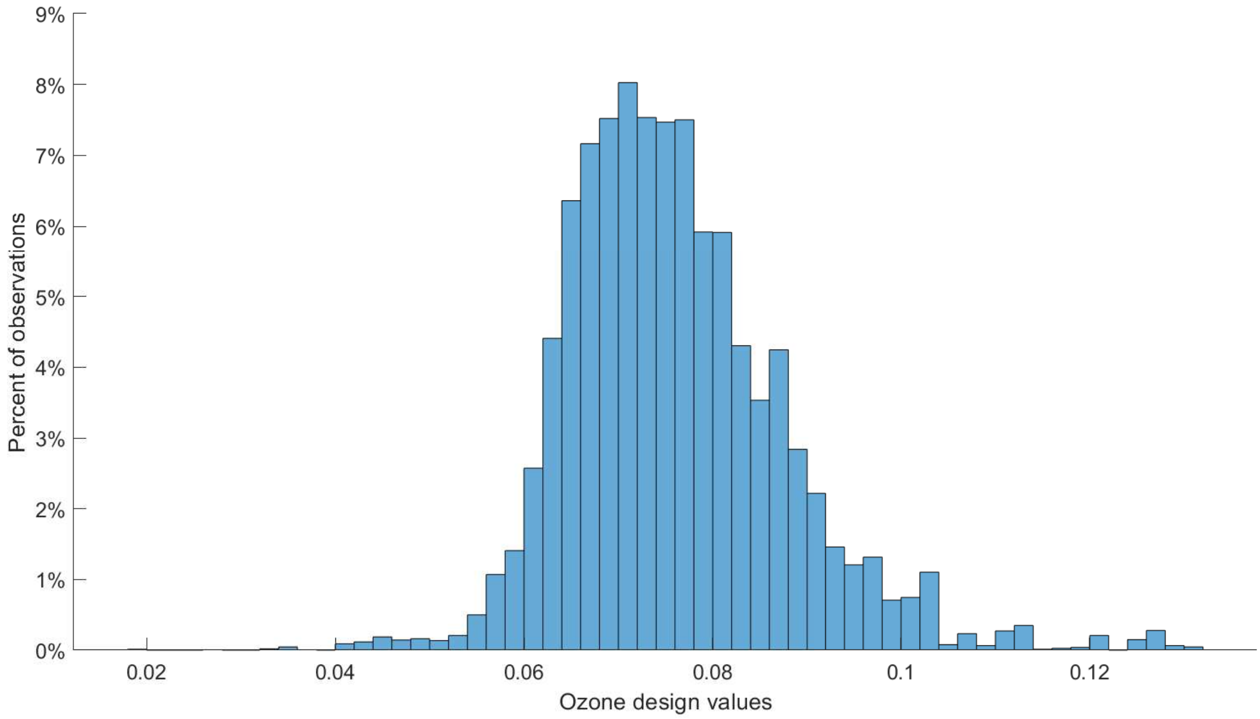
Figure 1
County-level design values.



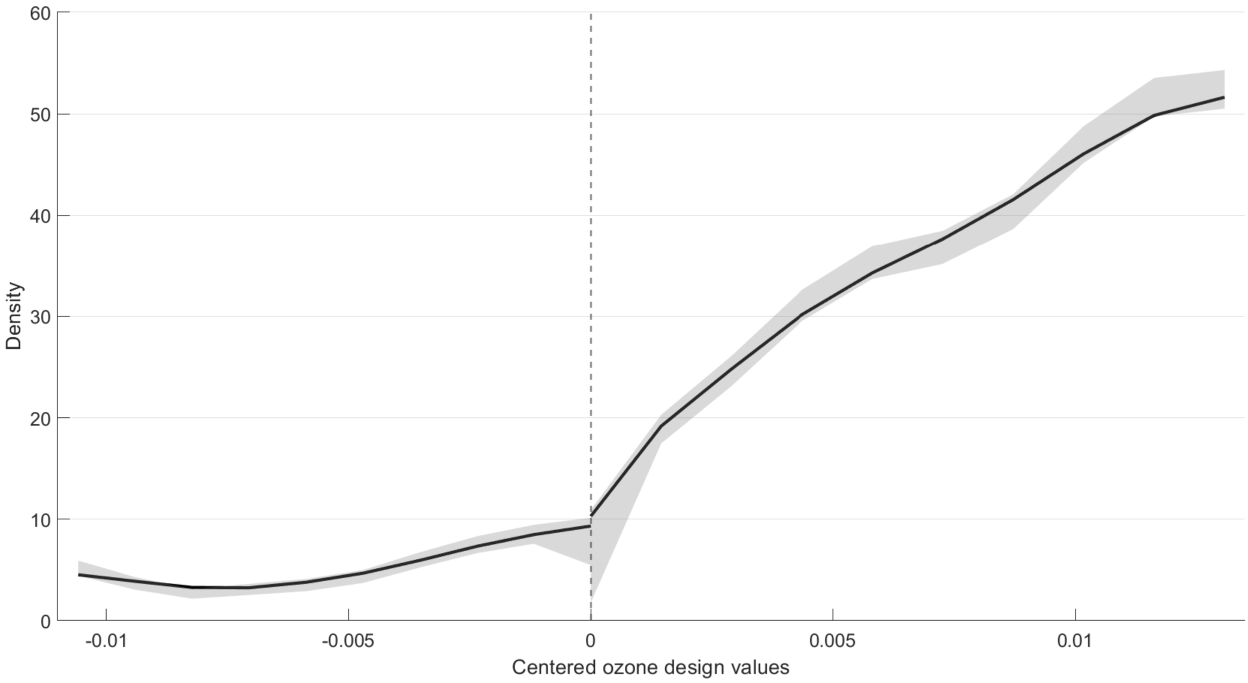
This figure presents the average DVs (in parts per million) from years 1999–2018 in the counties where TRI plants operate and where DV data is available. Counties with higher DVs (indicated by darker shades) correspond to those with greater concentrations of ozone pollution and are more likely to be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

Figure 2
Distribution of county-level design values.



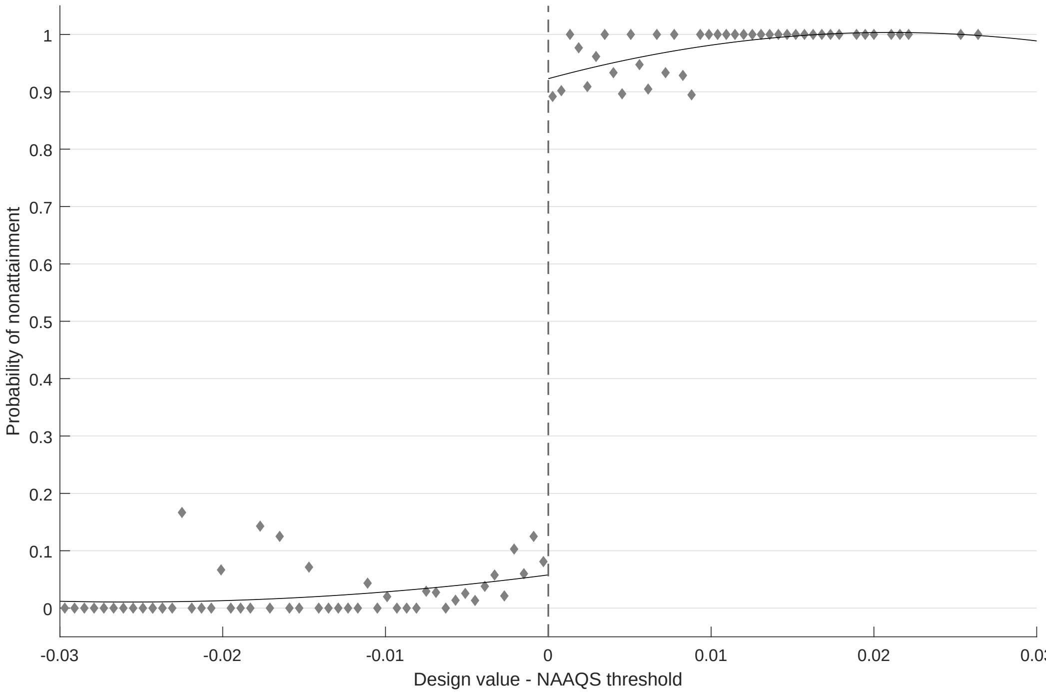
This figure presents the histogram of the county-level DVs (in parts per million) from years 1999–2018 in the counties where TRI plants operate and where DV data is available. The horizontal axis indicates the DV in 0.2% intervals. The vertical axis indicates the percentage of counties in our sample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

Figure 3
Density break test of the number of counties around NAAQS thresholds.



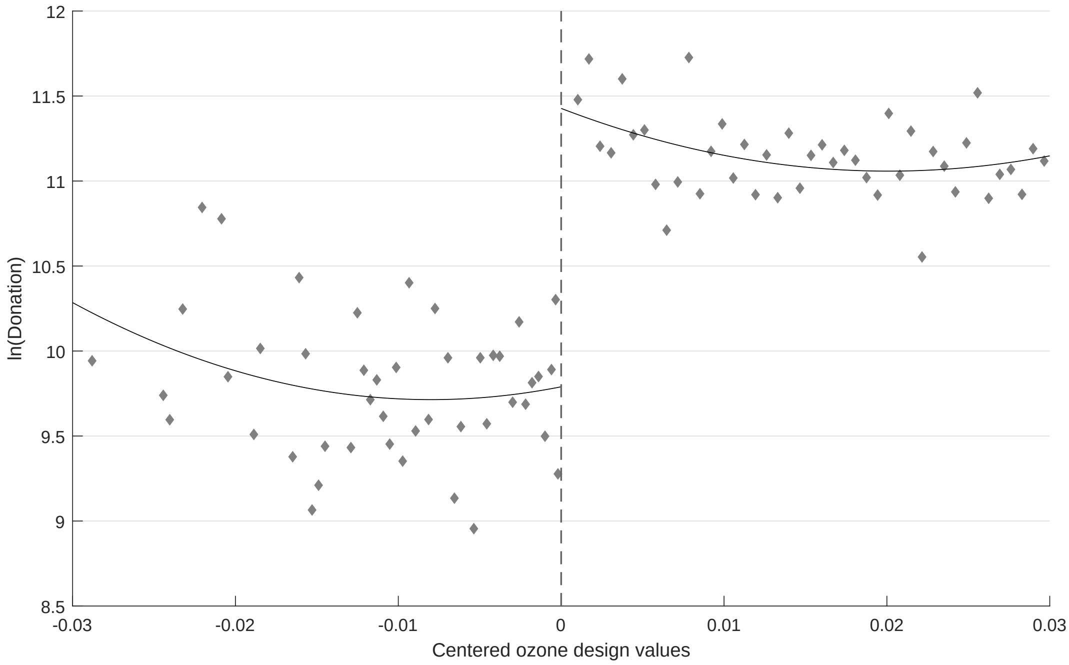
This figure presents the density of observations by the distance to the ozone NAAQS threshold. The unit of observation underlying the estimation of this density is at the county–year level, considering only the counties where TRI plants operate and where DV data is available from years 1999–2018. The 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
Probability of nonattainment.



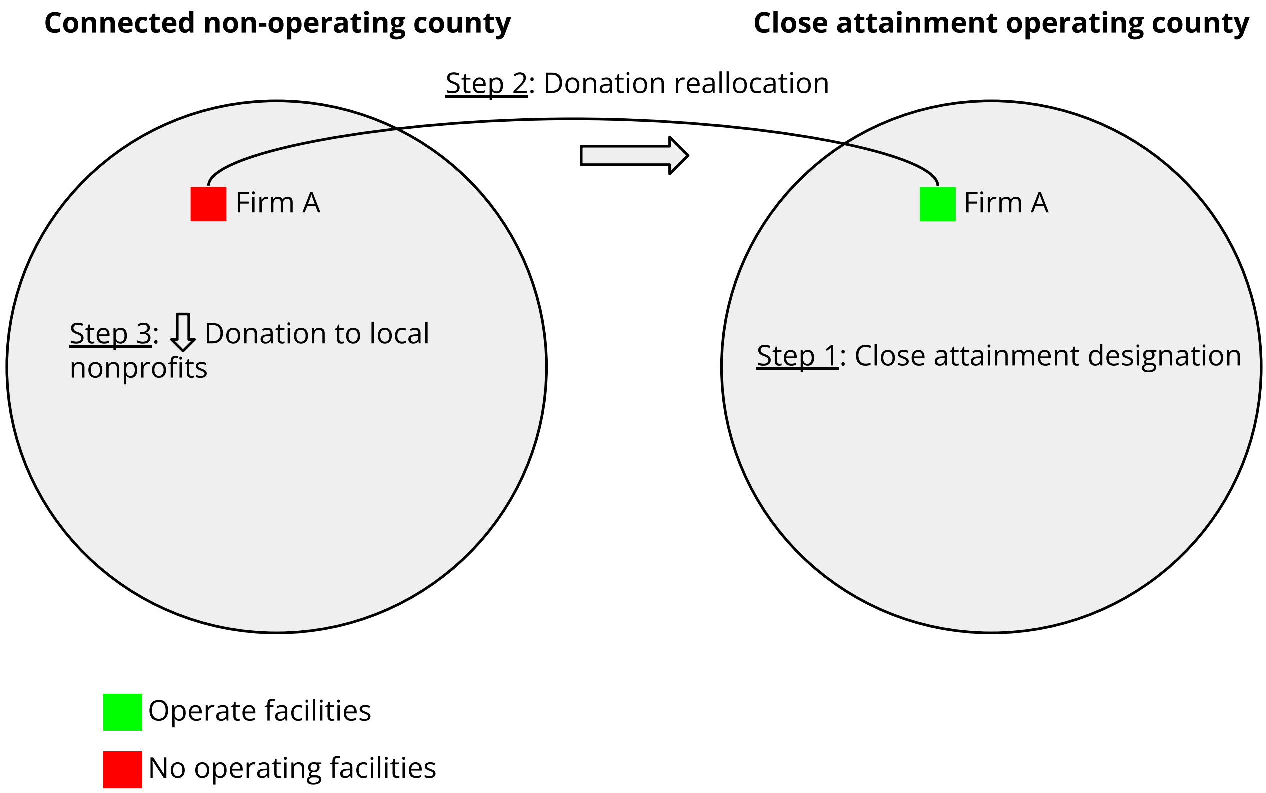
This figure presents the probability of nonattainment conditional on the distance of a county's DV from the NAAQS threshold. The unit of observation is at the county–year level, considering only the counties where TRI plants operate and where DV data is available from years 1999–2018. The vertical axis shows the probability of nonattainment. The horizontal axis shows the difference between a county's DV and the NAAQS threshold. The dashed vertical line at zero represents the NAAQS threshold for ozone nonattainment status. Observations on the right (left) of the line indicate that the county is in violation of (compliance with) the NAAQS threshold. Each dot in the figure represents the average of a dummy variable equal to one if a given county is designated nonattainment in year $t + 1$, and zero otherwise, using integrated mean squared error optimal bins following Calonico et al. (2014). 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. The solid lines on either side of the NAAQS threshold are two separate local quadratic polynomials fitted using the rectangular kernel and mean squared error optimal bandwidth following Calonico et al. (2014).

Figure 5
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 6
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) (>0)	130.196	30.000	279.041	41,316
Firm ozone (ton)	14.990	0.000	90.405	54,524
Facility ozone (ton)	9.738	0.000	59.597	66,131
Comply	0.705	1.000	0.456	54,524
Distrust	0.523	0.493	0.797	54,353
Closure	0.038	0.000	0.191	38,440
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
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
ln(Employees)	3.802	4.369	2.206	54,524
ln(Sales)	14.006	16.729	6.656	54,524
Paydex	66.390	68.000	9.392	40,764
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 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 facility characteristics.

	Year $(t-1)$		Δ from year $(t-2)$ to $(t-1)$	
	(1)	(2)	(3)	(4)
Core chemical	-0.011	0.051	0.000	0.006
	(0.014)	(0.035)	(0.002)	(0.006)
Permit	0.117**	-0.059	0.003	-0.008
	(0.049)	(0.043)	(0.003)	(0.006)
Source reduction	-0.005	-0.002	0.004	0.001
	(0.005)	(0.016)	(0.002)	(0.009)
Production ratio	0.004	0.014	-0.010	-0.006
	(0.011)	(0.041)	(0.006)	(0.023)
ln(Employees)	-0.086	-0.196	-0.061***	-0.032
	(0.065)	(0.162)	(0.019)	(0.043)
ln(Sales)	-0.141	-0.115	-0.234***	-0.092
	(0.159)	(0.129)	(0.085)	(0.165)
Paydex	1.076***	-0.549	0.212	0.169
	(0.220)	(0.518)	(0.132)	(0.209)
ln(HPV)	-0.028***	-0.006	0.003	0.005
	(0.011)	(0.011)	(0.002)	(0.006)
ln(Stack)	-0.006	0.028	-0.009***	0.005
	(0.019)	(0.042)	(0.004)	(0.012)
ln(Case)	-0.001	-0.001	0.000	-0.002
	(0.003)	(0.005)	(0.001)	(0.005)
Sample:	Full	Opt.	Full	Opt.

This table examines the differences in observable facility characteristics between those that operate 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 facility-level ozone emissions.

Dep. variable: *ln(Facility ozone)*$_t$	(1)	(2)	(3)	(4)	(5)
$Comply_{c,t}$	0.351***	0.265***	0.308***	0.188***	0.226***
	(2.60)	(2.66)	(2.63)	(2.84)	(2.70)
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	0.013
Covariates	No	Yes	Yes	Yes	Yes
Observations	24,891	26,243	10,849	47,722	25,565

This table 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). The unit of observation is at the facility–county–year level. 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(Facility 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 facility in year t. Facility-level covariates include *Core chemical*, *Permit*, *Source reduction*, *Production ratio*, *ln(Employees)*, *ln(Sales)*, and *Paydex*. 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*, *Core chemical*, *Permit*, *Source reduction*, *Production ratio*, *ln(Employees)*, and *ln(Sales)*. 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 the amount of local ozone emissions.

Dep. variable: *ln(Donation)*$_{t+1}$	(1)	(2)	(3)	(4)	(5)
$Comply_{c,t}$	0.112	0.167	0.044	0.127	0.097
	(1.12)	(1.61)	(0.27)	(1.02)	(0.82)
ln(Firm ozone)$_{t-1}$	0.014	0.009	-0.022	-0.007	-0.017
	(0.88)	(0.49)	(-0.84)	(-0.37)	(-0.85)
$Comply_{c,t}$ × *ln(Firm ozone)*$_{t-1}$	0.055**	0.056***	0.098***	0.066***	0.078***
	(2.31)	(2.79)	(3.04)	(2.73)	(3.38)
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 its local 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(Firm 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*, *Core chemical*, *Permit*, *Source reduction*, *Production ratio*, *ln(Employees)*, and *ln(Sales)*. 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
Local social capital.

Dep. variable: *ln(Donation)*$_{t+1}$	(1)	(2)	(3)	(4)	(5)
$Comply_{c,t}$	0.111	0.094	0.129	0.080	0.094
	(0.92)	(0.69)	(0.70)	(0.74)	(0.92)
$Distrust_t$	-0.179	-0.284**	-0.263	-0.164*	-0.300***
	(-1.52)	(-2.28)	(-1.46)	(-1.66)	(-3.18)
$Comply_{c,t} \times Distrust_t$	0.296**	0.381***	0.413**	0.236**	0.445***
	(2.21)	(2.68)	(1.98)	(2.14)	(4.08)
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 local social capital. 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. *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 $t+1$. $Distrust_t$ is a county-level social capital index based on data from the NRCRD at the Pennsylvania State University. Higher values represent lower social capital. $Comply_{c,t}$ 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*, *Core chemical*, *Permit*, *Source reduction*, *Production ratio*, *ln(Employees)*, and *ln(Sales)*. 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
Reallocation of donations from connected non-operating counties to attainment operating counties.

Dep. variable: Δ*Connected donation*$_{i,c,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ*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)
Δ*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, Δ*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, Δ*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). Covariates include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *KZ*, *Cash*, *Momentum*, *Stock returns*, *Core chemical*, *Permit*, *Source reduction*, *Production ratio*, *ln(Employees)*, and *ln(Sales)*. 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 8
Local newspaper closures.

Dep. variable: *ln(Donation)*$_{t+1}$	(1)	(2)	(3)	(4)	(5)
$Comply_{c,t}$	0.217***	0.363***	0.352***	0.257***	0.222**
	(2.60)	(3.57)	(3.17)	(3.31)	(2.33)
$Closure_{t-1}$	-0.076	-0.050	0.076	0.169	0.055
	(-0.66)	(-0.34)	(0.34)	(1.57)	(0.27)
$Comply_{c,t} \times Closure_{t-1}$	-0.318**	-0.541***	-0.600***	-0.463***	-0.383**
	(-2.50)	(-2.78)	(-2.70)	(-2.75)	(-2.45)
Kernel	Rec.	Rec.	Rec.	Rec.	Tri.
Bandwidth type	Opt.	Opt.	50% Opt.	150% Opt.	Opt.
Bandwidth estimate	0.008	0.010	0.005	0.015	0.012
Covariates	No	Yes	Yes	Yes	Yes
Observations	5,937	7,339	2,381	12,853	8,679

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*, *Core chemical*, *Permit*, *Source reduction*, *Production ratio*, *ln(Employees)*, and *ln(Sales)*. 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 9
Reputational risk.

Dep. variable: $ln(Donation)_{t+1}$	(1)	(2)	(3)	(4)	(5)	(6)
$Comply_{c,t}$	0.043	0.049	0.126	0.113	0.087	0.151
	(0.26)	(0.20)	(1.32)	(0.67)	(0.33)	(1.63)
$Peak\ RRI_{t-1}$	0.002	0.008	0.005			
	(0.32)	(1.04)	(0.93)			
$Comply_{c,t} \times Peak\ RRI_{t-1}$	0.028***	0.024**	0.019***			
	(3.72)	(2.12)	(2.89)			
$Current\ RRI_{t-1}$				0.001	0.005	0.004
				(0.12)	(0.41)	(0.43)
$Comply_{c,t} \times Current\ RRI_{t-1}$				0.039***	0.035**	0.030***
				(3.06)	(1.96)	(2.76)
Kernel	Rec.	Rec.	Rec.	Rec.	Rec.	Rec.
Bandwidth type	Opt.	50% Opt.	150% Opt.	Opt.	50% Opt.	150% Opt.
Bandwidth estimate	0.011	0.006	0.017	0.011	0.006	0.017
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,671	2,733	16,700	7,671	2,733	16,700

This table presents a firm's donation activities in response to a county's close attainment designation status conditional on the firm's 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 $t-1$. $Current\ RRI_{t-1}$ is a given firm's current value of the RRI measured in year $t-1$. The 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*, *Core chemical*, *Permit*, *Source reduction*, *Production ratio*, *ln(Employees)*, and *ln(Sales)*. 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
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*, *Core chemical*, *Permit*, *Source reduction*, *Production ratio*, *ln(Employees)*, and *ln(Sales)*. 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
Mean marginal donations and marginal damages of ozone pollution.

	(1)	(2)	(3)
Marginal donations ($ / tpy)	1,290.36	1,129.38	2,152.48
Baseline AP3 model			
Within-county marginal damages ($ / tpy)	3,430.59	4,020.88	2,765.17
All counties marginal damages ($ / tpy)	10,578.94	11,664.28	9,198.50
VSL OECD model			
Within-county marginal damages ($ / tpy)	1,777.47	2,083.32	1,432.70
All counties marginal damages ($ / tpy)	5,481.22	6,043.56	4,765.97
Krewski 5^{th} *pctile*			
Within-county marginal damages ($ / tpy)	2,285.27	2,678.94	1,840.41
All counties marginal damages ($ / tpy)	7,067.84	7,793.28	6,149.77
Krewski 95^{th} *pctile*			
Within-county marginal damages ($ / tpy)	4,447.64	5,197.93	3,595.33
All counties marginal damages ($ / tpy)	13,685.19	15,043.79	11,943.77
Sample	Opt.	50% Opt.	150% Opt.
Number of counties	437	292	591

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 5^{th} and 95^{th} 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. Column (1) uses the sample of counties located in the narrow window around the threshold by computing the mean squared error optimal bandwidth following Calonico et al. (2014). In columns (2) and (3), 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(Firm 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
ln(Facility ozone)	The natural logarithm of one plus the total amount of ozone air emissions (in pounds) in a given county of a given facility.	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
Distrust	A county-level social capital index based on data from the NRCRD at the Pennsylvania State University. Higher values represent lower social capital.	NRCRD
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
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
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
Production ratio	A given firm's average ozone production ratio across all plants in a given county.	P2
ln(Employees)	The natural logarithm of one plus a given firm's average number of employees across all plants in a given county.	NETS
ln(Sales)	The natural logarithm of one plus a given firm's average dollar amount of sales across all plants in a given county.	NETS
Paydex	A given firm's average paydex score across all plants in a given county. The paydex score ranges from 0 to 100 and is a business credit score based on a facility's trade credit performance. Higher values indicate lower solvency risk.	NETS
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, Mansur, Muller, & Yates, 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 (US EPA, 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) (US EPA, 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.

References for Appendix B

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Internet Appendix For Online Publication Only

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
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*, *Core chemical*, *Permit*, *Source reduction*, *Production ratio*, *ln(Employees)*, and *ln(Sales)*. 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.

Dep. variable: *ln(Donation)*$_{t+1}$	(1)	(2)	(3)	(4)	(5)	(6)
$Comply_{c,t}$	0.349***	0.451***	0.501***	0.440***	0.409***	0.394***
	(2.79)	(3.26)	(2.61)	(3.79)	(2.71)	(2.76)
Kernel	Epan.	Epan.	Epan.	Epan.	Rec.	Rec.
Bandwidth type	Opt.	Opt.	50% Opt.	150% Opt.	Opt.	Opt.
Bandwidth estimate	0.012	0.012	0.006	0.018	0.016	0.016
Polynomial order	1	1	1	1	2	3
Covariates	No	Yes	Yes	Yes	Yes	Yes
Observations	16,585	14,721	6,773	26,466	24,613	22,261

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*, *Core chemical*, *Permit*, *Source reduction*, *Production ratio*, *ln(Employees)*, and *ln(Sales)*. 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
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*, *Core chemical*, *Permit*, *Source reduction*, *Production ratio*, *ln(Employees)*, and *ln(Sales)*. 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.

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*, *Core chemical*, *Permit*, *Source reduction*, *Production ratio*, *ln(Employees)*, and *ln(Sales)*. 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
Winsorization.

Winsorize:	Top 2%	Top 3%	Top 4%	Top 5%
Dep. variable: *ln(Donation)*$_{t+1}$	(1)	(2)	(3)	(4)
Comply$_{c,t}$	0.374***	0.268**	0.239**	0.208**
	(2.72)	(2.20)	(2.08)	(2.20)
Kernel	Rec.	Rec.	Rec.	Rec.
Bandwidth type	Opt.	Opt.	Opt.	Opt.
Bandwidth estimate	0.011	0.011	0.011	0.011
Covariates	Yes	Yes	Yes	Yes
Observations	13,596	13,556	12,144	11,993

This table presents a firm's donation activities in response to a county's close attainment designation status after winsorizing the dollar amount of donations. We estimate the local linear regression specification given in Equation (1) using the mean squared error optimal bandwidth and rectangular kernels following Calonico et al. (2014). Columns (1) to (4) present the results after winsorizing the highest two to five percent of the values, 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. Covariates include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *KZ*, *Cash*, *Momentum*, *Stock returns*, *Core chemical*, *Permit*, *Source reduction*, *Production ratio*, *ln(Employees)*, and *ln(Sales)*. 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
Multiple designations.

No designation change:	One year	Two years	Three years
Dep. variable: *ln(Donation)*$_{t+1}$	(1)	(2)	(3)
$Comply_{c,t}$	0.466***	0.563***	0.562***
	(2.74)	(2.92)	(2.91)
Kernel	Rec.	Rec.	Rec.
Bandwidth type	Opt.	Opt.	Opt.
Bandwidth estimate	0.010	0.010	0.010
Covariates	Yes	Yes	Yes
Observations	4,018	4,273	4,268

This table presents a firm's donation activities in response to a county's close attainment designation status ensuring there are no subsequent changes in designation status. We estimate the local linear regression specification given in Equation (1) using the mean squared error optimal bandwidth and rectangular kernels following Calonico et al. (2014). Columns (1) to (3) present the results after restricting the sample to counties where there are no changes in designation status in following one to three years, 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. Covariates include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *KZ*, *Cash*, *Momentum*, *Stock returns*, *Core chemical*, *Permit*, *Source reduction*, *Production ratio*, *ln(Employees)*, and *ln(Sales)*. 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
Long term donation activity.

Panel A: Two-year forward donations					
Dep. variable: *ln(Donation)*$_{t+2}$	(1)	(2)	(3)	(4)	(5)
Comply$_{c,t}$	0.343***	0.381***	0.222**	0.321***	0.314***
	(3.27)	(3.41)	(2.36)	(5.57)	(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
Panel B: Three-year forward donations					
Dep. variable: *ln(Donation)*$_{t+3}$	(1)	(2)	(3)	(4)	(5)
Comply$_{c,t}$	0.240***	0.314***	0.272**	0.306***	0.312***
	(3.55)	(3.88)	(2.51)	(4.87)	(4.14)
Kernel	Rec.	Rec.	Rec.	Rec.	Tri.
Bandwidth type	Opt.	Opt.	50% Opt.	150% Opt.	Opt.
Bandwidth estimate	0.010	0.010	0.005	0.015	0.012
Covariates	No	Yes	Yes	Yes	Yes
Observations	12,915	10,984	4,663	21,573	14,982

This table presents a firm's long term donation activities in response to a county's close attainment designation status. Panel A (panel B) uses the two-year (three-year) forward donations. 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)*$_{t+2}$ (*ln(Donation)*$_{t+3}$) 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 $t+2$ ($t+3$). *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*, *Core chemical*, *Permit*, *Source reduction*, *Production ratio*, *ln(Employees)*, and *ln(Sales)*. 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
Placebo PM emissions

Dep. variable: *ln(Donation)*$_{t+1}$	(1)	(2)	(3)	(4)
Comply$_{c,t}$	0.383**	0.262**	0.391**	0.221***
	(2.08)	(2.10)	(2.26)	(3.22)
ln(Firm PM)$_{t-1}$	0.094	0.082	0.109	0.080***
	(1.28)	(1.46)	(1.51)	(3.58)
Comply$_{c,t}$ × *ln(Firm PM)*$_{t-1}$	0.068	0.541	0.027	-0.001
	(0.96)	(1.16)	(0.39)	(-0.04)
Kernel	Rec.	Rec.	Rec.	Tri.
Bandwidth type	Opt.	50% Opt.	150% Opt.	Opt.
Bandwidth estimate	0.011	0.006	0.017	0.012
Covariates	Yes	Yes	Yes	Yes
Observations	13,826	5,963	26,246	15,753

This table presents placebo tests for a firm's donation activities in response to a county's close attainment designation status conditional on local PM 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. *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(Firm PM)*$_{t-1}$ equals to the natural logarithm of one plus the total amount of PM 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*, *Core chemical*, *Permit*, *Source reduction*, *Production ratio*, *ln(Employees)*, and *ln(Sales)*. 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.11
Placebo RDD specifications.

	Placebo thresholds		Non-operating counties	
Dep. variable: *ln(Donation)*$_{t+1}$	(1)	(2)	(3)	(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*, *Core chemical*, *Permit*, *Source reduction*, *Production ratio*, *ln(Employees)*, and *ln(Sales)*. 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.