Environmental regulation, pollution, and shareholder wealth*

Seungho Choi[†], Ross Levine[‡], Raphael Jonghyeon Park[§], and Simon Xu[¶]

Abstract

This paper investigates the stock market's reaction to changes in the interaction between local environmental regulations and a firm's polluting behavior. Our identification strategy uses county-level noncompliance designations induced by discrete policy changes in the National Ambient Air Quality Standards as a source of exogenous variation in local regulatory stringency. On average, the market responds positively to firms exposed to noncompliance designations compared to non-exposed firms. In the cross-section, firms' value initially increases with noncompliance exposure but declines at higher levels. Examining the mechanisms reveals that this nonlinear variation arises from the offsetting effects of noncompliance exposure on incumbent firms, encompassing a tradeoff between the benefits of competitive advantages and the costs of regulatory compliance. Furthermore, short-term market reactions to noncompliance designations are consistent with their long-term effects on firms' accounting performance. Overall, the evidence suggests that the stock market internalizes the perceived benefits and costs of local environmental regulation.

JEL Classification: G14; G18; Q53; Q58
Keywords: environmental regulation, pollution, firm value, event study

*We greatly appreciate the comments of Pat Akey, Xin Chang, John Dougherty, Chris Florackis, Stefano Giglio, Po-Hsuan Hsu, Marcin Kacperczyk, Taehyun Kim, Heebum Lee, Ulrike Malmendier, Christine Parlour, Manh Pham, Joseph Shapiro, David Sraer, Chi-Yang Tsou, Annette Vissing-Jørgensen, Reed Walker, Endong Yang, Chelsea Yao, Aaron Yoon, Hong Zhang, Zoey Yiyuan Zhou, Qifei Zhu, and seminar participants at UC Berkeley Haas School of Business, UC Berkeley Department of Economics, AsianFA Annual Conference 2022, APAD Annual Conference 2022, CEPR Endless Summer Conference 2022, GRETA CREDIT 2022, Frontiers of Factor Investing Conference 2022, ICEF-CInSt International Finance Conference 2022, FIRN Corporate Finance Meeting 2022, FMA Annual Meeting 2022, Conference on CSR, the Economy and Financial Markets 2022, CAFM 2022, Boca Corporate Finance and Governance Conference 2022, SFS Cavalcade Asia-Pacific 2022, SWFA Annual Meeting 2023, FMCG 2023, CICF 2023, and Loyola Financial Ethics Conference 2024. We also thank the EPA for helpful discussions on data. All remaining errors are our own.

[†]Department of Finance, School of Business, Hanyang University, Seoul, 04763, South Korea; email seunghochoi@hanyang.ac.kr.

[‡]Hoover Institution, Stanford University, Stanford, CA 94305, United States; email rosslevine@stanford.edu.

[§]Finance Department, UTS Business School, University of Technology Sydney, Broadway, NSW 2007, Australia; email jonghyeon.park@uts.edu.au.

[¶]Harvard Business School, Harvard University, Boston, MA 02163, United States; email sxu@hbs.edu.

1. Introduction

There is a growing body of research on environmental regulations and financial markets. Studies have shown that environmental regulations affect the pricing of municipal bonds (Jha, Karolyi, & Muller, 2020), corporate bonds (Seltzer, Starks, & Zhu, 2022), and bank loans (Chen, Hsieh, Hsu, & Levine, 2023). Institutional investors have also begun to consider changes in environmental regulations when making portfolio decisions (Choi, Park, & Xu, 2023; Krueger, Sautner, & Starks, 2020). However, there is relatively less work that explores the interplay between environmental regulations and firm pollution, and their impact on the financial stock market. We aim to fill this gap by examining whether the stock market incorporates the consequences of local regulation on air pollution into the valuation of polluting firms.

Our study focuses on a key regulatory component of the Clean Air Act (CAA), specifically the designation of counties as either in compliance ("attainment") or noncompliance ("nonattainment") with the National Ambient Air Quality Standards (NAAQS) for ground-level ozone.[1] The NAAQS threshold, set by the United States Environmental Protection Agency (EPA), establishes the maximum allowable concentrations of ozone pollution. Counties that exceed this threshold are designated as nonattainment, while those that fall below it are classified as attainment. Nonattainment designations represent legally binding regulations enforced by the federal government, imposing stringent requirements on all firms operating facilities that emit ozone pollutants in nonattainment counties. These requirements include costly emission limits and pollution abatement measures (Becker, 2005; Becker & Henderson, 2000, 2001; Greenstone, 2002). In contrast, firms in attainment counties face less stringent regulations. We use county-level ozone nonattainment designations as a source of variation in local regulatory stringency to study how investors react to firms exposed to such designations.

This unique institutional setting allows us to precisely identify the firms that are exposed to nonattainment designations. For example, a firm that operates multiple ozone-emitting plants located exclusively in attainment counties is not affected by the regulation. Similarly, a firm that operates several polluting plants in nonattainment counties, but none of them emit ozone, is also not affected. To capture a firm's exposure to nonattainment designations, we first manually map plant-level chemical emissions into ozone and non-ozone pollutants to determine regulatory treatment at the plant-level based on the quantity of ozone emissions. We then combine the regulatory status of each plant with their geographic distribution across

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

attainment and nonattainment counties to generate a firm-level measure of nonattainment exposure.

To ensure that the nonattainment designations we study are not endogenously driven by changes in pollution levels that may be correlated with local economic activity, our empirical design relies on a natural experiment. Specifically, we exploit nonattainment designations induced by discrete policy changes in the NAAQS threshold from 1992 to 2019. These policy changes are based on the EPA's periodic revisions to reflect new scientific research on the health effects of ozone air pollution. As a consequence of these exogenously triggered NAAQS threshold changes, numerous counties were abruptly categorized as nonattainment, even if their pollution levels remained constant. Using this regulatory setting, we examine the stock price reactions to firms' nonattainment exposure. Our identification strategy bears resemblance to a controlled experiment, wherein we compare the abnormal stock returns between the most regulated and least regulated firms after random assignment of environmental regulations.

Theory offers varying predictions regarding the potential impact of nonattainment designations on shareholder value. On the one hand, nonattainment designations may benefit incumbent firms by providing competitive advantages that raise barriers to entry, thereby reducing local competition. Incumbents may also benefit from obtaining "grandfather" status, which allows them to operate at a cost advantage since incumbents are often shielded from the strictest regulations until they decide to expand operations (Becker & Henderson, 2000). These combined benefits may lead to an upward revision in firm valuation. On the other hand, compliance with stringent nonattainment regulations can be costly, as it forces firms to divert resources away from production towards emissions reduction and pollution abatement. Given an increase in expected compliance costs, shareholders may revise their beliefs downwards. Ultimately, it is an empirical question as to how the market reacts to the tradeoff between the benefits and costs of nonattainment designations on the valuation of incumbent firms.

Our analysis begins by employing a short-run event study methodology to compare the cumulative abnormal returns (CARs) between treated firms exposed to nonattainment designations and those with zero nonattainment exposure. Our event study is thus akin to studying changes in shareholder value at instances during which investors update their beliefs in response to the interaction between a firm's pollution and local environmental regulation. On average, our findings indicate a positive market response towards firms exposed to nonattainment designations when compared to non-exposed firms. The difference in the mean 11-day CARs between firms with non-zero nonattainment exposure and non-exposed firms is 1.215%, corresponding to a gain of approximately $107 million. These findings suggest that, on the extensive margin, the market views the benefits of nonattainment exposure as outweighing the costs associated with compliance.

Given that attentive investors can observe a county's monitored ozone pollution levels, they may anticipate a county's nonattainment status and adjust stock price valuations accordingly. This anticipation means that changes in shareholder value may not be solely attributable to exogenous variation in nonattainment exposure. To address this concern, we employ a regression discontinuity design (RDD) to decompose nonattainment designations into an unexpected (exogenous) component and an anticipated (predictable) component. Our findings show that the positive market response to nonattainment designations is entirely due to firms' exposure to the exogenous component. This result is consistent with investors updating their beliefs based on the new information contained in the unexpected component of nonattainment designations.

Next, we use cross-sectional regressions to investigate the variation in CARs that can plausibly be attributed to the offsetting effects of nonattainment exposure, encompassing gains from competitive advantages alongside a simultaneous increase in compliance costs. On the intensive margin, we find that nonattainment exposure has a significant nonlinear effect on firm value. Specifically, a firm's CAR shows an initial rise with growing nonattainment exposure, followed by a decline at higher levels. Consistent with the event study results, the cross-sectional variation we observe is entirely driven by firms' unexpected nonattainment exposure. Our findings indicate that despite firms initially capitalizing on competitive advantages from nonattainment exposure, the market interprets these benefits as gradually diminishing due to the mounting compliance costs linked with greater nonattainment exposure.

To enhance the validity of our findings, we examine the impact of attainment redesignations, which occur when a county successfully achieves compliance with the NAAQS and transitions from nonattainment to attainment status. With the relaxation of regulations, the expected compliance costs decrease, but the competitive advantages that previously benefited incumbents also diminish. As a result, we anticipate that the market will respond in the opposite direction to nonattainment designations. Using similar cross-sectional regressions and comparable measures of firms' exposure to attainment redesignations, we find that increases in such exposure lead to reduced shareholder value when exposure is low. This outcome suggests that the market does not perceive the decrease in compliance costs to adequately offset the decline in competitive advantages. However, beyond a certain threshold of attainment redesignation exposure, shareholder value begins to increase again, as the reduction in compliance costs compensates for the decline in competitive advantages.

So far, our results suggest that nonattainment designations contain value-relevant information that has stock-price implications. Our focus now shifts to understanding the underlying mechanisms that drive the market's responses to these designations. In terms of competitive advantages, we demonstrate that nonattainment designations hinder the births of new polluting plants in counties where incumbents operate. Using stacked difference-in-differences (DiD) regressions conducted at the county level, we show that nonattainment designations increase the concentration of sales and employees among ozone-emitting plants. Employing analogous DiD setups at the firm level, we document that firms with nonattainment exposure experience decreased competition in the product market and are able to secure a greater number of supply chain contracts and customer relationships.

Addressing costs, we investigate the possible regulatory compliance costs that facilities might incur during nonattainment designations. Since there is no data directly on plant-level pollution abatement costs, we examine a facility's observable regulatory enforcement and pollution abatement efforts as proxies for potential compliance costs. We find that higher nonattainment exposure at the facility level leads to an increased probability of violations, inspections, and evaluations. Moreover, heightened exposure also prompts facilities to undertake more source reduction activities, involving the treatment, recycling, and recovery of ozone emissions.

In our last set of analysis, we assess whether the short-term market reactions to nonattainment designations is consistent with the long-term effects of such designations. To do this, we examine the impact of firms' nonattainment exposure on their accounting performance. Our findings show that nonattainment exposure initially has a positive marginal effect on operating performance, as indicated by revenue, operating income, and gross profit margins. However, this effect becomes negative after a certain level of exposure is reached. In contrast, the marginal effect of nonattainment exposure on a firm's capital expenditures and cost of goods sold starts negative but gradually becomes positive. These results demonstrate that the market incorporates the valuation effects of nonattainment exposure into its reactions.

Our paper contributes to the literature linking environmental regulation to financial markets. Jha et al. (2020) demonstrate that an increase in regulatory stringency increases the yields of municipal bonds. Seltzer et al. (2022) find that firms with poor environmental profiles located in states with strict environmental regulations have higher corporate bond yields. Chen et al. (2023) document that a major legal ruling that holds creditors accountable for environmental liabilities results in a decline in bond and stock prices for affected firms, coupled with a widening of bank loan spreads. Krueger, Sautner, Tang, and Zhong (2023) show that mandatory environmental, social, and governance (ESG) disclosure leads to more accurate analysts' earnings forecasts and a decline in stock price crash risk. By leveraging the NAAQS as a natural experiment, our study offers a unique opportunity to explore the effects of local pollution regulation on shareholder value. We present evidence that the financial stock market internalizes the perceived benefits and costs of local environmental regulation, thereby influencing stock market valuations.

Our study further contributes to the literature concerning investor responses to environmental regulation. Past studies have examined how the stock market responds to shifts in firms' environmental impact, with firms involved in adverse events experiencing substantial stock price losses (Flammer, 2013; Karpoff, Lott, & Wehrly, 2005; Krueger, 2015b). Other studies have investigated stock market responses to mandatory disclosures concerning firms' ESG performance (Grewal, Riedl, & Serafeim, 2018) and greenhouse gas emissions (Jouvenot & Krueger, 2021; Krueger, 2015a), as well as the impact of events such as elections influencing climate change expectations (Ramelli, Wagner, Zeckhauser, & Ziegler, 2021), and the implications of climate policies such as the Paris Agreement (Monasterolo & de Angelis, 2020). We extend this literature by shifting the focus of market reactions from changes to firms' environmental outcomes to firms' exposure to environmental regulations. Moreover, the regulation we are studying differs from those related to environmental disclosures and climate policy, where uncertainties exist regarding enforceability and the affected parties. This distinction enables us to thoroughly investigate how the interaction between local pollution regulation and a firm's polluting behavior influences stock prices.

Lastly, our study adds to the understanding of the real effects of local environmental regulations. Bartram, Hou, and Kim (2022) demonstrate that localized climate policies have real spillover effects, such as the reallocation of greenhouse gas emissions and ownership stakes. Naaraayanan, Sachdeva, and Sharma (2021) document the real effects of environmental activist investing, which leads to reductions in targeted firms' toxic releases and greenhouse gas emissions. Research has also shown that a firm's environmental footprint can propagate along the supply chain (Dai, Liang, & Ng, 2021; Schiller, 2018), resulting in real effects on contracting decisions (Darendeli, Fiechter, Hitz, & Lehmann, 2022) and operating performance (Pankratz & Schiller, 2024). In our study, we focus on the regulation channel and document that a firm's exposure to local pollution regulations can simultaneously decrease competition in the product market and strengthen supply chain relationships, while also raising compliance costs. Collectively, these countervailing effects have a real impact on a firm's bottom line.

2. Institutional background and identification strategy

In this section, we discuss the regulatory framework that forms the basis of our identification strategy. The CAA mandates the EPA to establish NAAQS for six pollutants: carbon monoxide, nitrogen dioxide, ozone, sulfur dioxide, particulate matter, and lead. Our focus is on ozone because counties predominantly fail to meet NAAQS due to exceeding ozone limits, rather than violating them for other pollutants. This focus offers a larger treatment group for our analysis (Curtis, 2020).[2]

Central to the NAAQS is the EPA's annual designation of each county as either achieving attainment or falling out of attainment (nonattainment) based on the NAAQS threshold. These designations, mandated federally, are determined using data collected by ozone monitoring stations across the United States. Compliance assessment involves calculating summary statistics at the county level referred to as "design values" (DVs), computed by the EPA from monitor readings within each county. Counties with DVs surpassing the threshold for a specific standard are designated as nonattainment, while those falling below are classified as attainment. During our sample period from 1992 to 2019, the EPA successively implemented four distinct ozone standards, which are detailed in Internet Appendix Table IA.1.

Upon nonattainment designation of a county, the EPA mandates the state to formulate and adopt regulatory plans, referred to as State Implementation Plans (SIPs), which delineate strategies for restoring compliance with the NAAQS. While SIPs can exhibit variation across states, they must adhere to EPA guidelines and be approved by the EPA. Failure to submit or execute an acceptable SIP can lead to federal sanctions, including the withholding of federal grants, imposition of penalties, and construction bans on new polluting facilities. The SIP is enforced at the federal level and legally binding for *all* firms operating polluting plants within the nonattainment county, irrespective of factors such as the firm's historical environmental performance (Greenstone, 2002).

[2] Another advantage with focusing only on ozone is that the NAAQS specifies only one primary standard for ozone, while there exists both a primary and secondary standard for other pollutants such as particulate matter. The existence of only one standard for ozone allows us to precisely identify exposed and non-exposed firms.

2.1. *Compliance costs*

Environmental regulations under the SIP for nonattainment counties are designed to be stringent, involving regulatory restrictions on economic activities to mitigate emissions. Major sources of pollution are required to meet the "lowest achievable emission rate" (LAER), which entails the adoption of the cleanest available technology, irrespective of economic considerations. In attainment counties, environmental standards imposed on plants are notably less rigorous compared to those in nonattainment counties. Polluting plants in these regions are required to employ the "best available control technology" (BACT), with the EPA prioritizing the technology's economic impact on the plant in determining acceptable emission control measures. Utilizing plant-level survey data, Becker (2005) demonstrates that implementing BACT is considerably less financially burdensome for plants than adopting LAER technology.

Beyond capital expenditures such as LAER and BACT, SIPs also require states to develop plant-specific regulations for every major pollution source in nonattainment counties. Typically, these regulations take the form of emission limits, including adjustments to raw materials, operating procedures, and maintenance practices to curtail emissions (Becker & Henderson, 2000). Consequently, such regulations place more financially demanding compliance obligations on plants operating in nonattainment counties. Becker and Henderson (2001) find that that total operational costs are, on average, 17% higher for polluting plants in nonattainment regions compared to similar plants in attainment areas. Moreover, any incremental emissions from one pollution source must be offset by compensating another source within the same county to curtail its emissions (Nelson, Tietenberg, & Donihue, 1993). This practice, known as emissions offsets, constitutes one of the most substantial environmental expenditures for polluting plants in nonattainment areas (Shapiro & Walker, 2020). Apart from the costs of abatement compliance, plants in nonattainment counties are also subject to more sustained inspections and heightened oversight (Blundell, Gowrisankaran, & Langer, 2020).

2.2. *Competitive advantages*

While nonattainment designations increase compliance costs for plants relative to those in attainment counties, the stringent environmental regulations in nonattainment areas can provide competitive advantages to incumbent plants over new entrants in the form of barriers to entry and grandfather status. These designations often result in the exit of less efficient facilities and a reduction in ozone-emitting plants (Curtis, 2020; Henderson, 1996). For instance, studies document a significant decline in the establishment of manufacturing plants in nonattainment counties (Becker & Henderson, 2000; List, McHone, & Millimet, 2004; List, Millimet, Fredriksson, & McHone, 2003). Consequently, nonattainment designations amplify the costs of market entry, discouraging newcomers, and thereby shielding incumbents from additional competition (Ryan, 2012).

Nonattainment designations can also offer benefits to incumbent plants through grandfather status. Becker and Henderson (2000) show that existing plants are granted grandfather status, exempting them from the strictest regulations in nonattainment counties, until they undertake operational updates or expansions. Conversely, new entrants are subjected to expensive LAER requirements. Additionally, holding grandfather status in nonattainment counties confers a competitive edge to incumbent plants in the emissions offsets market. Nelson et al. (1993) demonstrate that local authorities typically grant operating permits to existing plants, while polluting plants seeking to enter or expand within nonattainment counties are obligated to offset their emissions.

2.3. Nonattainment designations as an identification strategy

Ultimately, the impact of competitive advantages and compliance costs related to nonattainment exposure on firm value is an empirical question. The ideal analysis of the stock price implications of environmental regulations would involve a controlled experiment in which environmental regulations are randomly assigned to polluting plants. One can then compare the abnormal stock returns between the most regulated and least regulated firms to causally attribute the difference to regulation. Obviously, such an ideal experiment would be unreasonably difficult to implement in practice.

Our identification strategy uses nonattainment designations as exogenous shocks to local regulatory stringency that is very close in spirit to this ideal experiment. A county can move from the attainment to the nonattainment designation in two ways. First, the county's ozone emissions can rise, pass the NAAQS threshold, and trigger the nonattainment designation. Second, the EPA can revise the NAAQS threshold by lowering it, triggering the nonattainment designation for some counties. A potential concern with the first way is that air pollution is driven by industrial activity, so that counties that are designated nonattainment due to changes in ozone emissions may correspond to those that have more underlying economic activities.

To address this concern, our empirical design relies on the second way, whereby we focus on nonattainment designations *induced* by discrete policy changes in the NAAQS threshold.[3]

[3]We focus on four discrete changes in the NAAQS threshold. In chronological order, these include the

Over our sample period, the EPA revised downwards the NAAQS threshold four times.[4] Given an exogenous revision in the NAAQS threshold, many counties suddenly found themselves in nonattainment relative to the year prior, even if their ozone emissions did not change by all that much. Therefore, the switch to nonattainment is triggered by the lowering of the NAAQS threshold that defines noncompliance, rather than by rising ozone emissions.

This regulatory design is illustrated in Figure 1. The figure shows the difference in the number of nonattainment counties between the current year and the previous year during the sample period 1992 to 2019. Notably, there are four distinct peaks that align with the implementation of revised NAAQS thresholds, leading to a substantial increase in the number of counties designated as nonattainment. In between the peaks, counties move in and out of nonattainment designations due to changes in their ozone pollution level.[5] Thus, our empirical analysis uses event studies that focus only on the nonattainment designations induced by the four policy changes.

We further exploit this regulatory design to control for potential anticipation of nonattainment designations. Borochin, Celik, Tian, and Whited (2022) show that estimated stock market reactions in event studies may be biased downwards due to event anticipation. In our setting, attentive investors may be able to anticipate a county's nonattainment status because the underlying ozone concentrations are observable. To address this issue, we exploit the regulatory design of DVs in a RDD to decompose nonattainment designations into an exogenous ("unexpected") and endogenous ("anticipated") component. We discuss this procedure in more detail in Section 4.2.

3. Data and variables

The core analyses in this study use pollution data from the EPA's TRI database. The TRI data file 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

1-Hour Ozone (1979) standard effective on January 6, 1992, 8-Hour Ozone (1997) standard effective on June 15, 2004, 8-Hour Ozone (2008) standard effective on July 20, 2012, and 8-Hour Ozone (2015) standard effective on August 3, 2018. For more details, see Table IA.1 of the Internet Appendix.

[4]The revised thresholds are based on new scientific research that reflects the ongoing health effects of air pollution during that period of time (Gibson, 2019).

[5]It is very rare for a county to be designated as nonattainment for a second time once it has been redesignated to attainment. Nonattainment designations are also fairly persistent; the mean duration of nonattainment for the sample of counties that we study is around 16 years. 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.

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.[6] Internet Appendix Table IA.2 lists the three-digit NAICS industries in TRI that are included in our sample. Similar to Akey and Appel (2021), the most common industries are chemical manufacturing (12.97% of sample), fabricated metal product manufacturing (12.64%), and transportation equipment manufacturing (8.22%).

We use the emissions data in TRI to classify whether a facility is a polluter of ozone.[7] In any given year, a facility is labeled as an ozone-emitting plant if it emits chemicals that are classified as volatile organic compounds or nitrogen oxides, both precursors to ozone formation.[8] Internet Appendix Table IA.1 shows the fraction of plants that are labeled as ozone emitters across major industries in nonattainment counties. Even within two-digit industry NAICS codes, there is a considerable amount of variation in the fraction of plants that are classified as ozone polluters. 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. Since our paper examines stock price reactions, we only use the facilities that are owned by public companies in TRI. To obtain parent companies' financial and stock price information, we manually match the TRI parent company names to those in Compustat and CRSP.

We manually search the Federal Register and hand-collect the effective dates of every nonattainment designation and redesignation to attainment. Furthermore, 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 the statistics that the EPA uses to determine whether a county is in compliance with the NAAQS. The rules that we use to calculate the DVs for different ozone standards as well as the relevant thresholds are given in Table IA.1 of the Internet Appendix.

[6]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).

[7]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.

[8]Ozone is not directly emitted by plants, but rather formed through chemical reactions in the atmosphere. Henceforth, we refer to emitters of ozone precursors as ozone emitters.

3.1. *Measure of nonattainment exposure*

To account for the possibility that a firm operates multiple plants in various counties, we develop a firm-level measure of nonattainment exposure. This measure takes into consideration the geographic distribution of a firm's plants across different counties and the level of ozone emissions at each plant. Formally, we define this measure as follows:

$$NA\ exposure_{i,t} = \ln\left(1 + \sum_{j} ozone_{j,i,t-1} \cdot NA_{j,i,t}\right), \tag{1}$$

where j denotes plant, i denotes firm, and t denotes year. $ozone_{j,i,t-1}$ is the total amount of ozone air emissions for plant j of firm i in year $t-1$ and $NA_{j,i,t}$ is a dummy variable equal to one if plant j of firm i is located in a nonattainment county in year t, and zero otherwise. *NA exposure* can be interpreted as a measure of a firm's time-varying exposure to nonattainment designations. For example, a multi-plant firm that operates many heavy ozone-emitting plants in nonattainment counties will have a higher value of *NA exposure*, indicating that the firm is more exposed to nonattainment designations.

We highlight three key points about the above definition. First, we lag plant ozone emissions by one year because the specific timing of the release of the TRI data implies that emissions data for a given year only becomes available the following year (Hsu, Li, & Tsou, 2023). Second, by weighting the nonattainment dummy by a plant's total amount of ozone emissions, this measure captures the fact that the intensity of regulation for a given plant in a nonattainment county is proportional to the intensity of its ozone emissions in that county. For example, a plant that does not emit any ozone in a nonattainment county is unaffected by the regulation. Third, we use the *amount* of ozone emissions as opposed to ozone emission intensity (i.e., ozone emissions per unit of production) since the EPA imposes emission limits in nonattainment counties based on the actual amount of ozone emissions.[9]

4. Empirical methodology

We examine the shareholder wealth effects of nonattainment designations using a short-run event study approach (MacKinlay, 1997). In our context, each nonattainment designation induced by the four discrete policy changes in the NAAQS threshold serves as an event. To estimate the market model parameters for each firm-event date pair, we use 250 trading days of return data, with the window ending 20 days before the event date. The CRSP value-weighted

[9] Our results are robust to various alternative definitions of *NA exposure*. See Section 8 for more details.

return acts as a proxy for the market return, and we calculate abnormal returns by subtracting the market-model expected return from the firm's stock return. Daily abnormal stock returns are accumulated to obtain the CAR from day t_1 before the event date to day t_2 after the event date. Considering that regulators tend to first focus on plants owned by larger firms in nonattainment areas before incorporating plants owned by smaller firms, we calculate value-weighted average CARs based on a firm's market capitalization in the quarter before the nonattainment designation (Becker & Henderson, 2000).[10]

To assess the significance of the mean CAR, we compute t-statistics that account for event-induced changes in variance (Boehmer, Musumeci, & Poulsen, 1991). Additionally, we perform a generalized nonparametric Wilcoxon sign-rank test to evaluate the significance of the median CAR. Our primary focus lies on the 5-day $(-2, +2)$ and 11-day $(-5, +5)$ CARs around the effective date of nonattainment designations. All CARs are expressed in %. We also apply winsorization to all CARs at the 1st and 99th percentiles to mitigate the impact of outliers.

4.1. Cross-sectional regressions

While the event study provides insight into shareholders' average reaction to nonattainment designations between exposed and non-exposed firms on the extensive margin, it does not capture potential nonlinearities in the effects of nonattainment exposure on firm value. Thus, we employ cross-sectional regressions to explore the variation in CARs driven by the tradeoffs between the benefits of competitive advantages and the rise in compliance costs associated with nonattainment exposure. Specifically, we estimate the following specification:

$$CAR_{i,t} = \beta_0 + \beta_1 NA\ \ exposure_{i,t} + \beta_2 NA\ \ exposure^2_{i,t} + \beta_3 X_t + \text{F.E.} + \varepsilon_{i,t} \tag{2}$$

for firm i and year t. The dependent variable is either the 5-day or 11-day CAR associated with each nonattainment designation. X_t represents a set of control variables for firms' financial characteristics including size, book-to-market ratio, return on assets, leverage, sales growth, cash, momentum, stock returns, and stock return volatility. Table A.1 in Appendix A describes the control variables in detail. Standard errors are clustered at the firm level because facilities are nested within firms. The coefficients of interest are β_1 and β_2. If the benefits of competitive advantages from increased nonattainment exposure are offset by the simultaneous increase in compliance costs, then we expect β_1 to be positive and β_2 to be negative.

[10] Brav, Geczy, and Gompers (2000) argue that value weighting is the appropriate method to compute average CARs if the goal is to quantify investors' average wealth change subsequent to an event.

We estimate two versions of the specification with different fixed effects. The first version includes event-year fixed effects and industry fixed effects based on Fama and French's (1997) 48 industry classifications. The second version replaces industry fixed effects with firm fixed effects. Since some firms may be exposed to nonattainment designations in one event year but not another, any time-invariant unobservables unique to firms may be controlled for by including a set of firm fixed effects. The inclusion of firm fixed effects ensures that coefficient estimates are derived only from those firms that experience a change in nonattainment exposure across different event years.

4.2. Event anticipation

Since a county's monitored ozone pollution levels are observable, attentive shareholders may be able to anticipate a county's nonattainment status, meaning that share prices may endogenize a portion of the effects of nonattainment exposure before the realization of the event. Thus, in the case of event anticipation, *NA exposure* may not be a fully exogenous measure of a firm's nonattainment exposure (Borochin et al., 2022). To isolate the component of *NA exposure* that is potentially predictable, we decompose nonattainment designations into an anticipated component and an unexpected component based on county-level DVs. The intuition is that counties with a DV far above the NAAQS threshold will most likely remain in nonattainment, while those with a DV far below the threshold will most likely remain in attainment. The question then becomes how far above or below the NAAQS threshold can one reasonably predict a county's designation status.

The idea underlying our approach is that nonattainment designations are essentially a random outcome in an arbitrarily small interval around the NAAQS threshold; for example, whether a county is in compliance with a DV slightly below the NAAQS threshold or in violation with a DV slightly above the threshold is arguably random. To operationalize this, we use a RDD to exploit the sharp increase in nonattainment probability when a county's DV violates the threshold to estimate an optimal "bandwidth" that determines the region where ozone concentrations are as good as randomly assigned, and hence, unpredictable. The full details of the RDD specification along with tests that support the identifying assumptions and the estimation results are presented in Section IA of the Internet Appendix.

We summarize the decomposition procedure in Figure 2, which plots a county's probability of nonattainment conditional on the distance of its DV from the threshold. As expected, the probability of nonattainment appears to be a continuous and smooth function of the centered DVs everywhere except at the NAAQS threshold, where there is a discontinuous jump upwards. The two dashed vertical lines on either side of the discontinuity represent the optimal bandwidth estimate. The region within the bounds of the optimal bandwidth is the unpredictable region; changes in the probability of nonattainment are attributable to random fluctuations in the underlying DVs and hence unpredictable. Thus, we define any county that belongs to the unpredictable region and is subsequently designated as nonattainment as an "unexpected" nonattainment. The region to the right of the optimal bandwidth is defined as the predicted nonattainment region. Any county that resides in this region and is subsequently designated as nonattainment is defined as an "anticipated" nonattainment.

The above decomposition allows us to measure a firm's exposure to unexpected and anticipated nonattainment designations, respectively, as follows:

$$\textit{Unexp. NA exposure}_{i,t} = \ln\left(1 + \sum_j ozone_{j,i,t-1} \cdot \textit{Unexp. NA}_{j,i,t}\right), \tag{3}$$

$$\textit{Antic. NA exposure}_{i,t} = \ln\left(1 + \sum_j ozone_{j,i,t-1} \cdot \textit{Antic. NA}_{j,i,t}\right), \tag{4}$$

where $\textit{Unexp. NA}_{j,i,t}$ ($\textit{Antic. NA}_{j,i,t}$) is a dummy variable equal to one if plant j of firm i is located in an unexpected (anticipated) nonattainment county in year t, and zero otherwise. All other variables are defined as in Equation (1). A higher value of *Unexp. NA exposure* (*Antic. NA exposure*) indicates that the firm has a greater exposure to unexpected (anticipated) nonattainment designations. We also estimate a similar cross-sectional regression as Equation (2), except we decompose *NA exposure* into its unexpected and anticipated components as follows:

$$\begin{aligned} CAR_{i,t} = \beta_0 &+ \beta_1 \textit{Unexp. NA exposure}_{i,t} + \beta_2 \textit{Unexp. NA exposure}^2_{i,t} + \beta_3 \textit{Antic. NA exposure}_{i,t} \\ &+ \beta_4 \textit{Antic. NA exposure}^2_{i,t} + \beta_5 X_t + \text{F.E.} + \varepsilon_{i,t}. \end{aligned} \tag{5}$$

The main coefficients of interest are β_1 and β_2, which capture the effects on firm value driven by the exogenous component of nonattainment exposure.

5. Results

5.1. Descriptive statistics

Table 1 presents summary statistics for the key variables used in our analyses. A full list of the variables used in this paper and their data sources can be found in Table A.1 in Appendix A. Internet Appendix Table IA.3 shows the distribution of TRI firms and plants, and also offers a breakdown of county nonattainment designations and attainment redesignations by state.

Throughout the sample period, the majority of states encountered counties designated as nonattainment at least once, while only 11 states remained entirely exempt from any counties receiving nonattainment status. In terms of redesignations to attainment, 20 states have all of their nonattainment counties redesignated back to attainment, while 8 states have never experienced an attainment redesignation event during our sample period.

For the event study on nonattainment designations, the final sample consists of 2,548 firm-event-years that pertain to 1,322 unique firms. Of these, about 43% (1,106 firm-event-years) belong to the treated group, constituting firms with non-zero exposure to nonattainment designations. The remaining non-exposed observations consist of firms operating either ozone-emitting plants exclusively within attainment counties or solely non-ozone-emitting plants within nonattainment counties during the time of the revisions to the NAAQS threshold. Within the treated group, the mean *NA exposure* is 8.551, with a standard deviation of 3.662, signifying significant variation in firms' exposure to nonattainment designations. The average treated firm is exposed to both exogenous and predictable nonattainment designations as both *Unexp. NA exposure (Treated group)* and *Antic. NA exposure (Treated group)* have non-zero means.

5.2. Event study for nonattainment designations

We analyze the statistical properties of the 5-day $(-2, +2)$ and 11-day $(-5, +5)$ CARs centered around the effective date of nonattainment designations induced by discrete policy changes in the NAAQS threshold. Table 2 reports the market's reaction to these nonattainment designations. Panel A provides a breakdown of the mean and median CARs, along with the associated test statistics, for firms exposed to nonattainment designations (*NA exposure* > 0) and those not exposed (*NA exposure* $= 0$). Columns (1) and (2) show that nonattainment designations are associated with positive abnormal stock returns. Specifically, for firms with non-zero nonattainment exposure, the average CARs are 0.449% ($t = 1.74$) and 1.157% ($t = 3.83$) for the $(-2, +2)$ and $(-5, +5)$ windows, respectively. The sign-rank test statistics for the median CARs are also positive and significant for both windows.

Columns (3) and (4) of Panel A in Table 2 indicate that firms with no nonattainment exposure experience either negative or insignificant abnormal stock returns. Columns (5) and (6) present the differences in mean and median CARs between exposed and non-exposed firms. The results show that exposed firms experience significantly higher CARs relative to non-exposed firms. The positive effect on shareholder wealth is also economically meaningful. Given that the average market capitalization of the firms in the nonattainment analysis is approximately \$8.84 billion, the average difference in CAR of 1.215% in column (5) translates to an estimated gain of approximately \$107 million (1.215% × \$8.84 billion) over the 11-day window.

Figure 3 provides a visual representation of the findings in Panel A of Table 2 by plotting the dynamics of the mean CARs for exposed (solid line) and non-exposed (dashed line) firms over the interval $(-20, +20)$. The graph shows that average CARs remain relatively stable leading up to the event date, showing a comparable trend for both exposed and non-exposed firms. However, on the effective date of nonattainment designation, there is a substantial increase in the CAR for exposed firms, while there is little upwards movement in the CAR for non-exposed firms. The gap between the two groups becomes even more pronounced in the period following the nonattainment designation effective date.

Panel B of Table 2 focuses only on exposed firms and decomposes market reactions to nonattainment designations into an unexpected and anticipated component. Columns (1) and (2) analyze firms where their unexpected nonattainment exposure (*Unexp. NA exposure*) is greater than their anticipated exposure (*Antic. NA exposure*), while columns (3) and (4) consider firms where *Antic. NA exposure* is greater. The results reveal that the positive market response to nonattainment designations is primarily driven by firms' exposure to the exogenous component, as evidenced by the positive and statistically significant CARs in columns (1) and (2). However, there are no noticeable market reactions to firms' exposure to the anticipated component, as shown by the statistically insignificant CARs in columns (3) and (4), implying that the market has already endogenized the expected impact of anticipated nonattainment designations into stock prices. Moreover, when comparing the differences in CARs relative to non-exposed firms in columns (5) to (8), we find that only firms with predominantly unexpected nonattainment exposure show significantly higher CARs compared to non-exposed firms. Overall, the findings in this section suggest that, on average, the market perceives the competitive advantages stemming from nonattainment exposure to outweigh the associated compliance costs on the extensive margin.

5.2.1. Cross-sectional analysis

In this section, we explore the cross-sectional variation in CARs, driven by the interaction between the competitive advantages and compliance costs associated with nonattainment exposure. The regression estimates from Equation (2) are presented in Table 3. Columns (1) and (5) use event-year fixed effects and industry fixed effects, while columns (3) and (7) replace industry fixed effects with firm fixed effects. We also provide the F-statistic and corresponding

p-value for the test of the joint significance of *NA exposure* and *NA exposure*^{2}. Across these specifications, the coefficient estimates on *NA exposure* are positive and significant, while those on *NA exposure*^{2} are negative and significant. Moreover, we reject the null hypothesis that both *NA exposure* and *NA exposure*^{2} are jointly equal to zero. These results suggest that although firms initially benefit from the competitive advantages of nonattainment exposure, the market perceives these advantages to gradually erode due to the rising compliance costs associated with higher nonattainment exposure.

Using the coefficient estimates in column (7) of Table 3, we visually depict the economic impact of *NA exposure* on CARs in Internet Appendix Figure IA.3. This figure plots the predicted values of CAR $(-5, +5)$ as a function of feasible values of *NA exposure*. *NA exposure* exhibits a positive marginal effect on CARs when its values are below the threshold labeled as the "Zero marginal effect". However, as *NA exposure* surpasses this threshold, marginal effects turn negative, indicating that increasing *NA exposure* starts to diminish CARs.

To examine whether the cross-sectional variation in CARs is driven by firms' exposure to unexpected or anticipated nonattainment designations, we present the results of estimating Equation (5) in columns (2), (4), (6), and (8) of Table 3. In all four columns, the coefficients corresponding to *Unexp. NA exposure* are positive and significant, while those for *Unexp. NA exposure*^{2} are negative and significant. However, none of the coefficients associated with anticipated nonattainment exposure are significant. Furthermore, the F-statistics and the corresponding p-value reject the null hypothesis that *Unexp. NA exposure* and *Unexp. NA exposure*^{2} are jointly equal to zero. These results align with those in Table 2, suggesting that the market responds only to shifts in a firm's exposure to the exogenous component of nonattainment designations, while the anticipated component has already been incorporated into stock price valuations. In summary, the findings reveal that on the intensive margin, firms benefit from competitive advantages while bearing manageable compliance costs when nonattainment exposure is lower. However, as nonattainment exposure surpasses a certain threshold, the burdens of compliance costs outweigh the benefits of competitive advantages, leading to an overall decrease in shareholder wealth.

5.3. Redesignation to attainment

Our analysis has so far focused on the value implications of nonattainment designations. However, once a county successfully achieves compliance with the NAAQS, it undergoes a redesignation back to attainment status, signifying a relaxation in regulatory standards. While a reduction in regulations decreases compliance costs, it also diminishes the competitive advantages previously enjoyed by incumbents. Consequently, we anticipate that a firm's exposure to attainment redesignations will yield an effect opposite to that of exposure to nonattainment designations. To assess this hypothesis, we construct a comparable measure of attainment redesignation exposure as follows:

$$Redesig\ exposure_{i,t} = \ln\left(1 + \sum_j ozone_{j,i,t-1} \cdot Redesig_{j,i,t}\right), \tag{6}$$

where j denotes plant, i denotes firm, and t denotes year. $ozone_{j,i,t-1}$ is the total amount of ozone air emissions for plant j of firm i in year $t-1$ and $Redesig_{j,i,t}$ is a dummy variable equal to one if plant j of firm i is located in a county that has been redesignated to attainment in year t, and zero otherwise.

We also decompose *Redesig exposure* into an unexpected and anticipated component following the same approach as in Figure 2, except we estimate the RDD (unreported) using the sample of attainment redesignation events. In this context, an unexpected attainment redesignation refers to any county located within the unpredictable region that subsequently experiences a redesignation to attainment. Conversely, an anticipated attainment redesignation pertains to a county situated within the predicted attainment region that subsequently undergoes redesignation to attainment. This decomposition allows us to quantify a firm's exposure to both unexpected and anticipated attainment redesignations, as outlined below:

$$Unexp.\ redesig\ exposure_{i,t} = \ln\left(1 + \sum_j ozone_{j,i,t-1} \cdot Unexp.\ redesig_{j,i,t}\right), \tag{7}$$

$$Antic.\ redesig\ exposure_{i,t} = \ln\left(1 + \sum_j ozone_{j,i,t-1} \cdot Antic.\ redesig_{j,i,t}\right), \tag{8}$$

where $Unexp.\ redesig_{j,i,t}$ ($Antic.\ redesig_{j,i,t}$) is a dummy variable equal to one if plant j of firm i is located in an unexpected (anticipated) attainment redesignation county in year t, and zero otherwise.

To investigate the impact of firms' attainment redesignation exposure on firm value, we conduct cross-sectional regressions similar to those employed for nonattainment exposure:

$$CAR_{i,t} = \beta_0 + \beta_1 Redesig\ exposure_{i,t} + \beta_2 Redesig\ exposure^2_{i,t} + \beta_3 X_t + \text{F.E.} + \varepsilon_{i,t}, \tag{9}$$

$$\begin{aligned} CAR_{i,t} = {} & \beta_0 + \beta_1 Unexp.\ redesig\ exposure_{i,t} + \beta_2 Unexp.\ redesig\ exposure^2_{i,t} \\ & + \beta_3 Antic.\ redesig\ exposure_{i,t} + \beta_4 Antic.\ redesig\ exposure^2_{i,t} + \beta_5 X_t + \text{F.E.} + \varepsilon_{i,t}, \end{aligned} \tag{10}$$

where the dependent variable is either the 5-day or 11-day CAR associated with each attainment redesignation. To estimate the above specifications, we begin with the sample of all firms that have been exposed to nonattainment designations. From this pool, we identify treated units as firm-event-year observations that subsequently have non-zero exposure to attainment redesignations. Since treated units might not be directly comparable to firms with no attainment redesignation exposure due to differences in certain dimensions, we utilize nearest neighbor propensity score matching with replacement to ensure a clean control sample, matching each treated unit to two observations without attainment redesignation exposure (Roberts & Whited, 2013). Internet Appendix Table IA.6 shows that there are no observable differences between treated and control observations after the matching. As outlined in Table 1, among the total of 4,708 firm-event-years utilized in this analysis, 1,705 pertain to the treated group, referring to those observations with non-zero attainment redesignation exposure.

We present the estimation results for Equations (9) and (10) in Table 4. A strikingly opposite pattern emerges compared to the results on nonattainment designations. Specifically, the coefficient estimates for *Redesig exposure* and *Unexp. redesig exposure* are negative and significant, while the estimates for *Redesig exposure*^{2} and *Unexp. redesig exposure*^{2} are positive and significant. Furthermore, except for column (3), across all other specifications, we reject the null hypothesis that *Redesig exposure* (*Unexp. redesig exposure*) and *Redesig exposure*^{2} (*Unexp. redesig exposure*^{2}) are jointly equal to zero. We find no significant effect of firms' exposure to anticipated attainment redesignations on CARs, as indicated by the insignificant coefficients on the anticipated components. These findings align with the interpretation that when firms exhibit low levels of attainment redesignation exposure, the market responds by penalizing them for marginal increases in such exposure because the reduction in compliance costs is insufficient to offset the erosion of competitive advantages. However, as a firm's attainment redesignation exposure surpasses a certain threshold, shareholder wealth begins to increase again because despite the firm's loss of competitive advantages, the reduction in compliance costs more than offsets this decline.

6. Mechanisms

In this section, we investigate the underlying mechanisms that generate the offsetting effects on the benefits and costs associated with nonattainment exposure, which in turn, shape the market's responses to incumbent firms' exposure to nonattainment designations.

6.1. Competition

We begin by examining the competitive advantages of nonattainment designations for incumbent firms. Specifically, we study the effect of nonattainment designations on new entrants, competition dynamics among incumbent firms at both the county and firm levels, and incumbents' supply chain contracts and customer relationships.

6.1.1. New entrants

We investigate the impact of a county's nonattainment designation on subsequent new TRI plant births within the same county. Following List et al. (2003) and Becker and Henderson (2000), we employ a fixed-effects panel Poisson regression model. The dependent variable, denoted as $\textit{Plant births}_t$, represents the count of new TRI plants in a given county in year t. The key explanatory variable is NA_{t-1}, a dummy variable equal to one if a county is designated nonattainment in year $t-1$, and zero otherwise. Given that our sample period from 1992 to 2019 spans four distinct ozone standard cohorts, we estimate a more stringent specification by allowing year and county fixed effects to vary across these cohorts using Year $\times$ Cohort and County $\times$ Cohort fixed effects, rather than relying solely on year and county fixed effects. To identify plant births, we rely on the initial year of operation for each facility from the National Establishment Time-Series (NETS) database. This is necessary because a plant's appearance in the TRI database for the first time does not necessarily correspond to its true first year of operation, since a plant reports to TRI only upon meeting specific reporting criteria.

We present the estimation results in Table 5. In column (1), we observe a significant reduction in the number of new TRI plants in the year following a county's nonattainment designation. In column (2), which incorporates county-level control variables in line with List et al. (2003), the results remain qualitatively similar.[11] Economically, using the coefficient estimate from column (2), a nonattainment designation for a county leads to an 11% decrease in the expected number of new TRI plants in the subsequent year. Columns (3) and (4) decompose nonattainment designations into an unexpected and anticipated component. *Unexp. NA* and *Antic. NA* are dummy variables equal to one if a county is designated as an unexpected or anticipated nonattainment, respectively, in a given year, and zero otherwise. In line with our prior results, we find that only the exogenous component of nonattainment designations leads to a reduction in the number of new plants. Anticipated nonattainment designations, on

[11] These control variables include the natural logarithm of one plus the population levels in a given year; the natural logarithm of one plus the employment levels in a given county; a given county's NOx emissions to employment ratio; and the change in a given county's employment levels.

the other hand, exhibit no discernible effect. From an economic perspective, the impact is even more pronounced, with unexpected nonattainment designations leading to a substantial 28% decrease. In summary, the findings of this section indicate that nonattainment designations impede new market entrants where incumbents operate. In subsequent sections, we delve into whether this translates into a competitive advantage for incumbents.

6.1.2. County-level competition

We study how county-level competition changes around nonattainment designations induced by discrete policy changes in the NAAQS threshold by using a DiD specification. County-level competition is measured through the Herfindahl-Hirschman Index (HHI), computed using facility-level sales and employee data from NETS. The outcome variables, *Sales HHI* and *Employees HHI*, are derived by summing squared sales or employee shares, respectively, for all ozone-emitting plants in a county during a given year. A higher value signifies greater concentration of sales and employees among ozone-emitting plants within a county.

Given the observed bias in conventional two-way fixed effects DiD models within staggered adoption designs (Baker, Larcker, & Wang, 2022), we adopt the approach recommended in the literature, employing a stacked DiD specification (Cengiz, Dube, Lindner, & Zipperer, 2019; Gormley & Matsa, 2011). Specifically, we first establish an event window spanning four years before (pre-nonattainment period) and four years after (post-nonattainment period) the event year. With four cohorts of nonattainment designations, we construct cohort-specific "clean" datasets. Within each cohort, treated units consist of counties newly designated as nonattainment, while control units comprise "clean" counties that are *always* in attainment during the event window.[12] These cohort-specific datasets are then pooled together, and a DiD regression is estimated on the stacked dataset, allowing for county and year fixed effects to vary by cohort. Formally, we estimate the following regression:

$$y_{c,t,k} = \beta NA_{c,k} \times Post_{t,k} + \tau_{c,k} + \rho_{t,k} + \varepsilon_{c,t,k}, \tag{11}$$

where the dependent variable refers to the county-level measures of competition. $NA_{c,k}$ is a dummy variable equal to one if county c is newly designated nonattainment in cohort k, and zero otherwise. $Post_{t,k}$ is a dummy variable equal to one for the event year and subsequent four years in cohort k, and zero otherwise. $\tau_{c,k}$ and $\rho_{t,k}$ are County $\times$ Cohort and Year $\times$ Cohort fixed effects, which subsume the main effects for $NA_{c,k}$ and $Post_{t,k}$, respectively.

[12] In this context, units that have never been treated will function as clean controls across all cohorts. Units treated in later cohorts might appear multiple times since they can also serve as controls for earlier cohorts.

The standard errors are clustered at the county-level. The DiD estimate, β, measures the average treatment effect of nonattainment designations on county-level competition. We also estimate the following DiD that decomposes nonattainment designations into an unexpected and anticipated component:

$$y_{c,t,k} = \beta_1 \, Unexp.\ NA_{c,k} \times Post_{t,k} + \beta_2 Antic.\ NA_{c,k} \times Post_{t,k} + \tau_{c,k} + \rho_{t,k} + \varepsilon_{c,t,k}, \tag{12}$$

where $Unexp.\ NA_{c,k}$ and $Antic.\ NA_{c,k}$ are dummy variables equal to one if county c is newly designated as an unexpected or anticipated nonattainment, respectively, in cohort k, and zero otherwise.

We present the results in Table 6. Columns (1) and (3) both show a significant and positive coefficient for *NA* $\times$ *Post*, indicating increased concentration of sales and employees among ozone-emitting plants in nonattainment-designated counties during the post-nonattainment period compared to those in always-attainment counties. Columns (2) and (4) reveal that this increase in concentration is only observed in unexpected nonattainment counties, with no noticeable concentration change in anticipated nonattainment counties. Economically, the coefficient estimate in column (2) suggests an approximate 4.6% increase in sales concentration among ozone-emitting plants in unexpected nonattainment counties, relative to the sample mean, in comparison to always-attainment counties.

Next, we examine the temporal dynamics of the changes in *Sales HHI* and *Emp HHI* to confirm the absence of pre-trends, which is a necessary condition for the validity of our DiD approach. We estimate the following dynamic version of Equation (12):

$$y_{c,t,k} = \sum_{\substack{\ell=-4 \\ \ell\neq-1}}^{\ell=+4} \gamma_\ell \, Unexp.\ NA_{c,k} \times \theta^{\ell}_{t,k} + \sum_{\substack{\ell=-4 \\ \ell\neq-1}}^{\ell=+4} \lambda_\ell Antic.\ NA_{c,k} \times \theta^{\ell}_{t,k} + \tau_{c,k} + \rho_{t,k} + \varepsilon_{c,t,k}, \tag{13}$$

where $\theta^{\ell}_{t,k}$ is a dummy variable that equals to one for year ℓ relative to the event year in cohort k, and zero otherwise. The dynamic effects, denoted as γ_ℓ and λ_ℓ, provide event-study style regression estimates that capture the varying trends in concentration measures for unexpected and anticipated nonattainment counties, respectively. We define the year prior to the nonattainment designation as the reference period, denoted by year $\ell = -1$. This choice allows us to express all dynamic effects relative to this reference year.

Figure 4 presents the dynamic effects from estimating Equation (13). There are no significant changes in sales or employee concentration preceding either unexpected or anticipated nonattainment designations. This finding supports the assumption that there are no differential responses in concentration before nonattainment designations. In the post-nonattainment period, unexpected nonattainment counties show increased sales and employee concentrations, while anticipated nonattainment counties display negligible changes in concentrations. Overall, this section's results indicate that nonattainment designations decrease competition among ozone-emitting plants, potentially favoring incumbent firms.

6.1.3. Firm-level competition

In this section, we explore the impact of nonattainment designations on firm-level competition by investigating their effects on product market competition and supply chain contracting. Similar to the previous section, we employ a stacked DiD approach, but now at the firm level. This allows us to investigate how firm-level competition evolves in response to nonattainment designations induced by discrete policy changes in the NAAQS threshold. We maintain an event window that spans four years prior to and four years following the event year. Within each cohort, treated firms are those newly exposed to nonattainment designations, while control firms are those that always maintain zero nonattainment exposure during the event window.[13] Formally, we estimate the following regression:

$$y_{i,t,k} = \beta NA\ exposure_{i,k} \times Post_{t,k} + \tau_{i,k} + \rho_{t,k} + \varepsilon_{i,t,k}, \tag{14}$$

where the dependent variables are firm-level outcome variables defined in the subsequent sections. $NA\ exposure_{i,k}$ is the continuous treatment variable that measures firm i's nonattainment exposure in cohort k. $Post_{t,k}$ is a dummy variable equal to one for the event year and subsequent four years in cohort k, and zero otherwise. We allow firm and year fixed effects to vary by cohort by including Firm $\times$ Cohort ($\tau_{i,k}$) and Year $\times$ Cohort ($\rho_{t,k}$) fixed effects. The standard errors are clustered at the firm-level. Similarly, we estimate the following regression that decomposes nonattainment exposure into an unexpected and anticipated component:

$$y_{i,t,k} = \beta_1 Unexp.\ NA\ exposure_{i,k} \times Post_{t,k} + \beta_2 Antic.\ NA\ exposure_{i,k} \times Post_{t,k} + \tau_{i,k} + \rho_{t,k} + \varepsilon_{i,t,k}, \tag{15}$$

where $Unexp.\ NA\ exposure_{i,k}$ and $Antic.\ NA\ exposure_{i,k}$ are continuous treatment variables that measure firm i's unexpected and anticipated nonattainment exposure, respectively, in

[13]Similar to the county-level analysis, firms that never experience nonattainment exposure act as controls across all cohorts. Firms treated in later cohorts may be included multiple times if they serve as controls for earlier cohorts.

cohort k.

6.1.3.1 *Product market competition*

Incumbent firms exposed to nonattainment designations might secure competitive advantages through reduced product market competition. We assess this hypothesis using two measures of firm-level product market competition. Firstly, we employ the product market fluidity measure (*Fluidity*) introduced by Hoberg, Phillips, and Prabhala (2014). This measure gauges the extent of product similarity between a firm and its competitors, as well as market instability resulting from competitor actions. A higher value signifies a more substantial competitive threat. Secondly, we utilize the total product similarity score (*Similarity*) developed by Hoberg and Phillips (2010, 2016), which reflects a firm's competitive pressure and its product-relatedness to each competitor. A higher value indicates heightened competitive pressure on the firm.[14]

Table 7 presents the results. In columns (1) and (3), the coefficient for $NA\ exposure \times Post$ is significantly negative, suggesting that firms with nonattainment exposure experience diminished competitive pressures in the post-nonattainment period. Columns (2) and (4) reveal that this reduction in competitive pressure is pronounced for firms exposed to unexpected nonattainment designations but not for those exposed to anticipated nonattainment designations. In terms of economic impact, a one standard deviation increase in a firm's unexpected nonattainment exposure corresponds to a decrease of around 7% in both its product market fluidity and similarity scores, relative to the sample mean. To summarize, our analysis suggests that incumbent firms with nonattainment exposure can gain competitive advantages due to reduced competitive pressure in their respective product markets.

6.1.3.2 *Supply chain contracting*

Another potential consequence of nonattainment designations reducing competition is an increase in the bargaining power and control of incumbent firms over the supply chain, thus enhancing their competitive advantages. To assess contractual relationships between customers and suppliers, we utilize data from FactSet Revere Supply Chain Relationships (Dai et al., 2021; Darendeli et al., 2022). This dataset offers insights into supply-chain information, such as identifying contractual relations between corporate customers and their suppliers, covering a wide array of over 20,000 firms globally, with data available from 2003 onwards. Using this dataset, we construct two primary outcome variables at the supplier firm-year level aimed

[14] Data for both measures can be accessed from `https://hobergphillips.tuck.dartmouth.edu/`.

at capturing contracting dynamics between corporate customers and suppliers. The first variable, *Number of new contracts*, is the number of newly initiated contracts made with corporate customers in a given supplier-year. Given that a supplier firm might engage in multiple contracts with the same customer, we also introduce a second variable, *Number of new customers*, which is the number of unique new corporate customers per supplier-year.

Table 8 reports the findings. Columns (1) to (4) present the stacked DiD estimation results based on Equations (14) and (15), using the sample of nonattainment designations from 2003 to 2019.[15] Meanwhile, columns (5) to (8) focus on the estimation results derived from a single cohort of nonattainment designations induced by the 8-Hour Ozone (2008) standard revision, which became effective in 2012. This selection ensures a balanced panel comprising four years both before and after the nonattainment designation. Across all model specifications, the estimated average treatment effects on $NA\ \ exposure \times Post$ and $Unexp.\ \ NA\ \ exposure \times Post$ are positive and significant. This result implies that, on average, firms exposed to nonattainment designations, particularly when exposure is unexpected, tend to observe increases in both the number of new contracts with corporate customers and the number of new corporate customers. These findings are economically meaningful, as indicated by the estimates in columns (6) and (8), where a one standard deviation increase in a firm's unexpected nonattainment exposure corresponds to a 37% increase in new contracts and a roughly 39% increase in the number of new customers (both relative to the sample mean).

Nonattainment designations may not only assist incumbent firms in securing more contracts and attracting new customers, but also, due to reduced competition, suppliers may be positioned to cultivate longer-term relationships with customers, resulting in extended contract durations for newly initiated agreements. This dynamic can further create competitive advantages for incumbents, as longer-term contracts can create hurdles for potential competitors by necessitating greater efforts to overcome customer switching costs. In the final two columns of Table 8, we analyze the dependent variable *Contract length (days)*, representing the average duration (in days) of newly initiated contracts between corporate customers and suppliers in a given supplier-year. Aligning with our expectations, the results demonstrate that a one standard deviation increase in a firm's unexpected nonattainment exposure leads to newly established contracts that are 173 days longer on average, equivalent to a 30% increase relative to the sample mean. Collectively, these findings highlight how nonattainment designations can create competitive advantages for incumbent firms through their interactions with customers

[15]This limited sample period is due to FactSet Revere data's availability commencing in 2003, resulting in only three cohorts of nonattainment designations.

along the supply chain.

6.2. Facility-level compliance costs

In this section, we investigate the regulatory compliance costs associated with nonattainment exposure. As discussed in Section 2.1, since pollution abatement under SIPs is applied at the plant-level, we explore how a facility's nonattainment exposure influences its compliance costs. We measure a facility's exposure to nonattainment designations in a manner analogous to firm-level nonattainment exposure, as follows:

$$Facility\ NA\ exposure_{j,t} = \ln\left(1 + ozone_{j,t-1} \cdot NA_{j,t}\right), \tag{16}$$

where $ozone_{j,t-1}$ is the total amount of ozone air emissions for plant j in year $t-1$ and $NA_{j,t}$ is a dummy variable equal to one if plant j is located in a nonattainment county in year t, and zero otherwise. Similarly, unexpected and anticipated facility-level nonattainment exposure are given by:

$$Facility\ Unexp.\ NA\ exposure_{j,t} = \ln\Big(1 + ozone_{j,t-1} \cdot Unexp.\ NA_{j,t}\Big), \tag{17}$$

$$Facility\ Antic.\ NA\ exposure_{j,t} = \ln\left(1 + ozone_{j,t-1} \cdot Antic.\ NA_{j,t}\right), \tag{18}$$

where $Unexp.\ NA_{j,t}$ ($Antic.\ NA_{j,t}$) is a dummy variable equal to one if plant j is located in an unexpected (anticipated) nonattainment county in year t, and zero otherwise.

We ideally wish to utilize a facility's pollution abatement costs as a direct measure of their regulatory compliance costs. However, due to the lack of available data specifically on plant-level pollution abatement costs, we approximate the potential compliance costs associated with nonattainment designations by investigating observable regulatory enforcement and source reduction activities at facilities (Xu & Kim, 2022). The underlying idea is that facilities with a higher frequency of regulatory enforcements and increased engagement in source reduction activities likely face elevated compliance costs.

Our analysis employs three regulatory enforcement measures based on EPA's ICIS-Air database: high priority violations (HPV), Title V inspections, and compliance evaluations. HPVs denote severe plant violations leading to high fines, increased reporting obligations, and intensive regulatory oversight. Title V inspections and compliance evaluations are tests performed to gauge and demonstrate a facility's compliance with CAA regulations. Failing these tests can label the facility as a high priority violator. We model these outcomes as dummy variables taking a value of one if a facility experiences a high priority violation (*HPV*), undergoes a Title V inspection (*Title V inspection*), or faces a compliance evaluation (*Compliance evaluation*) in a given year; otherwise, they take a value of zero.

Regarding facilities' engagement in source reduction, we use data from EPA's Pollution Prevention (P2) database. Plants reporting to the TRI database document the extent of source reduction activities at the chemical level aimed at limiting the release of hazardous substances. Ozone emissions can undergo treatment, recycling, or recovery before discharge into the environment, with treatment being the primary mode of abatement. Facilities must also detail the type of source reduction activities they undertake.[16] Our variables of interest are the natural logarithm of one plus the amount of onsite ozone air emissions that are treated (*Onsite treated*), undergo recovery (*Onsite recovery*), or are recycled (*Onsite recycle*) at a given facility in a particular year. Additionally, we create a dummy variable that takes a value of one if a facility engages in source reduction activities related to ozone, and zero otherwise (*SR activity*).

To assess the impact of facility-level nonattainment exposure on the aforementioned outcome variables, we employ a similar stacked DiD approach to the previous section, but conducted at the facility level. Within each cohort, treated facilities are those newly exposed to nonattainment designations, while control facilities are those maintaining zero nonattainment exposure throughout the event window. Formally, we estimate:

$$y_{j,t,k} = \beta \mathit{Facility\ NA\ exposure}_{j,k} \times \mathit{Post}_{t,k} + \tau_{j,k} + \rho_{t,k} + \varepsilon_{j,t,k}, \tag{19}$$

where $\mathit{Facility\ NA\ exposure}_{j,k}$ is the continuous treatment variable that measures facility j's nonattainment exposure in cohort k. $\mathit{Post}_{t,k}$ is a dummy variable equal to one for the event year and subsequent four years in cohort k, and zero otherwise. $\tau_{j,k}$ and $\rho_{t,k}$ are Plant $\times$ Cohort and Year $\times$ Cohort fixed effects, respectively. Furthermore, we also estimate the following decomposed specification:

$$\begin{aligned} y_{j,t,k} = {} & \beta_1 \mathit{Facility\ Unexp.\ NA\ exposure}_{j,k} \times \mathit{Post}_{t,k} + \beta_2 \mathit{Facility\ Antic.\ NA\ exposure}_{j,k} \times \mathit{Post}_{t,k} \\ & + \tau_{j,k} + \rho_{t,k} + \varepsilon_{j,t,k}, \end{aligned} \tag{20}$$

where $\mathit{Facility\ Unexp.\ NA\ exposure}_{j,k}$ and $\mathit{Facility\ Antic.\ NA\ exposure}_{j,k}$ are continuous treat-

[16] The most prevalent is "good operating practices", consisting of actions such as improved maintenance scheduling, record keeping, or procedure adjustments. The second most common abatement activity is "process modifications", involving actions such as equipment modification, layout changes, or adjustments to piping.

ment variables that measure facility j's unexpected and anticipated nonattainment exposure, respectively, in cohort k.

Table 9 presents the findings. Panel A focuses on regulatory enforcement variables, and Panel B on source reduction variables. The results suggest that a higher level of nonattainment exposure at the facility level is linked to an increased likelihood of encountering regulatory enforcement and engaging in source reduction activities. Notably, the rise in potential compliance costs is primarily driven by unexpected nonattainment exposure, whereas anticipated exposure does not exhibit significant effects on compliance costs. From an economic perspective, a one standard deviation increase in unexpected nonattainment exposure at the facility level corresponds to an 11% rise in the probability of HPVs relative to the sample mean, along with a 21% increase in the amount of ozone emissions subjected to treatment. In summary, the analyses suggest that compliance costs increase as facility-level nonattainment exposure rises.

7. Accounting performance

So far, we document that shareholder wealth initially rises with growing nonattainment exposure, but declines after surpassing a specific threshold. Investigating the mechanisms, we show that nonattainment exposure grants incumbent firms competitive advantages while also imposing compliance costs. In this section, we assess whether the short-term market reactions to nonattainment designations accurately reflect the long-term effects of such designations. Specifically, we explore how firms' nonattainment exposure impacts their accounting performance.

We begin our analysis by examining a firm's operating performance using three variables that are likely to be influenced by nonattainment exposure: *Rev/Assets*, the ratio of revenues to total assets; *OpI/Assets*, the ratio of operating income to total assets; and *GPM*, the gross profit margin calculated as sales minus the sum of cost of goods sold and selling, general, and administrative expenses, expressed as a fraction of sales. To investigate how a firm's investment behavior is affected by pollution abatement driven by nonattainment exposure, we use *CAPX/Assets*, the ratio of capital expenditures to total assets. Lastly, we examine changes in costs resulting from shifts in factors such as operational procedures and raw materials due to nonattainment exposure by utilizing *COGS/Assets*, the ratio of cost of goods sold to total assets.

Our empirical specification follows the same firm-level stacked DiD regression as in Equation (15), with the addition of quadratic terms to address the tradeoffs between the benefits and costs of nonattainment designations:

$$\begin{aligned}y_{i,t,k} &= \beta_1 \mathit{Unexp.\ NA\ exposure}_{i,k} \times \mathit{Post}_{t,k} + \beta_2 \mathit{Unexp.\ NA\ exposure}^2_{i,k} \times \mathit{Post}_{t,k} \\ &+ \alpha_1 \mathit{Antic.\ NA\ exposure}_{i,k} \times \mathit{Post}_{t,k} + \alpha_2 \mathit{Antic.\ NA\ exposure}^2_{i,k} \times \mathit{Post}_{t,k} \\ &+ \tau_{i,k} + \rho_{t,k} + \varepsilon_{i,t,k}\end{aligned} \tag{21}$$

where the dependent variable comprises the aforementioned accounting variables (expressed in %), and all other variables have been defined previously.

Table 10 presents the results. In columns (1) to (3), we observe a significantly positive coefficient on *Unexp. NA exposure* × *Post* and a significantly negative coefficient on *Unexp. NA exposure*^{2} × *Post*. This finding implies that in the post-nonattainment period, unexpected nonattainment exposure initially spurs growth in revenue, operating income, and gross profit margins, followed by a decline as exposure reaches excessive levels. This nonlinear pattern aligns with the interpretation that the competitive advantages of nonattainment exposure generate increased income initially, but this effect diminishes as rising compliance costs erode the gains. Columns (4) and (5) offer a more detailed analysis of the accounting consequences associated with the compliance costs of nonattainment exposure. The findings reveal that capital expenditures and cost of goods sold experience an initial decline when firms experience relatively low levels of unexpected nonattainment exposure, but start to increase once the exposure surpasses a certain threshold.

To gain insight into the economic magnitudes, we plot the marginal effects of unexpected nonattainment exposure on accounting performance in the post-nonattainment period in Figure 5. Panels A, B, and C show that the marginal effect of unexpected nonattainment exposure on *Rev/Assets*, *OpI/Assets*, and *GPM* is initially positive, reaching a specific point where it becomes negative. In contrast, panels D and E show that the marginal effect on *CAPX/Assets* and *COGS/Assets* starts as negative and gradually transitions to positive. This evolution is likely due to the mounting compliance obligations associated with greater nonattainment exposure. Overall, we find that firms' long-term accounting performance reflects the interplay between the benefits and costs of nonattainment designations, implying that the market incorporates the valuation effects of nonattainment designations into its initial reactions.

8. Robustness tests

We perform a number of robustness checks and falsification tests. For brevity, we report a concise summary of these tests, while the detailed descriptions and corresponding tables can be found on the Internet Appendix.

To rule out that other non-event characteristics such as size, value, growth, momentum, or industry are driving market reactions, we compute CARs with respect to alternative benchmark models. In Internet Appendix Table IA.7, we redo the analysis in Table 3 by using Fama and French's (1997) 48 value-weighted industry return as the benchmark return, or by applying Carhart (1997)'s four-factor model to calculate risk-adjusted event returns. These alternative ways of calculating abnormal returns leave the previous conclusions unaffected, which is in line with prior methodological research on event studies showing that benchmark returns used for risk adjustment rarely matter in the short-run (Brown & Warner, 1985; Kothari & Warner, 2007).

We explore a range of alternative definitions for our nonattainment exposure measure. These include dividing ozone emissions by the total number of ozone-emitting plants, incorporating different weightings such as by sales share, employee share, and chemical toxicity, and using core chemical ozone emissions as well as those specified in operating permits. Importantly, the baseline results remain qualitatively unchanged as shown in Internet Appendix Table IA.8. More details on the construction of these alternative measures can be found in Section IA.1 of the Internet Appendix.

Since nonattainment designations regulate the onsite ozone emissions of facilities, firms that produce offsite ozone emissions or non-ozone chemicals such as particulate matter should not be affected by nonattainment regulation. Consequently, we can define placebo treatment variables by substituting ozone emissions with offsite ozone emissions or particulate matter emissions in the definition of *NA exposure*. If market reactions are driven in response to actual regulatory exposure, the use of placebo treatment variables should have no impact on shareholder wealth. Our expectations are supported by the findings in Internet Appendix Table IA.9, which indicate no effect of placebo treatment variables on CARs.

To control for firms self-selecting into nonattainment counties, we use Heckman's (1979) two-stage least squares for correction, which we outline in more detail in Section IA.2 of the Internet Appendix. Our results remain qualitatively similar as shown in Internet Appendix Table IA.10. Finally, we provide evidence that there is no significant reallocation of ozone emissions from nonattainment counties to attainment counties among multi-plant firms, as demonstrated in Internet Appendix Table IA.11. This finding helps alleviate concerns that the positive reaction to nonattainment designations documented in Table 2 might be driven by multi-plant firms, who plausibly possess the capability to reallocate ozone emissions to plants situated in attainment counties. Further details can be found in Section IA.3 of the Internet Appendix.

9. Conclusion

Our study examines how local environmental regulations and firms' polluting behavior interact to affect shareholder wealth. Using nonattainment designations induced by discrete policy changes in the NAAQS threshold as an exogenous source of variation in local regulatory stringency, we document that the stock market internalizes the perceived benefits and costs of local environmental regulation. On average, the market responds positively to firms exposed to nonattainment designations in comparison to non-exposed firms. In the cross-section, a firm's CAR initially rises with increasing nonattainment exposure but declines at higher levels. We validate our findings further using attainment redesignations that signify a relaxation in regulation. In this context, a firm's CAR initially decreases with attainment redesignation exposure, then rises at higher levels.

We interpret these market reactions as responses to the tradeoffs between the benefits and costs of nonattainment designations. Exploring the mechanisms, we show that nonattainment designations can confer competitive advantages for incumbent firms. At the county level, these designations hinder new polluting plant births and increase the concentration of sales and employees among ozone-emitting plants. At the firm level, those exposed to nonattainment designations experience reduced product market competition and secure more supply chain contracts and customer relationships. Conversely, we also identify potential compliance costs linked to nonattainment designations, as greater facility-level nonattainment exposure leads to increased regulatory enforcement and participation in source reduction. Lastly, we demonstrate that a firm's exposure to nonattainment designations affects its long-term accounting performance in a manner consistent with the short-term market reactions.

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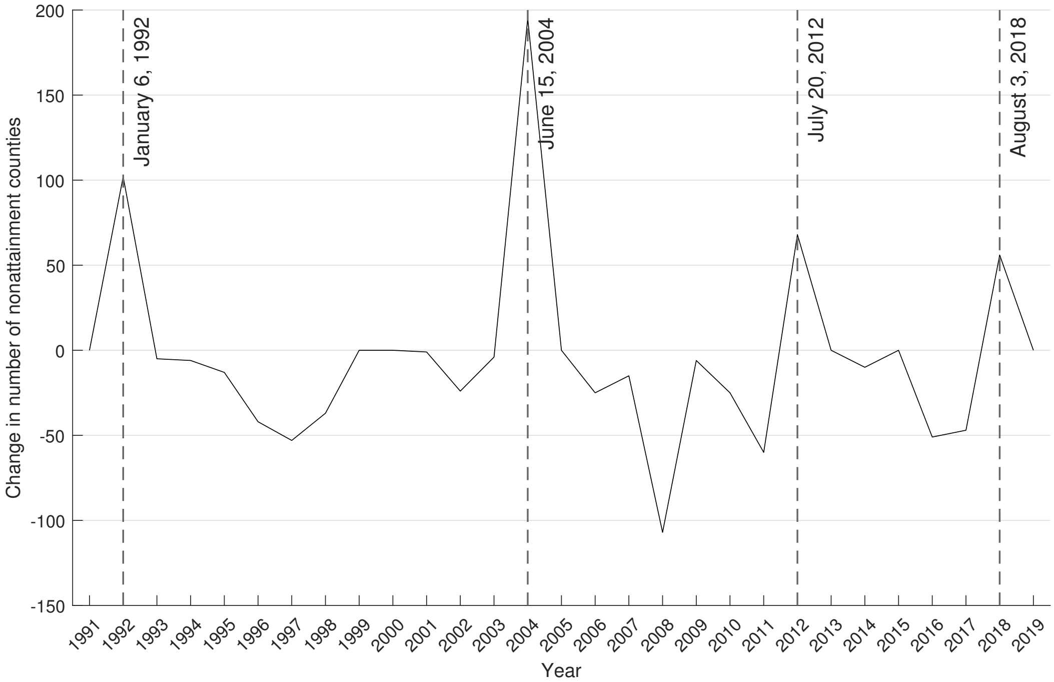
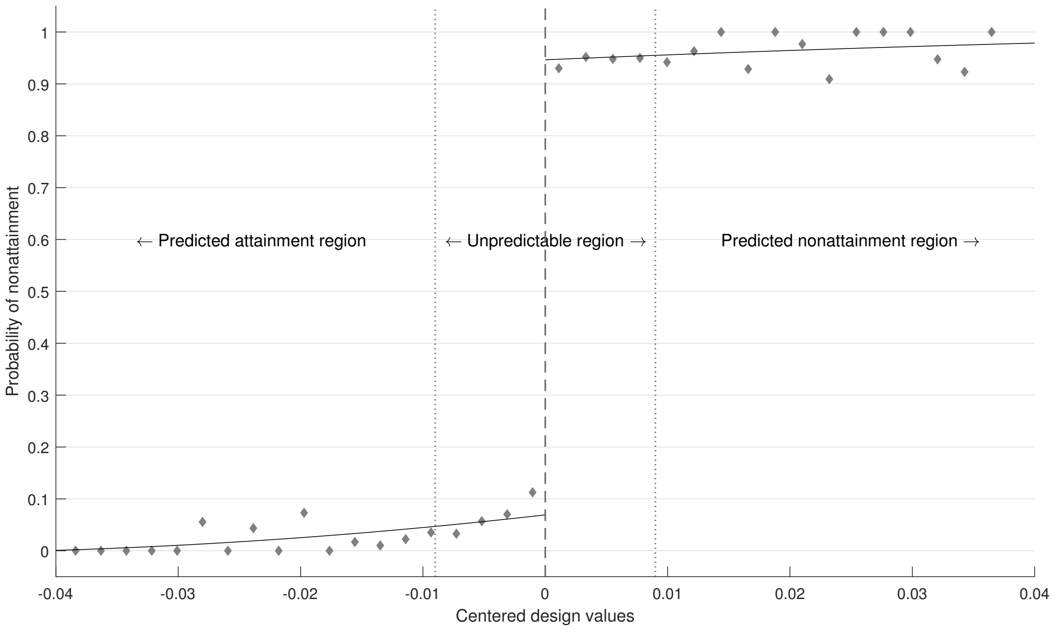
Figure 1
Policy changes in the NAAQS threshold and change in the number of nonattainment counties.



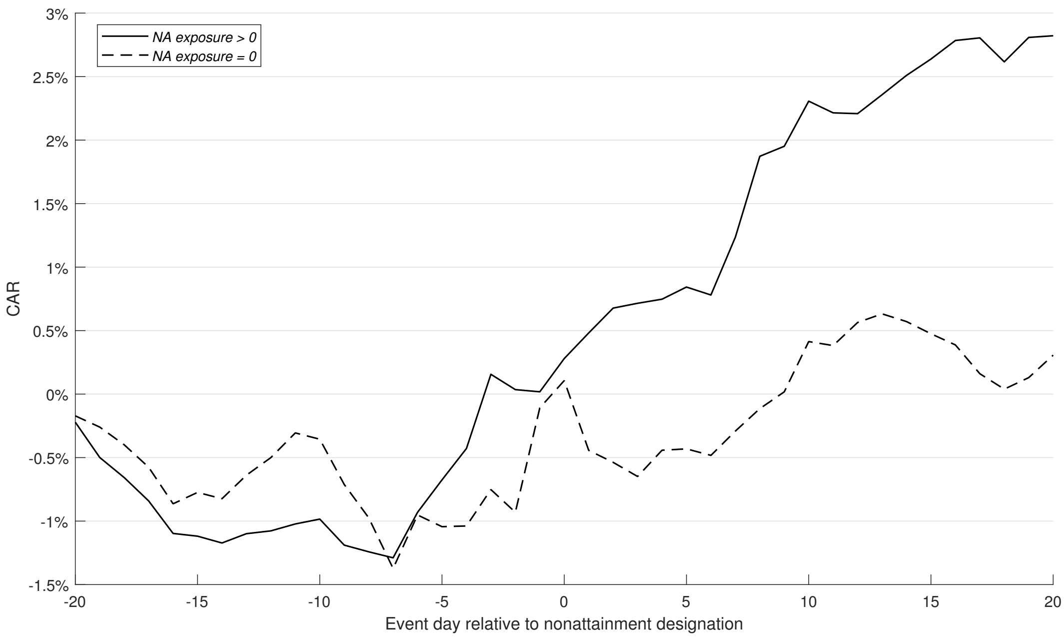
This figure shows the four discrete policy changes in the NAAQS threshold and the yearly change in the number of nonattainment counties during the sample period 1992 to 2019. In chronological order, the revisions to the NAAQS threshold include the 1-Hour Ozone (1979) standard effective on January 6, 1992, 8-Hour Ozone (1997) standard effective on June 15, 2004, 8-Hour Ozone (2008) standard effective on July 20, 2012, and 8-Hour Ozone (2015) standard effective on August 3, 2018. Each of these revisions is represented by a dashed vertical line. For more details, see Table IA.1 of the Internet Appendix. The solid black lines represent the difference in the number of nonattainment counties between the current year and the previous year.

Figure 2
Probability of nonattainment around ozone NAAQS thresholds.



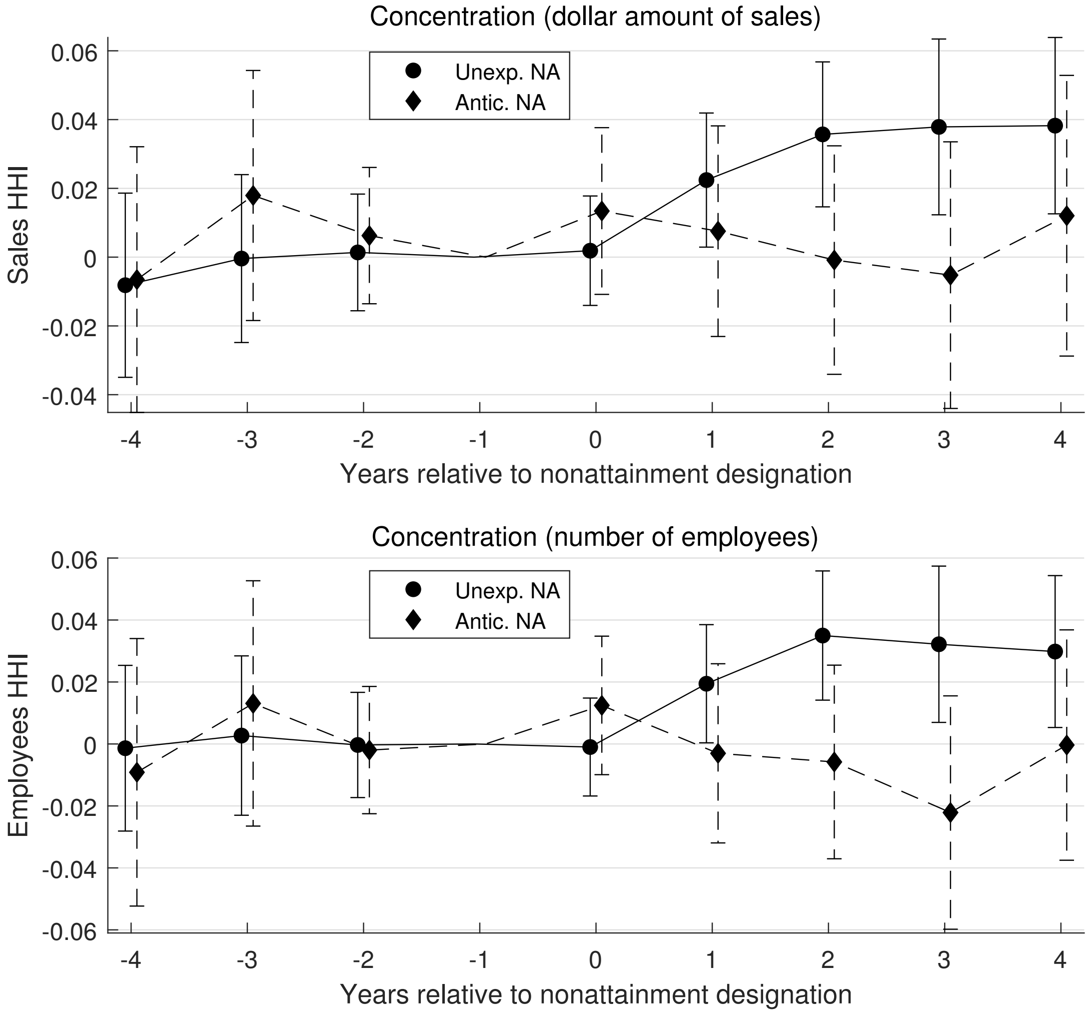
This figure presents the regression discontinuity relating centered DVs to the probability of nonattainment. The regression discontinuity is estimated from a local linear regression specification using the mean squared error optimal bandwidth with rectangular kernels following Calonico, Cattaneo, and Titiunik (2014). Further details are provided in Section IA of the Internet Appendix. The vertical axis shows the probability of nonattainment. The horizontal axis shows the centered DVs around zero by subtracting the NAAQS threshold from the DVs. 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 $NA_{c,t}$, defined as a dummy variable equal to one if county c is designated nonattainment in year t, 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 $NA_{c,t}$ on local quartic polynomials in centered DVs. The unpredictable region refers to the narrow region surrounding the NAAQS threshold, which is bounded by the mean squared error optimal bandwidth. The predicted nonattainment region refers to the region to the right of the optimal bandwidth. The predicted attainment region refers to the region to the left of the optimal bandwidth.

Figure 3
Dynamics of cumulative abnormal returns around nonattainment designations.



This figure shows the mean value-weighted CARs over the event window $(-20, +20)$ for nonattainment designations induced by discrete policy changes in the NAAQS threshold. The solid line plots the CARs for firms that are exposed to nonattainment designations ($NA\ exposure > 0$) and the dashed line plots the CARs for firms that are not exposed ($NA\ exposure = 0$).

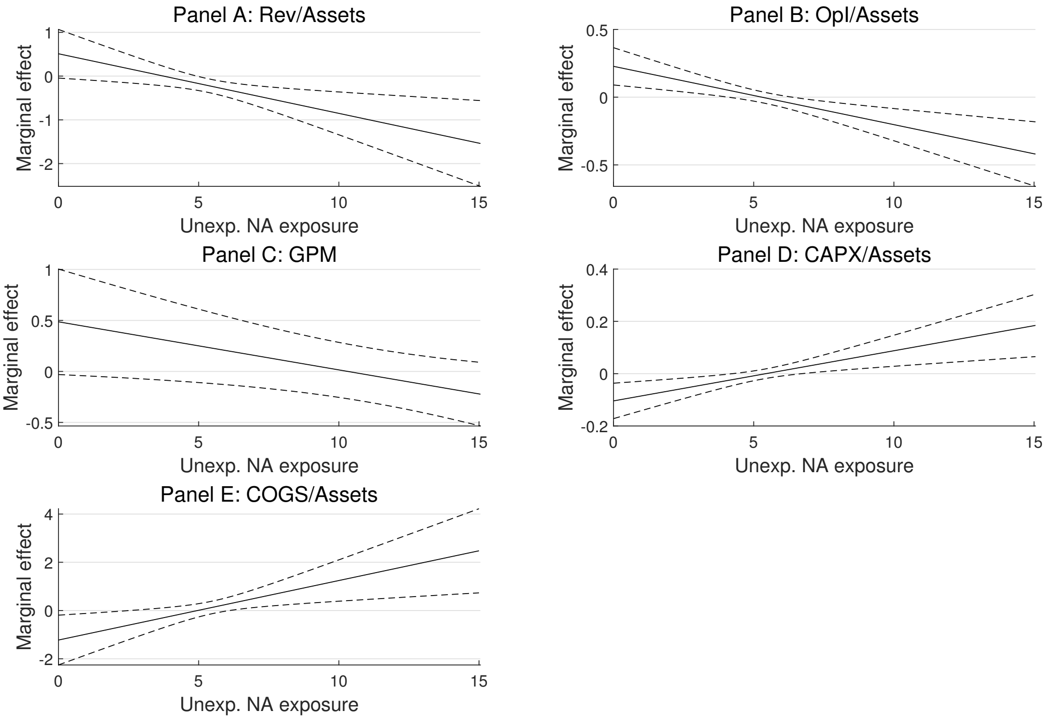
Figure 4
Dynamic effects of nonattainment designations on the concentration of sales and employees.



This figure plots the event study estimates and corresponding 95% confidence intervals based on the county-level stacked DiD regressions in columns (2) and (4) of Table 6. We focus on an event window of four years before to four years after nonattainment designations induced by discrete policy changes in the NAAQS threshold. Event year $t = -1$ is the omitted category, implying that all coefficient estimates are relative to this year. The outcome variables, *Sales HHI* and *Employees HHI*, are calculated by summing the squared sales or employee shares, respectively, of all ozone-emitting plants in a given county in a given year. *Unexp. NA* and *Antic. NA* are dummy variables equal to one if a county is designated as an unexpected or anticipated nonattainment, respectively, in a given year, and zero otherwise. The solid and dashed lines represent the dynamic effects of unexpected and anticipated nonattainment designations on the outcome variables, respectively.

Figure 5

Marginal effects of nonattainment exposure on accounting performance in the post-nonattainment period.



This figure plots the marginal effects of unexpected nonattainment exposure on measures of accounting performance in the post-nonattainment period. Panels A, B, C, D, and E plot the estimates of the marginal effects and corresponding 95% confidence intervals on *Rev/Assets*, *OpI/Assets*, *GPM*, *CAPX/Assets*, and *COGS/Assets*, respectively, based on the regression results in Table 10.

Table 1
Summary statistics.

Variables	N	Mean	Median	Std. dev.	P25	P75
Firm-level variables						
NA exposure	2,548	3.712	0.000	4.877	0.000	8.797
Unexp. NA exposure	2,548	2.308	0.000	4.162	0.000	2.398
Antic. NA exposure	2,548	2.346	0.000	4.265	0.000	2.079
NA exposure (Treated group)	1,106	8.551	9.396	3.662	6.405	11.167
Unexp. NA exposure (Treated group)	1,106	5.317	5.553	4.891	0.000	9.917
Antic. NA exposure (Treated group)	1,106	5.404	5.859	5.039	0.000	10.156
Redesig exposure	4,708	1.305	0.000	3.223	0.000	0.000
Unexp. redesig exposure	4,708	0.833	0.000	2.632	0.000	0.000
Antic. redesig exposure	4,708	0.504	0.000	2.111	0.000	0.000
Redesig exposure (Treated group)	1,705	7.304	8.148	3.785	4.290	10.204
Unexp. redesig exposure (Treated group)	1,705	4.664	3.452	4.574	0.000	8.856
Antic. redesig exposure (Treated group)	1,705	2.821	0.000	4.293	0.000	6.071
Fluidity	13,978	5.528	4.744	3.452	3.292	6.743
Similarity	14,432	2.120	1.159	3.597	1.036	1.630
Number of new contracts	8,539	3.443	1.000	7.468	0.000	3.000
Number of new customers	8,539	3.274	1.000	7.035	0.000	3.000
Contract length (days)	8,539	568.640	353.000	795.141	0.000	846.750
Rev/Assets	15,097	114.427	105.400	64.329	73.450	143.245
OpI/Assets	14,923	13.172	12.841	8.270	8.971	17.199
GPM	13,940	13.076	12.731	36.674	8.185	18.114
CAPX/Assets	15,097	5.176	4.232	3.954	2.491	6.753
COGS/Assets	14,928	81.040	70.111	56.560	44.109	103.938
ln(Size)	14,898	7.183	7.164	1.958	5.832	8.479
ln(BM)	14,898	0.531	0.540	0.151	0.430	0.635
ROA	14,898	0.136	0.132	0.080	0.094	0.175
Leverage	14,898	0.266	0.219	0.211	0.101	0.387
Sales growth	14,898	0.103	0.065	0.413	-0.013	0.157
Cash	14,898	0.095	0.055	0.113	0.019	0.131
Momentum	14,898	1.146	1.093	0.530	0.878	1.317
Stock returns	14,898	0.149	0.095	0.533	-0.126	0.328
Stock volatility	14,898	0.104	0.089	0.061	0.064	0.127
Facility-level variables						
Facility NA exposure	17,912	1.491	0.000	3.392	0.000	0.000
Facility Unexp. NA exposure	17,912	0.651	0.000	2.340	0.000	0.000
Facility Antic. NA exposure	17,912	0.770	0.000	2.605	0.000	0.000
Facility NA exposure (Treated group)	3,593	7.433	8.289	3.633	5.209	10.160
Facility Unexp. NA exposure (Treated group)	3,593	4.236	1.946	4.556	0.000	8.710
Facility Antic. NA exposure (Treated group)	3,593	3.197	0.000	4.419	0.000	7.497
HPV	126,485	0.021	0.000	0.144	0.000	0.000
Title V inspection	126,485	0.192	0.000	0.394	0.000	0.000
Compliance evaluation	126,485	0.258	0.000	0.438	0.000	1.000
Onsite treated	126,485	1.417	0.000	3.894	0.000	0.000
Onsite recovery	126,485	0.285	0.000	1.914	0.000	0.000
Onsite recycle	126,485	0.535	0.000	2.434	0.000	0.000
SR activity	126,485	0.086	0.000	0.281	0.000	0.000
County-level variables						
Plant births	54,460	0.054	0.000	0.268	0.000	0.000
NA	54,460	0.128	0.000	0.334	0.000	0.000
Unexp. NA	54,460	0.089	0.000	0.285	0.000	0.000
Antic. NA	54,460	0.039	0.000	0.193	0.000	0.000
Sales HHI	24,059	0.614	0.583	0.206	0.495	0.782
Employees HHI	24,059	0.596	0.565	0.209	0.464	0.757

This table reports summary statistics. Std. dev. displays the standard deviation, P25 the first and P75 the third quartile of the respective variable. Variable definitions are presented in Table A.1 in Appendix A.

Table 2
Cumulative abnormal returns around nonattainment designations.

Panel A: Full sample

	NA exposure > 0 ($N = 1,106$)		*NA exposure* $= 0$ ($N = 1,442$)		Difference: *NA exposure* > 0 vs. *NA exposure* $= 0$	
	Mean	Median	Mean	Median	Mean	Median
Event window	(1)	(2)	(3)	(4)	(5)	(6)
$(-2, +2)$	0.449*	0.359***	-0.536***	-0.913***	0.985***	1.271***
	(1.74)	(2.58)	(-2.83)	(-3.18)	(3.08)	(3.41)
$(-5, +5)$	1.157***	1.143***	-0.057	0.284	1.215***	0.860**
	(3.83)	(3.03)	(-0.33)	(0.74)	(3.47)	(2.06)

Panel B: Decomposition

	Unexpected ($N = 722$)		Anticipated ($N = 383$)		Difference: Unexpected vs. *NA exposure* $= 0$		Difference: Anticipated vs. *NA exposure* $= 0$	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Event window	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$(-2, +2)$	0.479*	0.346**	-0.351	-0.006	1.015***	1.259**	0.184	0.906
	(1.79)	(2.53)	(-0.75)	(-0.01)	(2.90)	(2.89)	(0.38)	(1.28)
$(-5, +5)$	1.189***	1.143**	0.242	-0.793	1.246***	0.860**	0.299	-1.076
	(3.64)	(2.01)	(0.54)	(-0.90)	(3.19)	(1.96)	(0.62)	(-1.53)

This table reports the mean and median value-weighted CARs around nonattainment designations induced by discrete policy changes in the NAAQS threshold. We consider event windows of 5 $(-2, +2)$ and 11 $(-5, +5)$ days. Panel A uses the full sample of firms and splits the sample into those that are exposed to nonattainment designations (*NA exposure* > 0) and those that are not exposed (*NA exposure* $= 0$). Panel B focuses only on the subsample of firms with non-zero nonattainment exposure. "Unexpected" refers to the sample of firms where their unexpected nonattainment exposure (*Unexp. NA exposure*) is greater than their anticipated nonattainment exposure (*Antic. NA exposure*). "Anticipated" refers to the sample of firms where *Antic. NA exposure* $>$ *Unexp. NA exposure*. *NA exposure* measures a firm's time-varying exposure to nonattainment designations based on the geographic distribution of its plants across nonattainment counties and the amount of ozone emissions at each plant. *Unexp. NA exposure* and *Antic. NA exposure* decompose a firm's exposure to nonattainment designations into an unexpected and anticipated component, respectively. The detailed definitions for *NA exposure*, *Unexp. NA exposure*, and *Antic. NA exposure* are given in Equations (1), (3), and (4), respectively. The t-statistics for the mean (reported in the parenthesis) account for event-induced changes in volatility and are calculated according to Boehmer et al. (1991). The test statistic for the median (reported in the parenthesis) is a generalized nonparametric Wilcoxon sign-rank test of the median CARs being equal to zero. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 3

Cross-sectional variation in cumulative abnormal returns around nonattainment designations.

Dep. variable:	CAR $(-2,+2)$				CAR $(-5,+5)$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NA exposure	0.281**		0.477***		0.365***		0.574***	
	(2.35)		(3.07)		(2.98)		(3.00)	
NA exposure^2	-0.025**		-0.043***		-0.033***		-0.054***	
	(-2.36)		(-3.18)		(-3.13)		(-3.16)	
Unexp. NA exposure		0.342***		0.503***		0.543***		0.674**
		(2.71)		(3.24)		(2.88)		(2.57)
Unexp. NA exposure^2		-0.030***		-0.042***		-0.052***		-0.066***
		(-2.63)		(-3.02)		(-3.03)		(-2.63)
Antic. NA exposure		-0.128		-0.122		0.021		-0.285
		(-1.23)		(-0.83)		(0.13)		(-1.36)
Antic. NA exposure^2		0.015		0.012		-0.002		0.022
		(1.60)		(0.92)		(-0.10)		(1.26)
ln(Size)	-0.001	-0.026	-0.404	-0.429	0.174	0.158	-0.225	-0.228
	(-0.02)	(-0.33)	(-1.35)	(-1.44)	(1.55)	(1.44)	(-0.50)	(-0.52)
ln(BM)	1.944*	1.873	5.981***	5.788***	4.619***	4.666***	8.457***	9.158***
	(1.67)	(1.61)	(3.12)	(3.01)	(2.84)	(2.86)	(2.79)	(2.98)
ROA	7.336***	7.362***	10.252***	10.232***	11.776***	11.888***	9.939*	10.587*
	(4.55)	(4.55)	(3.12)	(3.14)	(4.74)	(4.80)	(1.78)	(1.89)
Leverage	3.036***	3.051***	1.679	1.840	1.111	1.216	0.516	0.479
	(3.41)	(3.43)	(1.17)	(1.29)	(0.86)	(0.94)	(0.23)	(0.21)
Sales growth	-0.243	-0.260	0.314	0.391	-0.455	-0.464	-0.153	-0.141
	(-0.63)	(-0.68)	(0.39)	(0.49)	(-0.81)	(-0.83)	(-0.10)	(-0.09)
Cash	-0.641	-0.651	-2.190	-2.136	-0.073	-0.070	-1.101	-1.305
	(-0.60)	(-0.61)	(-1.14)	(-1.11)	(-0.05)	(-0.04)	(-0.38)	(-0.45)
Momentum	2.844***	2.812***	2.743***	2.687***	4.312***	4.264***	5.538***	5.520***
	(4.50)	(4.47)	(3.35)	(3.27)	(4.55)	(4.48)	(4.38)	(4.34)
Stock returns	-3.180***	-3.160***	-3.052***	-2.980***	-4.762***	-4.702***	-5.359***	-5.282***
	(-6.16)	(-6.14)	(-4.77)	(-4.64)	(-5.98)	(-5.88)	(-5.01)	(-4.94)
Stock volatility	2.481	2.547	0.484	0.154	7.906*	7.859*	6.615	7.382
	(0.81)	(0.83)	(0.12)	(0.04)	(1.67)	(1.65)	(0.97)	(1.09)
F-statistic	2.82	3.67	5.08	5.27	4.88	4.62	5.02	3.46
p-value	0.059	0.026	0.007	0.005	0.008	0.010	0.007	0.03
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	No	No	Yes	Yes	No	No
Firm F.E.	No	No	Yes	Yes	No	No	Yes	Yes
Observations	2,027	2,027	1,538	1,538	2,026	2,026	1,530	1,530
Adj R^2	0.10	0.10	0.07	0.07	0.11	0.11	0.09	0.09

This table reports the regression estimates from Equations (2) and (5) for nonattainment designations induced by discrete policy changes in the NAAQS threshold. The dependent variables are the 5-day $(-2,+2)$ and 11-day $(-5,+5)$ CARs. *NA exposure* measures a firm's time-varying exposure to nonattainment designations based on the geographic distribution of its plants across nonattainment counties and the amount of ozone emissions at each plant. *Unexp. NA exposure* and *Antic. NA exposure* decompose a firm's exposure to nonattainment designations into an unexpected and anticipated component, respectively. The detailed definitions for *NA exposure*, *Unexp. NA exposure*, and *Antic. NA exposure* are given in Equations (1), (3), and (4), respectively. The F-statistic and corresponding p-value is a test of the joint significance of *NA exposure* and *NA exposure*^{2} in columns (1), (3), (5), and (7), and *Unexp. NA exposure* and *Unexp. NA exposure*^{2} in columns (2), (4), (6), and (8). For all specifications, standard errors are robust to heteroskedasticity and clustered at the firm-level; 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
Cross-sectional variation in cumulative abnormal returns around attainment redesignations.

Dep. variable:	CAR $(-2,+2)$				CAR $(-5,+5)$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Redesig exposure	-0.168**		-0.137*		-0.290***		-0.273**	
	(-2.68)		(-1.78)		(-3.32)		(-2.37)	
Redesig exposure^2	0.017**		0.015*		0.031***		0.030**	
	(2.36)		(1.80)		(3.88)		(2.59)	
Unexp. redesig exposure		-0.183**		-0.232**		-0.334**		-0.443***
		(-2.41)		(-2.44)		(-2.59)		(-3.12)
Unexp. redesig exposure^2		0.020**		0.025**		0.033**		0.044***
		(2.47)		(2.62)		(2.52)		(2.89)
Antic. redesig exposure		-0.025		-0.028		0.107		0.141
		(-0.25)		(-0.27)		(0.91)		(0.89)
Antic. redesig exposure^2		0.004		0.003		-0.011		-0.011
		(0.39)		(0.28)		(-0.93)		(-0.67)
F-statistic	3.84	3.09	1.65	3.63	7.51	3.37	3.44	4.90
p-value	0.035	0.063	0.213	0.041	0.003	0.050	0.048	0.016
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	No	No	Yes	Yes	No	No
Firm F.E.	No	No	Yes	Yes	No	No	Yes	Yes
Observations	4,513	4,513	4,428	4,428	4,512	4,512	4,427	4,427
Adj R^2	0.10	0.09	0.13	0.10	0.09	0.06	0.14	0.13

This table reports the regression estimates from Equations (9) and (10) for attainment redesignations. The dependent variables are the 5-day $(-2,+2)$ and 11-day $(-5,+5)$ CARs. Each observation with non-zero exposure to attainment redesignations is matched to two observations with no exposure using nearest neighbor propensity score matching with replacement (Roberts & Whited, 2013). *Redesig exposure* measures a firm's time-varying exposure to attainment redesignations based on the geographic distribution of its plants across counties that have been redesignated and the amount of ozone emissions at each plant. *Unexp. redesig exposure* and *Antic. redesig exposure* decompose a firm's exposure to attainment redesignations into an unexpected and anticipated component, respectively. The detailed definitions for *Redesig exposure*, *Unexp. redesig exposure*, and *Antic. redesig exposure* are given in Equations (6), (7), and (8), respectively. Control variables include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *Cash*, *Momentum*, *Stock returns*, and *Stock volatility*. The F-statistic and corresponding p-value is a test of the joint significance of *Redesig exposure* and *Redesig exposure*^{2} in columns (1), (3), (5), and (7), and *Unexp. redesig exposure* and *Unexp. redesig exposure*^{2} in columns (2), (4), (6), and (8). For all specifications, standard errors are robust to heteroskedasticity and clustered at the firm-level; 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
The effect of nonattainment designations on new plant births.

Dep. variable: *Plant births*$_t$	(1)	(2)	(3)	(4)
NA_{t-1}	-0.131***	-0.121***		
	(-10.79)	(-6.14)		
Unexp. NA_{t-1}			-0.340***	-0.334***
			(-3.20)	(-9.30)
Antic. NA_{t-1}			0.039	0.044
			(0.41)	(0.99)
Controls	No	Yes	No	Yes
Year × Cohort F.E.	Yes	Yes	Yes	Yes
County × Cohort F.E.	Yes	Yes	Yes	Yes
Log likelihood	-8,101.5	-6,791.8	-8,093.4	-6,784.0
Observations	17,746	14,017	17,746	14,017
Pseudo R^2	0.12	0.12	0.12	0.12

This table reports the fixed-effects Poisson regression estimates that examines the effect of nonattainment designations on new plant births. We focus on the four years before and after nonattainment designations induced by discrete policy changes in the NAAQS threshold. The dependent variable, *Plant births*, counts the number of new TRI plants in a given county in a given year. *NA* is a dummy variable equal to one if a county is designated nonattainment in a given year, and zero otherwise. *Unexp. NA* and *Antic. NA* are dummy variables equal to one if a county is designated as an unexpected or anticipated nonattainment, respectively, in a given year, and zero otherwise. Control variables include the natural logarithm of one plus the population levels in a given year; the natural logarithm of one plus the employment levels in a given county; a given county's NOx emissions to employment ratio; and the change in a given county's employment levels. For all specifications, standard errors are robust to heteroskedasticity and clustered at the county-level; z-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
The effect of nonattainment designations on the concentration of sales and employees.

Dep. variable:	*Sales HHI*		*Employees HHI*	
	(1)	(2)	(3)	(4)
NA × *Post*	0.021***		0.018***	
	(2.84)		(2.39)	
Unexp. NA × *Post*		0.028***		0.023***
		(3.13)		(2.64)
Antic. NA × *Post*		0.002		0.002
		(0.11)		(0.12)
Year × Cohort F.E.	Yes	Yes	Yes	Yes
County × Cohort F.E.	Yes	Yes	Yes	Yes
Observations	23,677	23,677	23,677	23,677
Adj R^2	0.75	0.75	0.76	0.76

This table reports results from county-level stacked DiD regressions examining the effect of nonattainment designations on the concentration of sales and employees among ozone-emitting plants in a given county. We focus on an event window of four years before to four years after nonattainment designations induced by discrete policy changes in the NAAQS threshold. The dependent variables, *Sales HHI* and *Employees HHI*, are calculated by summing the squared sales or employee shares, respectively, of all ozone-emitting plants in a given county in a given year. *NA* is a dummy variable equal to one if a county is designated nonattainment in a given year, and zero otherwise. *Unexp. NA* and *Antic. NA* are dummy variables equal to one if a county is designated as an unexpected or anticipated nonattainment, respectively, in a given year, and zero otherwise. *Post* is a dummy variable equal to one for the nonattainment designation year and the subsequent four years, and zero otherwise. For all specifications, standard errors are robust to heteroskedasticity and clustered at the county-level; 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
The effect of nonattainment designations on firm-level competition.

Dep. variable:	*Fluidity*		*Similarity*	
	(1)	(2)	(3)	(4)
NA exposure × *Post*	-0.020**		-0.020*	
	(-1.97)		(-1.72)	
Unexp. NA exposure × *Post*		-0.087***		-0.031***
		(-3.07)		(-6.39)
Antic. NA exposure × *Post*		0.001		0.010
		(0.14)		(1.64)
Controls	Yes	Yes	Yes	Yes
Year × Cohort F.E.	Yes	Yes	Yes	Yes
Firm × Cohort F.E.	Yes	Yes	Yes	Yes
Observations	13,929	13,929	14,385	14,385
Adj R^2	0.66	0.66	0.62	0.62

This table reports results from firm-level stacked DiD regressions examining the effect of nonattainment designations on firm-level competition. We focus on an event window of four years before to four years after nonattainment designations induced by discrete policy changes in the NAAQS threshold. The dependent variable in columns (1) and (2) is *Fluidity*, which is constructed by Hoberg et al. (2014) and reflects both the degree of product similarity of a given firm with its competitors and the product market's instabilities arising from competitor actions. A higher value is associated with a more significant competitive threat for the firm. The dependent variable in columns (3) and (4) is *Similarity*, which is constructed by Hoberg and Phillips (2010, 2016) and reflects the amount of competition a given firm faces and the product relatedness to each competitor. A higher value is associated with more competitive pressure for the firm. *NA exposure* measures a firm's time-varying exposure to nonattainment designations based on the geographic distribution of its plants across nonattainment counties and the amount of ozone emissions at each plant. *Unexp. NA exposure* and *Antic. NA exposure* decompose a firm's exposure to nonattainment designations into an unexpected and anticipated component, respectively. The detailed definitions for *NA exposure*, *Unexp. NA exposure*, and *Antic. NA exposure* are given in Equations (1), (3), and (4), respectively. *Post* is a dummy variable equal to one for the nonattainment designation year and the subsequent four years, and zero otherwise. Control variables include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *Cash*, *Momentum*, *Stock returns*, and *Stock volatility*. For all specifications, standard errors are robust to heteroskedasticity and clustered at the firm-level; 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
The effect of nonattainment designations on supply chain contracts and customers.

	Full sample				8-Hour Ozone (2008) sample					
Dep. variable:	*Number of new contracts*		*Number of new customers*		*Number of new contracts*		*Number of new customers*		*Contract length (days)*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
NA exposure × *Post*	0.073**		0.067**		0.140**		0.143**		8.784**	
	(1.99)		(1.99)		(2.01)		(2.08)		(2.32)	
Unexp. NA exposure × *Post*		0.153**		0.141***		0.306**		0.310**		41.622**
		(2.76)		(2.98)		(2.38)		(2.44)		(3.06)
Antic. NA exposure × *Post*		0.040		0.045		0.084		0.080		3.396
		(0.61)		(0.75)		(0.47)		(0.46)		(0.45)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Cohort F.E.	Yes	Yes	Yes	Yes	No	No	No	No	No	No
Firm × Cohort F.E.	Yes	Yes	Yes	Yes	No	No	No	No	No	No
Year F.E.	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,525	8,525	8,525	8,525	3,368	3,368	3,368	3,368	3,368	3,368
Adj R^2	0.33	0.33	0.33	0.33	0.26	0.26	0.26	0.26	0.17	0.17

This table reports results from firm-level stacked DiD regressions examining the effect of nonattainment designations on supply chain contracts and customers. We focus on an event window of four years before to four years after nonattainment designations induced by discrete policy changes in the NAAQS threshold. Columns (1) to (4) use the full sample of nonattainment designations, while columns (5) to (10) use the subsample of nonattainment designations induced by the introduction of the 8-Hour Ozone (2008) standard in 2012. *Number of new contracts* is the number of newly initiated contracts made with corporate customers in a given supplier-year. *Number of new customers* is the number of unique new corporate customers per supplier-year. *Contract length (days)* is the average length (in days) of newly initiated contracts made with corporate customers in a given supplier-year. *NA exposure* measures a firm's time-varying exposure to nonattainment designations based on the geographic distribution of its plants across nonattainment counties and the amount of ozone emissions at each plant. *Unexp. NA exposure* and *Antic. NA exposure* decompose a firm's exposure to nonattainment designations into an unexpected and anticipated component, respectively. The detailed definitions for *NA exposure*, *Unexp. NA exposure*, and *Antic. NA exposure* are given in Equations (1), (3), and (4), respectively. *Post* is a dummy variable equal to one for the nonattainment designation year and the subsequent four years, and zero otherwise. Control variables include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *Cash*, *Momentum*, *Stock returns*, and *Stock volatility.* For all specifications, standard errors are robust to heteroskedasticity and clustered at the firm-level; 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
The effect of nonattainment designations on regulatory compliance costs.

Panel A: Regulatory enforcement

Dep. variable:	*HPV*		*Title V inspection*		*Compliance evaluation*	
	(1)	(2)	(3)	(4)	(5)	(6)
Facility NA exposure × *Post*	0.001**		0.003***		0.001**	
	(2.23)		(5.78)		(2.36)	
Facility Unexp. NA exposure × *Post*		0.001**		0.004***		0.002***
		(2.32)		(6.22)		(2.75)
Facility Antic. NA exposure × *Post*		0.000		0.000		0.001
		(0.48)		(0.52)		(0.81)
Year × Cohort F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Plant × Cohort F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	126,363	126,363	126,363	126,363	126,363	126,363
Adj R^2	0.18	0.18	0.82	0.82	0.54	0.54

Panel B: Source reduction

Dep. variable:	*Onsite treated*		*Onsite recovery*		*Onsite recycle*		*SR activity*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Facility NA exposure × *Post*	0.063***		0.010**		0.041***		0.007***	
	(9.52)		(2.48)		(7.56)		(10.50)	
Facility Unexp. NA exposure × *Post*		0.081**		0.025***		0.049**		0.010**
		(2.53)		(2.60)		(2.14)		(2.10)
Facility Antic. NA exposure × *Post*		0.018		0.004		0.025		0.002
		(1.26)		(0.96)		(1.59)		(0.73)
Year × Cohort F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant × Cohort F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	126,363	126,363	126,363	126,363	126,363	126,363	126,363	126,363
Adj R^2	0.87	0.87	0.80	0.80	0.74	0.74	0.46	0.46

This table reports results from facility-level stacked DiD regressions examining the effect of nonattainment designations on facilities' regulatory compliance costs. We focus on an event window of four years before to four years after nonattainment designations induced by discrete policy changes in the NAAQS threshold. In Panel A, the dependent variables are dummy variables that take a value of one if a facility experiences a high priority violation (*HPV*), undergoes a Title V inspection (*Title V inspection*), or faces a compliance evaluation (*Compliance evaluation*) in a given year. Otherwise, they take a value of zero. In Panel B, the dependent variables consist of the natural logarithm of one plus the amount of onsite ozone air emissions that are treated (*Onsite treated*), undergo recovery (*Onsite recovery*), or are recycled (*Onsite recycle*) at a given facility in a given year. Additionally, there is a dummy variable that takes a value of one if a facility undertakes source reduction activities related to ozone, and zero otherwise (*SR activity*). *Facility NA exposure* measures a plant's time-varying exposure to nonattainment designations based on the county where it operates and the amount of ozone it emits. *Facility Unexp. NA exposure* and *Facility Antic. NA exposure* decompose a plant's exposure to nonattainment designations into an unexpected and anticipated component, respectively. The detailed definitions for *Facility NA exposure*, *Facility Unexp. NA exposure*, and *Facility Antic. NA exposure* are given in Equations (16), (17), and (18), respectively. *Post* is a dummy variable equal to one for the nonattainment designation year and the subsequent four years, and zero otherwise. For all specifications, standard errors are robust to heteroskedasticity and clustered at the county-level; 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
The effect of nonattainment designations on accounting performance.

Dep. variable:	*Rev/Assets*	*OpI/Assets*	*GPM*	*CAPX/Assets*	*COGS/Assets*
	(1)	(2)	(3)	(4)	(5)
Unexp. NA exposure × *Post*	0.510*	0.228***	0.487*	-0.104***	-1.224**
	(1.80)	(3.24)	(1.84)	(-3.01)	(-2.32)
Unexp. NA exposure^2 × *Post*	-0.068***	-0.022***	-0.024**	0.010***	0.123***
	(-2.68)	(-3.47)	(-2.30)	(3.09)	(2.66)
Antic. NA exposure × *Post*	-0.271	0.031	-1.307	-0.033	-0.030
	(-1.04)	(0.47)	(-1.11)	(-0.79)	(-0.12)
Antic. NA exposure^2 × *Post*	0.034	-0.001	0.094	0.002	-0.024
	(1.43)	(-0.09)	(1.12)	(0.53)	(-1.05)
Controls	Yes	Yes	Yes	Yes	Yes
F-statistic	7.32	6.04	2.67	4.78	4.05
p-value	0.000	0.002	0.069	0.008	0.017
Year × Cohort F.E.	Yes	Yes	Yes	Yes	Yes
Firm × Cohort F.E.	Yes	Yes	Yes	Yes	Yes
Observations	15,056	14,683	13,900	14,852	14,886
Adj R^2	0.92	0.63	0.13	0.62	0.90

This table reports results from firm-level stacked DiD regressions examining the effect of nonattainment designations on firms' accounting performance. We focus on an event window of four years before to four years after nonattainment designations induced by discrete policy changes in the NAAQS threshold. The dependent variables are the ratio of revenues to total assets (*Rev/Assets*), ratio of operating income to total assets (*OpI/Assets*), gross profit margin calculated as sales minus the sum of cost of goods sold and selling, general and administrative expenses as a fraction of sales (*GPM*), the ratio of capital expenditures to total assets (*CAPX/Assets*), and the ratio of cost of goods sold to total assets (*COGS/Assets*). All dependent variables are expressed in %. *NA exposure* measures a firm's time-varying exposure to nonattainment designations based on the geographic distribution of its plants across nonattainment counties and the amount of ozone emissions at each plant. *Unexp. NA exposure* and *Antic. NA exposure* decompose a firm's exposure to nonattainment designations into an unexpected and anticipated component, respectively. The detailed definitions for *NA exposure*, *Unexp. NA exposure*, and *Antic. NA exposure* are given in Equations (1), (3), and (4), respectively. *Post* is a dummy variable equal to one for the nonattainment designation year and the subsequent four years, and zero otherwise. Control variables include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *Cash*, *Momentum*, *Stock returns*, and *Stock volatility*. The F-statistic and corresponding p-value is a test of the joint significance of *Unexp. NA exposure* × *Post* and *Unexp. NA exposure*^{2} × *Post*. For all specifications, standard errors are robust to heteroskedasticity and clustered at the firm-level; 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.

Appendix A: Variable definitions

Table A.1

Variable definitions.

Variable	Definitions	Data source
CAR	Cumulative abnormal returns (in %) calculated based on the CRSP value-weighted return index over a 250-day estimation period ending 20 days before the event date.	CRSP
NA exposure	For a given firm i, we measure its exposure to nonattainment designations in year t, denoted $NA\ exposure_{i,t}$, as $$\ln\left(1+\sum_j ozone_{j,i,t-1}\cdot NA_{j,i,t}\right),$$ where $ozone_{j,i,t-1}$ is the total amount of ozone air emissions for plant j of firm i in year $t-1$ and $NA_{j,i,t}$ is a dummy variable equal to one if plant j of firm i is located in a nonattainment county in year t, and zero otherwise.	TRI; Federal Register
Unexp. NA exposure	The same expression as *NA exposure* except $NA_{j,i,t}$ is replaced with *Unexp.* $NA_{j,i,t}$, which is a dummy variable equal to one if plant j of firm i is located in an *unexpected* nonattainment county in year t, and zero otherwise.	TRI; Federal Register; AQS
Antic. NA exposure	The same expression as *NA exposure* except $NA_{j,i,t}$ is replaced with *Antic.* $NA_{j,i,t}$, which is a dummy variable equal to one if plant j of firm i is located in an *anticipated* nonattainment county in year t, and zero otherwise.	TRI; Federal Register; AQS
Redesig exposure	For a given firm i, we measure its exposure to attainment redesignations in year t, denoted $Redesig\ exposure_{i,t}$, as $$\ln\left(1+\sum_j ozone_{j,i,t-1}\cdot Redesig_{j,i,t}\right),$$ where $ozone_{j,i,t-1}$ is the total amount of ozone air emissions for plant j of firm i in year $t-1$ and $Redesig_{j,i,t}$ is a dummy variable equal to one if plant j of firm i is located in a county that has been redesignated to attainment in year t.	TRI; Federal Register
Unexp. redesig exposure	The same expression as *Redesig exposure* except $Redesig_{j,i,t}$ is replaced with *Unexp.* $redesig_{j,i,t}$, which is a dummy variable equal to one if plant j of firm i is located in a county that experiences an *unexpected* attainment redesignation in year t, and zero otherwise.	TRI; Federal Register; AQS
Antic. redesig exposure	The same expression as *Redesig exposure* except $Redesig_{j,i,t}$ is replaced with *Antic.* $redesig_{j,i,t}$, which is a dummy variable equal to one if plant j of firm i is located in a county that experiences an *anticipated* attainment redesignation in year t, and zero otherwise.	TRI; Federal Register; AQS
Fluidity	The product market fluidity measure constructed by Hoberg et al. (2014). A higher value is associated with a more significant competitive threat for the firm.	Hoberg et al. (2014)
Similarity	The total product similarity score constructed by Hoberg and Phillips (2010, 2016). A higher value is associated with more competitive pressure for the firm.	Hoberg and Phillips (2010, 2016)
Number of new contracts	The number of newly initiated contracts made with corporate customers in a given supplier-year.	Factset Revere
Number of new customers	The number of unique new corporate customers per supplier-year.	Factset Revere
Contract length (days)	The average length (in days) of newly initiated contracts made with corporate customers in a given supplier-year.	Factset Revere
Rev/Assets	Ratio of revenues to total assets in % ($revt/at\times 100$).	Compustat
OpI/Assets	Ratio of operating income to total assets in % ($oibdp/at\times 100$).	Compustat
GPM	Gross profit margin calculated as sales minus the sum of cost of goods sold and selling, general and administrative expenses as a fraction of sales in % ($(sale-cogs-xsga)/sale\times 100$).	Compustat
CAPX/Assets	Ratio of capital expenditures to total assets in % ($capx/at\times 100$).	Compustat
COGS/Assets	Ratio of cost of goods sold to total assets in % ($cogs/at\times 100$).	Compustat
ln(Size)	The logarithm of one plus the book value of assets ($\log(1+at)$).	Compustat
ln(BM)	The natural logarithm of one plus the book-to-market ratio ($\log(1+at/(at-ceq+prcc\_f\times csho))$).	Compustat
ROA	Net income divided by total assets (ni/at).	Compustat

Table A.1 continued

Variable	Definitions	Data source
Leverage	Total liabilities divided by total assets ($(dltt + dlc)/at$).	Compustat
Sales growth	The logarithm of current year sales divided by previous year sales ($\log(sale_t/sale_{t-1})$).	Compustat
Cash	Cash divided by total assets (che/at).	Compustat
Momentum	Cumulative 12-month return of a stock, excluding the immediate past month.	CRSP
Stock returns	The annual stock return of the firm.	CRSP
Stock volatility	The standard deviation of stock returns over the past 12 months.	CRSP
Facility NA exposure	For a given plant j, we measure its exposure to nonattainment designations in year t, denoted $Facility\ NA\ exposure_{j,t}$, as $$\ln\left(1 + ozone_{j,t-1} \cdot NA_{j,t}\right),$$ where $ozone_{j,t-1}$ is the total amount of ozone air emissions for plant j in year $t-1$ and $NA_{j,t}$ is a dummy variable equal to one if plant j is located in a nonattainment county in year t, and zero otherwise.	TRI; Federal Register
Facility Unexp. NA exposure	The same expression as *Facility NA exposure* except $NA_{j,t}$ is replaced with *Unexp.* $NA_{j,t}$, which is a dummy variable equal to one if plant j is located in an *unexpected* nonattainment county in year t, and zero otherwise.	TRI; Federal Register; AQS
Facility Antic. NA exposure	The same expression as *Facility NA exposure* except $NA_{j,t}$ is replaced with *Antic.* $NA_{j,t}$, which is a dummy variable equal to one if plant j is located in an *anticipated* nonattainment county in year t, and zero otherwise.	TRI; Federal Register; AQS
HPV	A dummy variable equal to one if a facility experiences a high priority violation, and zero otherwise.	ICIS-Air
Title V inspection	A dummy variable equal to one if a facility undergoes a Title V inspection, and zero otherwise.	ICIS-Air
Compliance evaluation	A dummy variable equal to one if a facility faces a compliance evaluation, and zero otherwise.	ICIS-Air
Onsite treated	The natural logarithm of one plus the amount of onsite ozone air emissions that are treated.	TRI P2
Onsite recovery	The natural logarithm of one plus the amount of onsite ozone air emissions that undergo recovery.	TRI P2
Onsite recycle	The natural logarithm of one plus the amount of onsite ozone air emissions that are recycled.	TRI P2
SR activity	A dummy variable that takes a value of one if a facility undertakes source reduction activities related to ozone, and zero otherwise.	TRI P2
Plant births	The number of new TRI plants in a given county in a given year.	NETS
NA	A dummy variable equal to one if a county is designated nonattainment in a given year, and zero otherwise	Federal Register
Unexp. NA	A dummy variable equal to one if a county is designated as an unexpected nonattainment in a given year, and zero otherwise.	Federal Register
Antic. NA	A dummy variable equal to one if a county is designated as an anticipated nonattainment in a given year, and zero otherwise.	Federal Register
Sales HHI	Sum of squared sales shares of all ozone-emitting plants in a given county in a given year.	NETS
Employees HHI	Sum of squared employee shares of all ozone-emitting plants in a given county in a given year.	NETS

Internet Appendix For Online Publication Only

IA. Regression discontinuity design

Formally, we perform the RDD by using a nonparametric, local linear estimation. Small neighborhoods on the left- and right-hand sides of the NAAQS threshold are used to estimate discontinuities in nonattainment probability. We follow Calonico et al. (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 estimation if the absolute difference between the DV for that observation and the threshold is less than the bandwidth. The sample consists of all counties with available DV data across the four discrete policy changes in the NAAQS threshold.

The local linear regression model can therefore be specified as

$$NA_{c,t} = \alpha + \beta Noncompliance_{c,t-1} + \phi f(R_{c,t-1}) + \varepsilon_{c,t} \tag{IA.1}$$

for county c and year t. $NA_{c,t}$ is a dummy variable equal to one if county c is designated nonattainment in year t, and zero otherwise. $Noncompliance_{c,t-1}$ is a dummy variable equal to one if county c's DV is in violation of the NAAQS threshold in year $t-1$, and zero otherwise. $R_{c,t-1}$ is the centered DV (i.e., the running variable in RDD parlance), defined as the difference between the DV of county c in year $t-1$ and the NAAQS threshold. Negative (positive) values indicate that the county is in compliance with (violation of) the NAAQS threshold. We use local linear functions in the running variable with rectangular kernels as represented by $f(R_{c,t-1})$. 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 identifying assumption of the RDD is that, around the NAAQS threshold, a county's designation status is as good as randomly assigned. In the following sections, we perform two standard tests for the RDD validity that counties cannot precisely manipulate the running variable so that their DVs are right below the NAAQS threshold (Lee & Lemieux, 2010). If this assumption is satisfied, then the variation in a county's designation status around the NAAQS threshold should be as good as that from a randomized experiment.

IA.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 to avoid noncompliance. The first test that we conduct evaluates whether the distribution of DVs is continuous around the NAAQS threshold. Any discontinuity would suggest a nonrandom assignment of attainment versus nonattainment status around the threshold.

In practice, however, it is unlikely that counties could strategically manipulate their DVs. Since all counties are evaluated on the same standards, the EPA's federal enforcement power limits the states' ability to overlook non-compliers. Additionally, studies show that nonattainment designations often depend on weather patterns (Cleveland & Graedel, 1979; Cleveland, Kleiner, McRae, & Warner, 1976). Combined with the fact that ozone emissions are a result of complex chemical reactions in the atmosphere between pollutants such as volatile organic compounds and nitrogen oxides, it is extremely difficult for counties to manipulate their ozone concentration levels precisely around the NAAQS threshold. 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.

Internet Appendix Figure IA.2 plots the local density of centered DVs, estimated separately on either side of the NAAQS threshold with the corresponding 95% confidence interval bounds, calculated using the plug-in estimator proposed by Cattaneo, Jansson, and Ma (2020). Observations on the left (right) of the vertical dashed line indicate that the county is in compliance with (violation of) the NAAQS threshold. If counties were manipulating their DVs to strategically avoid nonattainment designations, one would expect to see a bunching of counties just below the NAAQS thresholds. As shown in the figure, there is no evidence for a discontinuous jump around the threshold. Using the density break test following Cattaneo et al. (2020),[17] we fail to reject the null hypothesis that counties are unable to manipulate their pollution levels in order to be right below the NAAQS threshold (p-value = 0.712).

IA.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 Internet Appendix Table IA.4, we examine whether there are any preexisting differences between plants operating in counties that violate and comply with the thresholds. The variables that we examine include a dummy variable equal to one if a plant emits ozone core chemicals as defined by TRI, and zero otherwise (*Core chemical*);[18] a dummy variable equal to one if a plant holds operating permits for ozone emissions, and zero otherwise (*Permit*); the plant's ozone production ratio (*Production ratio*);[19] the logarithm of one plus the dollar amount of sales at the plant (*ln(Sales)*); the logarithm of one plus the number of employees at the plant (*ln(Employees)*); the plant's minimum paydex score in a given year (*Paydex*);[20] dummy variables that take a value of one if a facility experiences a high priority violation (*HPV*), undergoes a Title V inspection (*Title V inspection*), or faces a compliance evaluation (*Compliance evaluation*), and zero otherwise; the natural logarithm of one plus the amount of onsite ozone air emissions that are treated (*Onsite treated*), undergo recovery (*Onsite recovery*), or are recycled (*Onsite recycle*) at a given facility; and a dummy variable equal to one if a facility undertakes source reduction activities related to ozone, and zero otherwise (*SR activity*).

In column (1) of Internet Appendix Table IA.4, we examine these characteristics in the year preceding the designation ($t-1$). In column (2), we examine the change in these characteristics between years $t-2$ and $t-1$. Both columns report the differences using a narrow window around the NAAQS threshold by computing the mean squared error optimal bandwidth following Calonico et al. (2014). As can be seen in both columns, there are no systematic

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

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

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

[20]This variable is obtained from NETS and represents the facility's trade credit performance on a scale of 0 to 100. Higher paydex scores indicate greater ability to meet contractual repayment obligations.

or statistically significant differences in facility characteristics in the optimal neighborhood around the threshold, which lends support to our identification strategy.

IA.3. Estimation results

We present the estimation results of Equation (IA.1) in Table IA.5 of the Internet Appendix. The coefficient estimate of β captures the discontinuity at the NAAQS threshold and is equal to the difference in the probability of nonattainment between counties that marginally violate the NAAQS threshold and those that marginally comply with the threshold. In column (1), we estimate the baseline specification without any covariate adjustments. Noncompliance based on DVs leads to an increase in the probability of nonattainment by roughly 70%. In column (2), following Curtis (2020), the point estimates on β and optimal bandwidth selection are covariate-adjusted by including additional county-level covariates such as the natural logarithm of one plus the employment levels in a given county, a given county's NOx 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. We obtain qualitatively similar results.

Internet Appendix Table IA.5 also provides the estimates of the optimal bandwidth. The bandwidth estimate of 0.009 in both columns implies that counties with DVs that are within 0.009 ppm of the NAAQS threshold have ozone concentration levels that are as good as randomized. Counties with DVs that exceed the threshold by more than 0.009 ppm are considered to be far "enough" *above* the threshold that they will most likely be designated nonattainment in the following year. Similarly, counties with DVs that are below the threshold by more than 0.009 ppm are considered to be far "enough" *below* the threshold that they will most likely remain in attainment in the following year.

IB. Additional robustness tests

IA.1. Alternative measures of nonattainment exposure

We employ various alternative definitions of our nonattainment exposure measure. First, we consider the possibility of multi-plant firms reallocating production (and hence, emissions) from nonattainment counties to attainment counties. To address this concern, we calculate an alternative measure by dividing ozone emissions by the total number of ozone-emitting plants owned by the firm when defining *NA exposure*. This adjustment acknowledges that a multi-plant firm with equivalent ozone emissions in nonattainment counties as a single-plant firm would have lower nonattainment exposure due to its ability to redistribute emissions. Another concern is that *NA exposure* may not reflect the relative importance of a firm's different polluting plants. For example, if ozone-emitting plants that contribute a significant portion of a firm's revenue are located in nonattainment counties, the impact could be more substantial. We conduct robustness checks by constructing measures of nonattainment exposure based on plant-level sales and employee data from NETS. In these alternative measures, we weight each plant's ozone emissions by their corresponding sales share or employee share.

Considering the varying toxicity levels of different chemicals, we incorporate the inherent heterogeneity by multiplying the mass of each chemical by its toxicity, derived from the EPA's Risk-Screening Environmental Indicator model. Given our focus on air emissions, we follow the approach of Gamper-Rabindran (2006) and utilize the inhalation toxicity weight. Consequently, we redefine *NA exposure* by incorporating toxicity-weighted ozone emissions. To address concerns regarding reporting errors in the TRI data, we narrow our focus to core ozone chemicals. Core chemical groups consist of chemicals that remained consistent in the TRI list throughout our sample period, ensuring uniform reporting requirements across all reporting years. Moreover, routine inspections and audits are more likely to ensure accurate reporting for the core chemical groups. Thus, we redefine *NA exposure* by considering only ozone emissions from core chemicals. Lastly, some ozone chemicals can only be emitted if the plant possesses operating permits issued by the EPA. To account for this, we redefine *NA exposure* by considering ozone emissions specified in operating permits. Our main results remain robust when employing all of these alternative measures of nonattainment exposure, as demonstrated in Internet Appendix Table IA.8.

IA.2. Self-selection

Firms may self-select into nonattainment counties if they expect the regulation to be implemented. For example, firms that are already equipped with LAER technology may expect an implementation of mandatory pollution abatement that increases the cost of its local competitors. While decomposing nonattainment designations into an unexpected component already attempts to mitigate potential self-selection issues, we take additional steps by employing a Heckman (1979) two-stage least squares estimation for further correction. In the first stage, we use a probit model to predict realized nonattainment status. The main independent variable is the county's noncompliance based on prior year DVs and following Curtis (2020), we include four additional county-level control variables. These variables include the county's employment levels, employment changes, NO_x emissions to employment ratio, and MSA status. Column (1) of Internet Appendix Table IA.10 presents the first-stage estimation results. As expected, a county's noncompliance based on prior year DVs positively predicts future realized nonattainment status.

In the second stage, we use the predicted probability of a county's nonattainment status to compute the inverse Mills ratio $IMR_{c,t}$ for county c in event year t. Since the IMR absorbs hidden factors that may affect a county's implementation of regulation, a firm is affected by the hidden factors in all counties where it operates polluting plants. To aggregate these factors' effect at the firm-level, we construct the firm-event year weighted average Heckman correction variable $HC_{i,t}$ using county-event year level IMR as follows:

$$HC_{i,t} = \frac{\sum_c \#Plant_{i,c,t} \times IMR_{c,t}}{\sum_c \#Plant_{i,c,t}} \tag{IA.2}$$

for firm i, county c, and year t. The variable $\#Plant_{i,c,t}$ is the number of polluting plants that firm i owns in county c in year t. Then, we include the variable $HC_{i,t}$ in the estimation of Equations (2) and (5). The results are presented in columns (2) to (5) of Internet Appendix Table IA.10. The findings are qualitatively unchanged from Table 3 and more importantly, the Heckman correction variable enters insignificantly in all specifications, indicating that the self-selection problem is not a major concern in these analyses.

IA.3. Intrafirm reallocation

We test the possibility that the positive reaction to nonattainment designations on the extensive margin is driven by multi-plant firms who plausibly have an advantage in that they can reallocate ozone emissions to plants located in attainment counties. For example, multi-plant firms may strategically time their investment cycles to expand into areas with attainment status, benefiting from the less stringent regulatory requirements in those locations.

To assess whether multi-plant firms are reallocating emissions among their facilities, we employ a stacked DiD approach at the facility level. Specifically, we narrow down the sample to include only plants located in attainment counties that emit ozone before the nonattainment designation events. Within each cohort of nonattainment designations, we categorize treated facilities as those belonging to firms that operate one or more other plants with non-zero nonattainment exposure. Control facilities are those associated with firms where all plants always maintain zero nonattainment exposure throughout the event window. Formally, we estimate the following regressions:

$$y_{j,i,t,k} = \beta \, Other\ NA\ exposure_{j,i,k} \times Post_{t,k} + \tau_{j,k} + \nu_{i,k} + \rho_{t,k} + \varepsilon_{j,i,t,k}, \tag{IA.3}$$

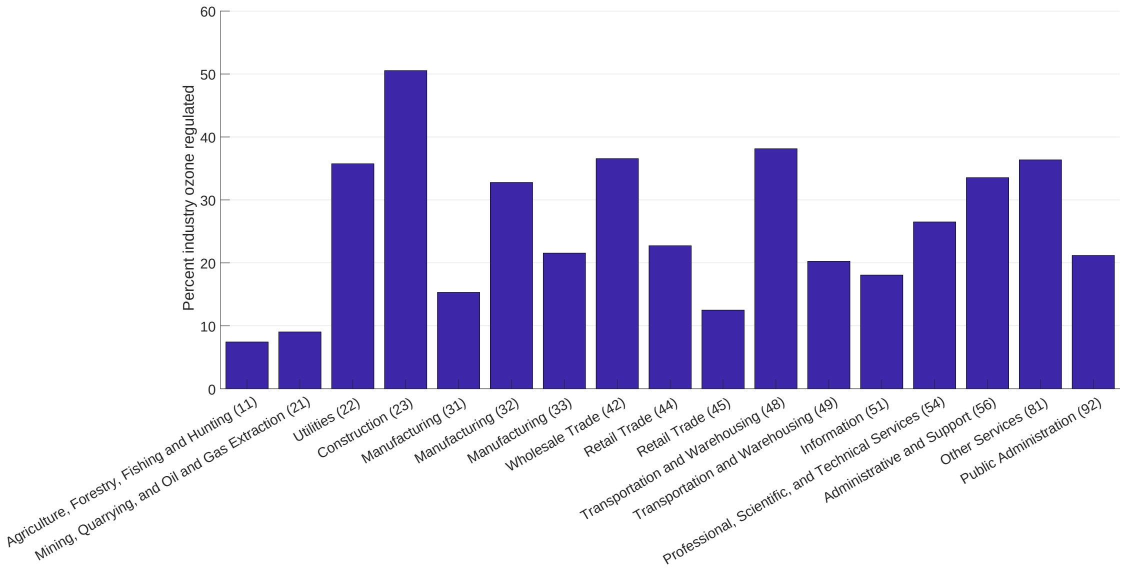
$$y_{j,i,t,k} = \beta_1 Other\ Unexp.\ NA\ exposure_{j,i,k} \times Post_{t,k} + \beta_2 Other\ Antic.\ NA\ exposure_{j,i,k} \times Post_{t,k} + \tau_{j,k} + \nu_{i,k} + \rho_{t,k} + \varepsilon_{j,i,t,k}, \tag{IA.4}$$

where the dependent variable are measures of facility-level ozone emissions and production. $Other\ NA\ exposure_{j,i,k}$ is a dummy variable equal to one if plant j belongs to firm i that operates one or more plants with non-zero nonattainment exposure in cohort k, and zero otherwise. $Other\ Unexp.\ NA\ exposure_{j,i,k}$ and $Other\ Antic.\ NA\ exposure_{j,i,k}$ are dummy variables equal to one if plant j belongs to firm i that operates one or more plants with non-zero unexpected or anticipated nonattainment exposure in cohort k, respectively, and zero otherwise. $Post_{t,k}$ is a dummy variable equal to one for the event year and subsequent four years in cohort k, and zero otherwise. $\tau_{j,k}$, $\nu_{i,k}$, and $\rho_{t,k}$ are Plant × Cohort, Firm × Cohort, and Year × Cohort fixed effects, respectively.

Columns (1) and (2) of Internet Appendix Table IA.11 show that none of the coefficients on $Other\ NA\ exposure_{j,i,k} \times Post_{t,k}$ and $Other\ Unexp.\ NA\ exposure_{j,i,k} \times Post_{t,k}$ are statistically significant. This finding implies that facilities situated in attainment counties and belonging to firms with nonattainment exposure do not exhibit emissions that are notably different from those of firms without nonattainment exposure. Consequently, we do not find any evidence of intrafirm reallocation of ozone emissions from nonattainment counties to attainment counties for multi-plant firms. Our results are consistent with the results of Cui and Ji (2016), who also do not find any evidence of intrafirm ozone emissions leakage for multi-plant firms operating in nonattainment and attainment counties. One potential explanation for the absence of intrafirm emissions reallocation could be the time required by firms to make the necessary investments to shift production, thus making it difficult for firms to strategically time their investments to expand into attainment counties. Additionally, the benefits from the less stringent regulations in attainment counties may be offset by the costs of sacrificing local supply chains and local customers in nonattainment counties, which may make reallocation less appealing.

We also examine whether nonattainment designations impact the production of plants owned by multi-plant firms in attainment counties. As proxies for plant-level production, we use the production ratio, the the natural logarithm of facility sales, and the natural logarithm of facility employment. The results presented in the subsequent columns of Internet Appendix Table IA.11 indicate that nonattainment designations do not exhibit any spillover effects on the production of facilities belonging to multi-plant firms located in attainment counties.

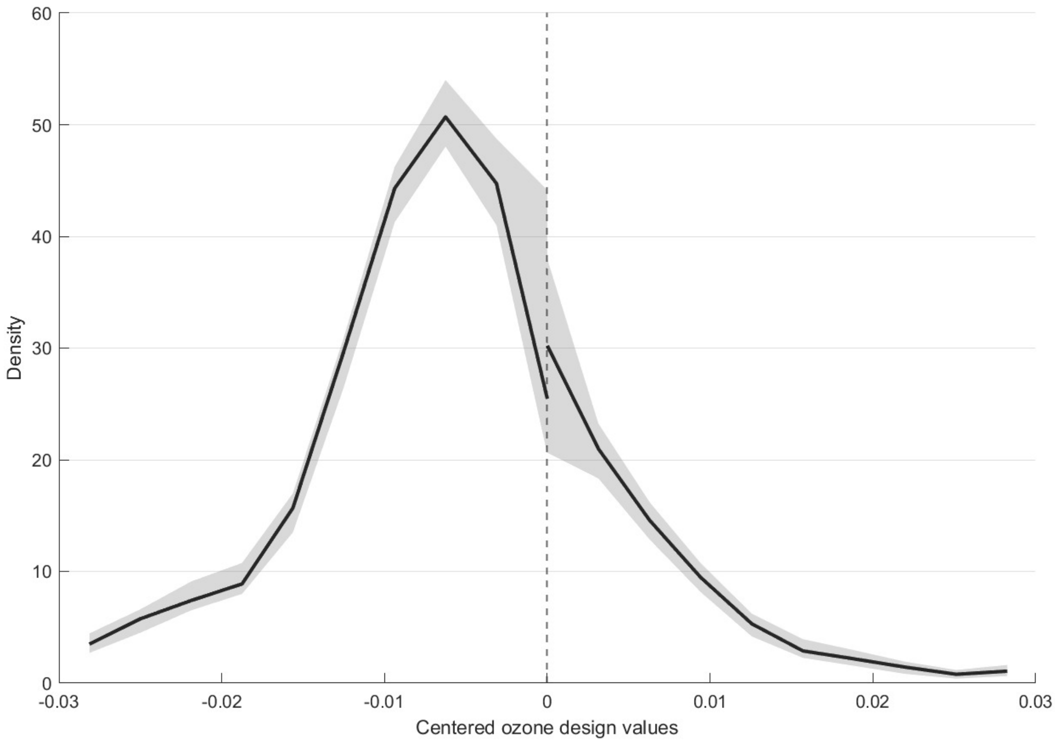
Figure IA.1
Fraction of ozone plants by industry in nonattainment counties.



This figure shows the fraction of ozone-emitting plants by major industry (categorized using two-digit industry NAICS codes) in nonattainment counties.

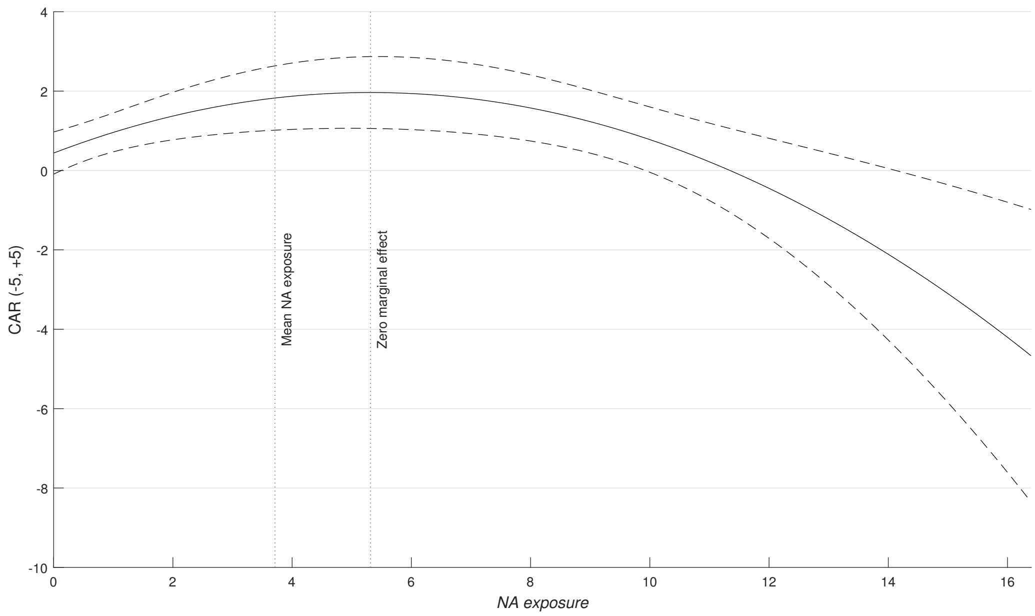
Figure IA.2

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 horizontal axis shows the centered DVs around zero by subtracting the NAAQS threshold from the DVs. 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. 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 0.712.

Figure IA.3
Predicted cumulative abnormal returns as a function of nonattainment exposure.



This figure plots the predicted CAR $(-5, +5)$ as a function of *NA exposure* based on the regression specification in column (7) of Table 3. The corresponding 95% confidence intervals are shown as dashed lines. "Mean NA exposure" is the mean value of *NA exposure*. "Zero marginal effect" is the value of *NA exposure* where the marginal effect on CAR $(-5, +5)$ is zero.

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. 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

Distribution of TRI firms, plants, county nonattainment designations, and attainment redesignations by state.

	Mean # TRI parent firms	Mean # TRI plants	# Counties nonattainment	# Counties redesignated	# Counties total
Alaska	3.04	3.86	0	0	29
Alabama	66.57	112.04	2	2	67
Arkansas	60.86	103.11	1	1	75
Arizona	37.39	54.43	4	2	15
California	151.14	297.50	42	5	58
Colorado	31.68	48.75	9	7	64
Connecticut	40.07	63.29	8	0	8
District of Columbia	1.80	2.40	1	1	1
Delaware	12.96	14.29	3	0	3
Florida	67.79	117.96	7	7	67
Georgia	84.79	154.79	23	23	159
Hawaii	5.04	13.32	0	0	5
Iowa	54.04	100.68	0	0	99
Idaho	11.36	12.54	0	0	44
Illinois	117.71	207.71	12	12	102
Indiana	109.64	209.29	24	24	92
Kansas	46.75	64.14	2	2	105
Kentucky	65.04	98.71	16	16	120
Louisiana	54.50	98.18	17	17	64
Massachusetts	63.43	78.79	14	0	14
Maryland	28.79	35.82	14	7	24
Maine	15.07	20.75	12	11	16
Michigan	89.36	176.71	39	39	83
Minnesota	66.96	109.29	0	0	87
Missouri	66.46	115.14	8	8	115
Mississippi	45.71	78.93	1	1	82
Montana	8.11	11.96	0	0	56
North Carolina	103.57	175.36	23	23	100
North Dakota	10.07	14.79	0	0	53
Nebraska	23.43	45.32	0	0	93
New Hampshire	21.61	24.39	7	6	10
New Jersey	54.57	78.14	21	0	21
New Mexico	14.86	20.93	1	0	33
Nevada	17.11	22.21	2	1	17
New York	84.39	126.68	30	0	62
Ohio	143.18	298.04	34	34	88
Oklahoma	54.61	79.50	0	0	77
Oregon	33.32	50.39	5	3	36
Pennsylvania	124.50	222.50	49	32	67
Rhode Island	15.36	16.39	5	0	5
South Carolina	64.89	97.14	2	2	46
South Dakota	15.11	17.61	0	0	66
Tennessee	91.61	144.86	14	14	95
Texas	148.11	399.14	23	4	254
Utah	32.93	43.68	7	2	29
Virginia	64.36	98.04	37	36	133
Vermont	5.18	5.64	0	0	14
Washington	41.36	54.89	4	4	39
Wisconsin	95.75	159.50	11	11	72
West Virginia	31.07	42.71	10	10	55
Wyoming	8.39	12.86	3	0	23

This table reports the average number of TRI parent firms, the average number of TRI plants, the number of counties ever obtained a nonattainment designation, the number of counties ever obtained an attainment redesignation, and the total number of counties for each state during the sample period from 1992 to 2019.

Table IA.4
Preexisting differences in facility characteristics.

	Year $(t-1)$	Δ from year $(t-2)$ to $(t-1)$
	(1)	(2)
Core chemical	0.005	0.000
	(0.024)	(0.008)
Permit	-0.016	0.003
	(0.040)	(0.005)
Production ratio	0.013	-0.021
	(0.025)	(0.027)
ln(Sales)	-0.305	0.139
	(0.326)	(0.232)
ln(Employees)	-0.026	0.051
	(0.105)	(0.064)
Paydex	-0.265	0.751
	(0.645)	(0.539)
HPV	-0.001	-0.007
	(0.006)	(0.006)
Title V inspection	0.015	-0.001
	(0.024)	(0.007)
Compliance evaluation	0.038	0.015
	(0.028)	(0.017)
Onsite treated	0.019	-0.036
	(0.211)	(0.080)
Onsite recovery	0.139	0.046
	(0.112)	(0.066)
Onsite recycle	-0.077	-0.014
	(0.089)	(0.037)
SR activity	0.015	0.014
	(0.012)	(0.012)
Sample:	Optimal	Optimal

This table examines the differences in observable facility characteristics between those that operate in counties that are in violation of the NAAQS thresholds and those operating in counties that are in compliance. In column (1), these characteristics are measured in the year preceding the designation $(t-1)$. Column (2) considers the change in these characteristics between years $t-2$ and $t-1$. We focus on 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.

Table IA.5

Noncompliant design values and probability of nonattainment.

Dep. variable: $NA_{c,t}$	(1)	(2)
$Noncompliance_{c,t-1}$	0.697^{***}	0.696^{***}
	(21.63)	(18.54)
Kernel	Rectangular	Rectangular
Bandwidth type	Optimal	Optimal
Bandwidth estimate	0.009	0.009
Covariates	No	Yes
Observations	1,269	1,055

This table presents the probability of nonattainment designation when a given county's DV is in violation of the NAAQS threshold. We estimate the local linear regression specification given in Equation (IA.1) using the mean squared error optimal bandwidth with rectangular kernels following Calonico et al. (2014). $NA_{c,t}$ is a dummy variable equal to one if county c is designated nonattainment in year t, and zero otherwise. $Noncompliance_{c,t-1}$ is a dummy variable equal to one if county c's DV is in violation of the NAAQS threshold in year $t-1$, and zero otherwise. County-level covariates include the natural logarithm of one plus the employment levels in a given county, a given county's NOx emissions to employment ratio, the change in a given county's employment levels, and a dummy variable equal to one if the county is located in a MSA. For all specifications, standard errors are clustered by county and bias-corrected following Calonico et al. (2014); t-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table IA.6
Differences between firm characteristics using propensity score matching.

	Treatment ($N = 1,705$)	Control ($N = 3,410$)	Difference	
Variables	Mean	Mean	Estimate	p-value
ln(Size)	8.215	8.203	0.012	0.926
ln(BM)	0.513	0.517	-0.004	0.487
ROA	0.144	0.143	0.001	0.688
Leverage	0.273	0.277	-0.004	0.705
Sales growth	0.107	0.102	0.005	0.651
Cash	0.074	0.078	-0.004	0.257
Momentum	1.168	1.160	0.008	0.619
Stock returns	0.156	0.147	0.009	0.554
Stock volatility	0.090	0.094	-0.003	0.198

This table presents the mean firm characteristics across two subsamples based on propensity score matching. Each observation with non-zero exposure to attainment redesignations is matched to two observations with no exposure using nearest neighbor propensity score matching with replacement (Roberts & Whited, 2013). We test for differences in the means between the two subsamples and provide the p-values. Standard errors are clustered at the firm-level. *, **, 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

Cross-sectional variation in cumulative abnormal returns around nonattainment designations using alternative asset pricing models.

Dep. variable:	CAR FFM				CAR FF48			
	$(-2,+2)$		$(-5,+5)$		$(-2,+2)$		$(-5,+5)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NA exposure	0.334**		0.353*		0.413***		0.565***	
	(2.23)		(1.69)		(3.09)		(3.01)	
NA exposure^2	-0.029**		-0.034*		-0.040***		-0.055***	
	(-2.24)		(-1.79)		(-3.59)		(-3.26)	
Unexp. NA exposure		0.373**		0.367*		0.459***		0.697***
		(2.35)		(1.77)		(3.15)		(2.77)
Unexp. NA exposure^2		-0.028**		-0.033*		-0.041***		-0.067***
		(-1.97)		(-1.71)		(-3.14)		(-2.79)
Antic. NA exposure		-0.138		-0.138		-0.073		-0.239
		(-0.95)		(-0.65)		(-0.52)		(-1.10)
Antic. NA exposure^2		0.013		0.016		0.005		0.016
		(1.01)		(0.86)		(0.40)		(0.89)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,538	1,538	1,535	1,535	1,520	1,520	1,516	1,516
Adj R^2	0.07	0.07	0.05	0.05	0.06	0.05	0.08	0.08

This table examines the cross-sectional variation in CARs for nonattainment designations induced by discrete policy changes in the NAAQS threshold using alternative asset pricing models. The dependent variables are the 5-day $(-2,+2)$ and 11-day $(-5,+5)$ CARs. In columns (1) to (4), CARs are risk adjusted using Carhart's (1997) four-factor model. In columns (5) to (8), CARs are calculated using Fama and French's (1997) 48 value-weighted industry return as the benchmark return. *NA exposure* measures a firm's time-varying exposure to nonattainment designations based on the geographic distribution of its plants across nonattainment counties and the amount of ozone emissions at each plant. *Unexp. NA exposure* and *Antic. NA exposure* decompose a firm's exposure to nonattainment designations into an unexpected and anticipated component, respectively. The detailed definitions for *NA exposure*, *Unexp. NA exposure*, and *Antic. NA exposure* are given in Equations (1), (3), and (4), respectively. Control variables include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *Cash*, *Momentum*, *Stock returns*, and *Stock volatility.* For all specifications, standard errors are robust to heteroskedasticity and clustered at the firm-level; 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
Alternative measures of nonattainment exposure.

$Z=$	*#Plants*	*Sales*	*Employees*	*Toxicity*	*Core chemical*	*Permit*
Dep. variable: CAR $(-2,+2)$	(1)	(2)	(3)	(4)	(5)	(6)
Unexp. NA exposure (Z)	0.566***	0.502***	0.509***	0.189**	0.526***	0.460**
	(2.82)	(2.65)	(2.66)	(2.24)	(3.42)	(2.28)
Unexp. NA exposure (Z)^2	-0.057***	-0.054***	-0.055***	-0.008*	-0.045***	-0.041**
	(-2.60)	(-2.84)	(-2.85)	(-1.79)	(-3.35)	(-2.38)
Antic. NA exposure (Z)	-0.040	0.011	0.019	-0.014	-0.177	-0.214
	(-0.23)	(0.07)	(0.12)	(-0.18)	(-1.22)	(-1.20)
Antic. NA exposure (Z)^2	(-0.23)	0.001	0.001	0.001	0.016	0.021
	(0.16)	(0.09)	(0.04)	(0.35)	(1.31)	(1.34)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,538	1,538	1,538	1,538	1,538	1,538
Adj R^2	0.07	0.07	0.07	0.06	0.07	0.07

This table examines the cross-sectional variation in CARs for nonattainment designations induced by discrete policy changes in the NAAQS threshold using alternative measures of nonattainment exposure. The dependent variable is the 5-day $(-2,+2)$ CAR. *Unexp. NA exposure (#Plants)* and *Antic. NA exposure (#Plants)* are measures of unexpected and anticipated nonattainment exposure where each plant's ozone emissions are divided by the total number of ozone-emitting plants owned by the firm, respectively. *Unexp. NA exposure (Sales)* and *Antic. NA exposure (Sales)* are measures of unexpected and anticipated nonattainment exposure where each plant's ozone emissions are sales share-weighted, respectively. *Unexp. NA exposure (Employees)* and *Antic. NA exposure (Employees)* are measures of unexpected and anticipated nonattainment exposure where each plant's ozone emissions are employee share-weighted, respectively. *Unexp. NA exposure (Toxicity)* and *Antic. NA exposure (Toxicity)* are measures of unexpected and anticipated nonattainment exposure using toxicity-weighted ozone emissions, respectively. *Unexp. NA exposure (Core chemical)* and *Antic. NA exposure (Core chemical)* are measures of unexpected and anticipated nonattainment exposure using core chemical ozone emissions, respectively. *Unexp. NA exposure (Permit)* and *Antic. NA exposure (Permit)* are measures of unexpected and anticipated nonattainment exposure using ozone emissions specified in operating permits, respectively. Control variables include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *Cash*, *Momentum*, *Stock returns*, and *Stock volatility.* For all specifications, standard errors are robust to heteroskedasticity and clustered at the firm-level; t-statistics are reported in the parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table IA.9
Placebo nonattainment exposure.

$Z =$	*Offsite ozone*		*PM*	
Dep. variable: CAR $(-2,+2)$	(1)	(2)	(3)	(4)
NA exposure (Z)	-0.060		-0.016	
	(-0.25)		(-0.08)	
NA exposure (Z)^2	-0.001		0.016	
	(-0.05)		(0.68)	
Unexp. NA exposure (Z)		-0.266		-0.224
		(-1.12)		(-0.77)
Unexp. NA exposure (Z)^2		0.026		0.026
		(1.09)		(0.72)
Antic. NA exposure (Z)		-0.003		-0.261
		(-0.01)		(-1.11)
Antic. NA exposure (Z)^2		-0.006		0.041
		(-0.16)		(1.52)
Controls	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes
Observations	1,538	1,538	1,538	1,538
Adj R^2	0.10	0.10	0.06	0.06

This table examines the cross-sectional variation in CARs for nonattainment designations induced by discrete policy changes in the NAAQS threshold using placebo measures of nonattainment exposure. The dependent variable is the 5-day $(-2,+2)$ CAR. *NA exposure (Offsite ozone)* measures a firm's exposure to nonattainment designations based on offsite ozone emissions. *Unexp. NA exposure (Offsite ozone)* and *Antic. NA exposure (Offsite ozone)* are measures of unexpected and anticipated nonattainment exposure based on offsite ozone emissions. *NA exposure (PM)* measures a firm's exposure to nonattainment designations based on onsite particulate matter emissions. *Unexp. NA exposure (PM)* and *Antic. NA exposure (PM)* are measures of unexpected and anticipated nonattainment exposure based on onsite particulate matter emissions. Control variables include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *Cash*, *Momentum*, *Stock returns*, and *Stock volatility*. For all specifications, standard errors are robust to heteroskedasticity and clustered at the firm-level; 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

Cross-sectional variation in cumulative abnormal returns around nonattainment designations using Heckman correction.

	First stage		Second stage			
Dep. variable:	NA_t	Dep. variable:	CAR $(-2,+2)$		CAR $(-5,+5)$	
	(1)		(2)	(3)	(4)	(5)
$Noncompliance_{t-1}$	1.241***	*NA exposure*	0.487***		0.515***	
	(26.39)		(3.09)		(2.69)	
$ln(County\ emp)_{t-1}$	1.556***	*NA exposure*^{2}	-0.042***		-0.047***	
	(9.07)		(-3.11)		(-2.74)	
$Nox\text{-}county\ emp\ ratio_{t-1}$	0.036	*Unexp. NA exposure*		0.514***		0.686***
	(0.81)			(3.25)		(2.59)
$\Delta County\ emp_{t-1}$	-0.003	*Unexp. NA exposure*^{2}		-0.041***		-0.065***
	(-0.71)			(-2.94)		(-2.61)
MSA	2.216*	*Antic. NA exposure*		-0.115		-0.304
	(1.87)			(-0.78)		(-1.46)
		Antic. NA exposure^2		0.012		0.026
Year F.E.	Yes			(0.93)		(1.48)
County F.E.	Yes	*HC*	0.738	0.820	-0.357	-0.540
Observations	46,693		(0.43)	(0.48)	(-0.16)	(-0.24)
R^2	0.36					
		Controls	Yes	Yes	Yes	Yes
		Year F.E.	Yes	Yes	Yes	Yes
		Firm F.E.	Yes	Yes	Yes	Yes
		Observations	1,475	1,475	1,469	1,469
		Adj R^2	0.07	0.07	0.08	0.08

This table reports the first- and second-stage estimation results for cross-sectional regressions of CARs for nonattainment designations using Heckman correction. Column (1) presents the first-stage results using a probit model where the dependent variable, NA_t, is a dummy variable equal to one if a given county is designated nonattainment in year t, and zero otherwise. The explanatory variables are $Noncompliance_{t-1}$, which is a dummy variable equal to one if a given county's DV is in violation of the NAAQS threshold in year $t-1$, and zero otherwise; $ln(County\ emp)_{t-1}$, defined as the natural logarithm of one plus the employment levels in a given county; $NOx\text{-}county\ emp\ ratio_{t-1}$, defined as a given county's NOx emissions to employment ratio; $\Delta County\ emp_{t-1}$, equal to the change in a given county's employment levels; and *MSA*, which is a dummy variable equal to one if the county is located in a MSA. Columns (2) to (5) present the second-stage results where a Heckman correction variable, *HC*, is included in all regressions. The dependent variables are the 5-day $(-2,+2)$ and 11-day $(-5,+5)$ CARs. *NA exposure* measures a firm's time-varying exposure to nonattainment designations based on the geographic distribution of its plants across nonattainment counties and the amount of ozone emissions at each plant. *Unexp. NA exposure* and *Antic. NA exposure* decompose a firm's exposure to nonattainment designations into an unexpected and anticipated component, respectively. The detailed definitions for *NA exposure*, *Unexp. NA exposure*, and *Antic. NA exposure* are given in Equations (1), (3), and (4), respectively. Control variables include *ln(Size)*, *ln(BM)*, *ROA*, *Leverage*, *Sales growth*, *Cash*, *Momentum*, *Stock returns*, and *Stock volatility*. Standard errors are robust to heteroskedasticity and clustered at the county-level in the first stage and firm-level in the second stage; 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
The effect of nonattainment designations on the intrafirm reallocation of production.

Dep. variable:	*ln(Ozone)*		*Production ratio*		*ln(Sales)*		*ln(Employees)*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Other NA exposure × *Post*	0.037		0.012		0.034		0.034	
	(0.49)		(1.04)		(1.41)		(1.49)	
Other Unexp. NA exposure × *Post*		0.019		0.017		0.029		0.031
		(0.26)		(1.43)		(1.22)		(1.43)
Other Antic. NA exposure × *Post*		0.004		-0.001		0.014		0.000
		(0.06)		(-0.10)		(0.61)		(0.02)
Year × Cohort F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant × Cohort F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Cohort F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,842	42,842	42,842	42,842	31,382	31,382	31,382	31,382
Adj R^2	0.82	0.82	0.50	0.50	0.93	0.93	0.94	0.94

This table reports results from facility-level stacked DiD regressions examining the effect of nonattainment designations on the intrafirm reallocation of production from facilities in nonattainment counties to those in attainment counties. We focus on an event window of four years before to four years after nonattainment designations induced by discrete policy changes in the NAAQS threshold. The sample consists only of plants in attainment counties that emit ozone prior to the nonattainment designation events. *ln(Ozone)* is the natural logarithm of one plus the total amount of ozone air emissions for a given plant. *Production ratio* is a given plant's ozone production ratio. *ln(Sales)* is the natural logarithm of one plus the dollar amount of sales for a given plant. *ln(Employees)* is the natural logarithm of one plus the number of employees for a given plant. *Other NA exposure* is a dummy variable equal to one if a given plant belongs to a firm that operates one or more plants with non-zero nonattainment exposure, and zero otherwise. *Other Unexp. NA exposure* and *Other Antic. NA exposure* are dummy variables equal to one if a given plant belongs to a firm that operates one or more plants with non-zero unexpected or anticipated nonattainment exposure, respectively, and zero otherwise. *Post* is a dummy variable equal to one for the nonattainment designation year and the subsequent four years, and zero otherwise. For all specifications, standard errors are robust to heteroskedasticity and clustered at the county-level; 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.