Smokestacks and the Swamp*

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Abstract

We examine the causal effect of politicians' partisan ideologies on the industrial pollution decisions of constituent firms. Using a regression discontinuity design involving close U.S. congressional elections, we show that plants increase pollution and invest less in emissions abatement following close Republican wins. We also find evidence of reallocation: firms shift pollution away from areas newly represented by Democrats. However, costs rise and M/B ratios decline, suggesting that support for politicians' ideological demands can be privately costly. Pollution-related illnesses spike around plants in areas represented by Republicans, suggesting that firms' pass-through of politicians' ideological differences can have real consequences for local communities.

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1 Introduction

When Amazon Inc. announced its plans in November 2018 to build a $2.5 billion second headquarters in Queens, many New Yorkers were elated, including a majority of residents in the district of Rep. Alexandria Ocasio-Cortez (D–NY, widely known as "AOC").[1] However, AOC herself was staunchly and vocally opposed to the project – the largest economic development project in New York State history – and was triumphant when Amazon canceled the project three months later (citing political opposition), tweeting that "[t]oday was the day a group of dedicated, everyday New Yorkers and their neighbors defeated Amazon's corporate greed, its worker exploitation and the power of the richest man in the world." Notably, given that AOC and other New York politicians opposed the deal against the wishes of their own voters, it appears that Amazon's decision was seemingly driven by the *personal ideologies* of local politicians rather than the preferences of local residents.[2]

Do firms such as Amazon routinely bend to the ideological will of their local political representatives? The canonical median voter model (Downs, 1957) leaves little room for politicians' personal ideologies to affect economic outcomes, as politicians are assumed to simply cater to voter preferences. However, as the AOC example illustrates, modern politicians can hold views on important issues that are starkly at odds with their constituents.[3] As a result, firms may have no choice but to comply with the partisan ideologies of local officials, even if such ideologies do not reflect the prevailing sentiment among voters. However, little is currently known about the effects of politicians' partisan ideological beliefs on local companies.[4]

Motivated by the Amazon-AOC example, this paper studies the causal effects of politicians' partisan ideologies on a more generalizable economic outcome: namely, the industrial pollution decisions

[1] Vielkind, Jimmy, "Most in Ocasio-Cortez's District Opposed Her on Amazon Deal, Poll Finds," *Wall Street Journal*, April 10, 2019.

[2] More than two-thirds of New York voters supported Amazon's plan according to a Siena College poll, and voters singled out AOC as the "biggest villain' in the debacle (https://ny.curbed.com/2019/3/18/18271134/amazon-new-york-voters-losing-hq2-bad-siena-poll). Despite a majority of voters being against her position, AOC later tweeted that she was "[w]aiting on the haters to apologize after we were proven right on Amazon and saved the public billions."

[3] Alesina (1988), Lee, Moretti, and Butler (2004), and List and Sturm (2006) (among others) show that, as a result of their individual preferences or their party affiliation, candidates may have different private utility than their constituents, and that this in turn can result in different policy outcomes. We refer to such differences as candidates'/parties' "ideologies." For simplicity, we assume such "ideologies" also include any differences in beliefs between politicians and voters.

[4] In contrast, far more is known about the causes and effects of increased *voter* polarization. See, e.g., Boxell, Gentzkow, and Shapiro (2021).

of constituent firms. We focus on firms' industrial pollution decisions for five reasons. First, while examples such as Amazon are highly visible, they are also highly idiosyncratic and difficult to extrapolate to other firms. In contrast, nearly all goods-producing firms release emissions, thereby allowing us to estimate the effects of politicians' ideologies on a larger and more representative sample. Second, while most firm financial and operating variables such as leverage or investment are largely non-partisan, pollution and environmental issues are a major source of partisan frictions. For example, Figure 1 shows a 60-point divide between House Democrats' and House Republicans' median environmental voting records, a divide which has grown noticeably over the past 30 years.[5] Third, U.S. law requires polluting firms to report annual plant-level, chemical-level discharge and production data, thus providing extremely granular information on the operating decisions of nearly all emitting facilities located in a Congressional district (including private firms). Fourth, federal pollution law applies equally to all firms, allowing us to largely abstract from legislative channels of political influence, which often involve many actors. Finally, given firms' increased focus on climate change and environmental governance, firm-level industrial pollution decisions are an increasingly important outcome variable in their own right.

The main challenge in estimating the causal effect of politicians' ideologies on economic outcomes is empirical: it is difficult to separate the effects of politicians' ideologies from effects such as shifting voter ideologies or changing economic conditions.[6] To overcome this challenge, we follow the existing literature and focus on the outcomes of close U.S. House of Representatives elections using a regression discontinuity design (RDD or RD design). Our RD design compares facility-level emissions across districts where a Democratic candidate just won or just lost their elections. The running variable in these regressions is the winning candidate's margin of victory. The key identifying assumption is that the winning candidate was elected for reasons that are at least partly due to chance. This assumption seems reasonable; for example, many of the margins of victory in our sample involve only tens or hundreds of votes, and similar assumptions have been used elsewhere in many

[5]We measure politicians' environmental voting records using the League of Conservation Voters annual scorecard.

[6]Identifying the effects of politicians' ideologies on firm outcomes is also difficult because legislation generally affects all firms at once and reflects the ideologies of many politicians; using speeches or other forms of political voice is complicated by the lack of a measurable connection or time frame between the speech and firms' actions; and measuring firms' responses to politicians' ideological beliefs is challenging because this information is difficult to disentangle from firm-level financial statements and requires detailed information on firms' business decisions.

different contexts.[7] We also confirm that voters' opinions of the environment are identical regardless of whether a Democrat or Republican wins, thereby supporting the arguments in Lee, Moretti, and Butler (2004) and Ferreira and Gyourko (2009) that close-election RD results are not caused by shifting voter preferences.

Our primary hypothesis is that, all else equal, closely-elected Democrats will be more ideologically predisposed to pay attention to the monitoring and enforcement of existing federal environmental laws within their districts.[8] As a result, when a Democrat is elected, state and federal regulators may either implicitly or explicitly face incentives to strengthen their oversight of the toxic emissions produced by facilities located in the politician's district. Hence, we argue that the monitoring and enforcement of existing federal industrial pollution regulations will be stronger in districts represented by Democrats than Republicans. This argument is consistent with Glaeser and Shleifer (2001), who argue that under- and over-enforcement of existing regulations can occur for purely political reasons, and with a growing literature documenting political interference in the regulatory process (albeit not for partisan purposes, as our paper shows).[9]

How should firms respond to such partisan differences in regulators' monitoring and enforcement postures? The answer depends on firms' objectives and existing emissions profiles. Firms with a low probability of exceeding permitted emissions levels may be largely unaffected by expected increases in monitoring and enforcement following a close Democrat win. However, for firms with a higher likelihood of exceeding permitted emissions levels, increases in the probability of inspections and enforcement may lead to meaningful increases in the marginal cost of maintaining high pollution levels. As such, high-pollution firms may find it optimal (from a net present value perspective) to invest in pollution-reduction activities that were previously deemed to be too expensive.[10] This

[7]See, e.g., Lee, Moretti, and Butler (2004), Ferreira and Gyourko (2009), Cuñat, Giné, and Guadalupe (2012), Do, Lee, Nguyen, and Nguyen (2012), Akey (2015), and Cuñat, Giné, and Guadalupe (2020). Questions have been raised in the political science literature about whether close U.S. House elections are "random" enough to satisfy the identifying assumptions behind RD (see, e.g., Snyder, 2005 and Caughey and Sekhon, 2011), but such concerns have largely been found to be invalid (Eggers, Fowler, Hainmueller, Hall, and Snyder Jr., 2015, de la Cuesta and Imai, 2016, and this paper).

[8]This assumption mirrors that of Di Giuli and Kostovetsky (2014), who state that "[t]he Democratic Party platform places more emphasis on CSR-related issues such as environmental protection [and others]."

[9]See, e.g., Fisman and Wang (2015), Mehta, Srinivasan, and Zhao (2020), Mehta and Zhao (2020), and Akey, Heimer, and Lewellen (2021).

[10]A profit-maximizing firm would invest in a pollution-reduction project if and only if the marginal cost of investing is smaller than the marginal expected value loss from not investing (for example, the probability of an inspection multiplied by the expected loss given inspection due to pecuniary penalties, lost reputation, and other factors). This analysis

logic gives rise to our main prediction: that firms' relative pollution levels will fall and pollution abatement activities will increase following the close election of a Democrat versus a Republican.

We present five main results. First, our regression discontinuity tests provide strong evidence that winning candidates' political party affiliations affect subsequent emissions in their districts. At the threshold, we find that emissions increase by approximately 20% when a facility is represented by a closely-elected Republican relative to a closely-elected Democrat. This result is robust to our selection of bandwidth and estimation approaches following the existing RD literature (Calonico, Cattaneo, and Titiunik, 2014; Cattaneo, Idrobo, and Titiunik, 2019). In contrast, we find no increases in plant production at the RD threshold. To explain the decline in pollution, we present evidence that firms increase investment in abatement technologies and in post-production recycling and treatment following close Democrat wins.

Our baseline result survives a battery of robustness tests. We do not find any discontinuities related to local economic conditions such as GDP growth, unemployment, or credit growth, and we present evidence using the Yale Climate Opinion Maps that there are no discontinuities related to district voters' views about the environment. A McCrary (2008) test confirms that there is no manipulation of the assignment variable. Following Lowes and Montero (2021), we also perform a residualized RD test based on the residuals from a first-stage regression including Congressional district and state $\times$ chemical $\times$ year fixed effects and obtain similar results. We similarly obtain discontinuities for districts represented by governors of both parties, though magnitudes are larger for Democratic governors. We find results that go in opposite directions for seats that flip from Democrat to Republican and Republican to Democrat, respectively, as expected. We also exploit *within-party* variation in environmental ideology and show that our results are stronger for more ideological candidates, supporting differences in ideology as the key driver of our results. Placebo tests and standard error restrictions further confirm the overall robustness of our findings. Collectively, we present strong evidence that politicians' ideologies affect the industrial pollution decisions of firms.

Second, we present evidence that firms reallocate pollution between their various facilities based on the party affiliation of the politicians representing each facility in Congress. We first present the

assumes a Friedman (1970)-style firm objective function; if firms care about objectives other than just profit maximization or shareholder value, they may naturally respond differently (Hart and Zingales, 2017).

results of OLS regressions with firm $\times$ chemical $\times$ time fixed effects. We find that, within the same firm-chemical-year triad, pollution at the facility-chemical-year level declines following a Democratic election victory. We then augment these tests with Giroud and Mueller (2019)-style tests where we examine how a facility's pollution depends on the political party representation of the firm's other facilities. We find that a win by a local Republican is associated with relatively larger increases in pollution (but not production) and relative decreases in post-production recycling and treatment when a firm's other plants are represented by Democrats, supporting reallocation. These findings suggest that firms manage their environmental footprints as rigorously as they manage other parts of their production footprints, and complement Buntaine, Greenstone, He, Liu, Wang, and Zhang (2021) by showing that firms effectively "turn up" their pollution reduction efforts at some plants and "turn down" their efforts at other plants when a closely-elected Democrat takes office.

Third, despite firms' best efforts at reallocating pollution, we provide evidence suggesting that such reallocation is imperfect. We begin by rolling up emissions at the firm level and showing that total firm-level emissions fall following a close Democratic victory. This suggests that firms are unable to fully offset emissions declines in newly-Democratic districts with emissions increases elsewhere. Using data from Compustat, we then confirm that these emissions reductions are costly to the firm: firm-level COGS increases by approximately 4% and market-to-book levels decline by approximately the same amount when the share of a firm's facilities represented by a closely-elected Democrat goes from zero to one. Hence, while multi-plant firms are able to offset a sizable proportion of the costly emissions reductions they undertake in districts closely won by Democrats, these adjustments are nonetheless imperfect and result in significantly higher firm-level costs and a lower M/B ratio.

Fourth, we find that the pass-through of political ideologies through firms' pollution decisions appears to have a significant impact on the health of local communities. We split Congressional districts into smaller areas (3-digit Zip codes) and sort areas into those with high or low numbers of polluting plants per year. We then examine whether the difference between respiratory-related illnesses in high-plant versus low-plant areas increases when the local representative is a Republican.[11] We find that the incidence of respiratory illnesses increases by 7–8% after a district switches

[11] We focus on respiratory illnesses (illnesses with a CMS Major Diagnostic Category code of 4) since these illnesses are more likely to be caused by exposure to emissions (see Hoek, Krishnan, Beelen, Peters, Ostro, Brunekreef, and Kaufman, 2013 for a review).

from Democrat to Republican in areas with a high numbers of plants (but no difference in areas with fewer plants). Payments for respiratory-related hospital visits also increase by 7–13% in high-plant areas within districts represented by a Republican versus a Democrat. We also find evidence that the reallocation of pollution leads to an effective reallocation of health costs across districts containing different facilities of the same firm.

The human costs of these effects are large. Our estimates imply that each Democrat-to-Republican switch in a single House seat will be associated with 67 additional hospital visits costing around $628,000 per year. These estimates imply that, if all 221 current Democratic representatives were replaced with Republicans in the next election cycle, we would expect an additional 29,614 hospital visits costing more than $277 million during the following cycle due to increased industrial pollution at constituent firms.

Finally, we examine the mechanisms through which the partisan ideological beliefs of U.S. representatives may affect constituent firms' pollution decisions. One advantage of our setting is that federal laws are consistent across states, making it highly unlikely that representatives are affecting firms directly through legislative orders or the threat of future action. In addition, we show that our results are not driven by changes at the state level. This leaves regulatory interference by politicians as a plausible potential mechanism. In particular, we hypothesize that Democratic representatives (and their staffs) may pay more attention to the monitoring and enforcement of environmental regulations relative to Republican representatives, and may lean on regulators to increase inspections and enforcement activities at plants in their districts.[12] If this is true, firms would be subject to different environmental monitoring and enforcement regimes based on the political party of their U.S. representative, leading firms to potentially re-optimize their pollution decisions.

Consistent with this hypothesis, we find that inspection propensities are higher and enforcement actions are more common at facilities represented by closely-elected Democrats, even though pollution at these facilities is lower, on average, than otherwise-identical facilities represented by closely-elected Republicans. The magnitude of the increase in inspection propensity is large; conditional on receiving at least one EPA inspection, inspections increase by approximately 20% after a Democrat

[12] In most U.S. states, state and local regulators are the primary enforcers of federal environmental regulations, working in conjunction with a small regulatory team at the EPA. Our hypothesis is that representatives (and their staffs) are leaning on these regulators, many of whom likely work and reside in the representative's district.

wins a close election. We also find results along the extensive margin: firms are approximately 7% more likely to be inspected for the first time after a Democratic win. These findings complement Innes and Mitra (2015), who also show that inspections rise following Democratic victories in close Congressional elections.[13]

In addition to increased inspection frequencies, we find that enforcement actions also rise following close-election wins by Democratic candidates. However, the increase in enforcement actions consists primarily of informal enforcement actions such as cease-and-desist letters that carry no pecuniary penalties. We find that such informal enforcement actions rise by 46%. In contrast, while formal enforcement actions also rise, once we condition on the increase in inspections, we find economically small changes in formal enforcement actions and monetary fines. Given the potential costs (both in fines and in reputational losses) associated with formal enforcement actions, these results provide evidence – albeit speculative – that a material fraction of firms are over-polluting under Republican representatives and that such firms reduce pollution under Democratic representatives to a level that does not trigger an increase in formal enforcement actions (supporting the arguments in Blundell, Gowrisankaran, and Langer, 2020). Consistent with this argument, we find that the reduction in pollution following a close Democratic win is larger for firms with high ex-ante pollution levels, who are arguably at the most risk of being formally sanctioned in the event of a violation.

Our empirical setting allows us to rule out a number of competing explanations. For example, the literature on political power has shown that powerful politicians can intervene to help constituent firms. However, while our results are (unsurprisingly) stronger for more powerful politicians, we only find results for *highly ideological* (powerful) politicians, suggesting that, while political power is an amplification mechanism in our setting, it is ideology rather than power that is driving our main results. Another concern is that our results might reflect a firm's own political ideologies rather than the ideologies of the politician representing the firm (Di Giuli and Kostovetsky, 2014; Hutton, Jiang, and Kumar, 2014; Fos, Kempf, and Tsoutsoura, 2021). However, there is no reason to think that a firm's own political ideology would change as the result of a narrow election win by a single politician. A third concern is that our health results may be picking up other partisan changes that affect

[13] Like our paper, Innes and Mitra (2015) study a regression discontinuity setting involving close Congressional elections. However, Innes and Mitra (2015)'s RD tests only examine inspections; they do not examine the other pieces of our causal chain (e.g. pollution, production, and enforcement), nor do they examine reallocation, firm outcomes, or health effects.

high-plant areas more than low-plant areas. However, we run a placebo test involving illnesses that are unlikely to be caused by industrial pollution (e.g. infectious diseases) and find no evidence that these ailments systematically increased in high-plant areas of Congressional districts represented by Republicans. While other observable and unobservable factors could still contribute to our findings, we believe that the most likely explanation for our findings, given the evidence available, stems from differences in politicians' ideologies.

Our paper contributes to a number of areas of the literature. First, while other papers have studied the causal effects of political parties and political ideologies on economic outcomes (see, e.g., Alesina, 1988; Lee, Moretti, and Butler, 2004; List and Sturm, 2006; Ferreira and Gyourko, 2009), our paper is one of the first (to our knowledge) to link the partisan ideology of individual politicians directly to firm behavior and community health outcomes. By showing that firms support politicians' ideological demands at a sizable potential cost to shareholders, our paper is consistent in spirit with favor-trading models such as Shleifer and Vishny (1994), though here, the politician's "favor" is effectively a tax (increased inspections and enforcement) instead of a subsidy. Our paper also contributes to the literature on political polarization by examining how *politicians*' polarization affects firms, as opposed to studying the effects of politically polarized economic agents within firms (see, e.g., Di Giuli and Kostovetsky, 2014; Hutton, Jiang, and Kumar, 2014; Kempf and Tsoutsoura, 2021; Fos, Kempf, and Tsoutsoura, 2021; Engelberg, Guzman, Lu, and Mullins, 2021).

Turning to firms' environmental policies and practices, a growing literature has shown that financial constraints (Cohn and Deryugina, 2018; Bartram, Hou, and Kim, 2021; Xu and Kim, 2021), limited liability (Akey and Appel, 2021), environmental activism by institutional holders (Akey and Appel, 2019; Naaraayanan, Sachdeva, and Sharma, 2020), the listing status of firms (Shive and Forster, 2020), CEO hometown favoritism (Li, Xu, and Zhu, 2021), and supplier networks (Schiller, 2018) can have a significant impact on firms' environmental policies. We add to this literature by showing that actors outside of a firm's own ecosystem – in particular, individual facilities' U.S. Representatives – can play a major role in determining firms' environmental policies, emissions, and the health of surrounding communities.

Finally, by showing that political ideology explicitly affects environmental inspections and enforcement, our paper contributes to the large economics literature on the enforcement of environmental regulations (see, e.g., Greenstone, 2002; Greenstone, List, and Syverson, 2012; Walker, 2013; Innes and Mitra, 2015; He, Wang, and Zhang, 2020; Buntaine, Greenstone, He, Liu, Wang, and Zhang, 2021) and on the political economy of regulatory enforcement more generally (see, e.g., Dinç, 2005; Benmelech and Moskowitz, 2010; Fisman and Wang, 2015; Mehta, Srinivasan, and Zhao, 2020; Mehta and Zhao, 2020; Akey, Heimer, and Lewellen, 2021). In the environmental economics sphere, our paper contributes to the literature on the political economy of pollution (see, e.g., Konisky and Woods, 2010; Beland and Boucher, 2015; Monogan III, Konisky, and Woods, 2017; Lipscomb and Mobarak, 2017; Heitz, Wang, and Wang, 2020; Lueck, Pastrana, and Torrens, 2021) and complements the literature on the relationship between political ideologies and firm pollution (see, e.g., Helland and Whitford, 2003; Neumayer, 2003; Fredriksson, Neumayer, Damania, and Gates, 2005), which has primarily studied cross-country settings. Relative to these papers, we use a sharper identification strategy, exploit within-country variation in political ideologies, and specifically examine plant-level, firm-level, and community-level effects.

2 Data

2.1 EPA Emissions and Compliance Data

Our main data source for emissions is the Toxics Release Inventory (TRI) database produced by the U.S. Environmental Protection Agency (EPA). Most U.S. facilities that release toxic chemicals into the air, water, or certain land repositories are required to report their annual emissions releases to the EPA. The TRI database contains emissions data for approximately 770 chemicals spanning 33 categories. Facilities (plants) are required to report the annual number of pounds released for each chemical covered by the TRI program, as well as other information including plant coordinates and information about the plant's owners. The database is organized at the facility-chemical-year level. The TRI database also includes information about a plant's production ratio, which measures the annual percentage change in the quantity of output for each production process that contributes to the plant's emissions.

We also obtain information on facilities' waste management activities from the EPA. The EPA's waste management hierarchy consists of five components, namely source reduction, recycling, energy recovery, treatment, and disposal. By eliminating pollution at the top of the production process, source reduction (also known as abatement) is the waste management activity most preferred by the EPA, with disposal being the EPA's least preferred activity. We obtain facility-chemical-year level data on abatement investment from the EPA's Pollution Prevention (P2) database, which is a companion database to TRI, and data on recycling, energy recovery, and treatment from TRI (following Li, Xu, and Zhu, 2021). While TRI and P2 are self-reported, there are strong incentives to report truthfully and the EPA conducts regular audits to verify data integrity, leading to a high degree of confidence in data quality (see, e.g., Greenstone, 2003; Akey and Appel, 2019, 2021).

We also obtain federal environmental compliance data from the EPA's Enforcement and Compliance History Online (ECHO) data set. To determine whether a plant is in compliance with applicable federal laws, EPA staff and state regulators conduct regular inspections that involve interviews, records reviews, and plant visits. Violations discovered by regulators can lead to either formal or informal enforcement actions. The ECHO data set contains information on whether a given enforcement action is formal or informal, the agency that initiated the action, and any penalties imposed on the facility.[14] Informal enforcement activities generally include warning letters or Notices of Violation, while formal enforcement activities may result in Administrative Compliance Orders (or state equivalent actions) and judicial referrals to the State Attorney General or to the Department of Justice. Most of the inspections and enforcement actions in our sample are related to the Clean Air Act (CAA) program and the National Pollutant Discharge Elimination System (NPDES) under the Clean Water Act (CWA) program.

It is important to note that most pollution permits specify complicated pollution limits by day, hour, or even minute that often change based on seasonal factors, production factors, or time-varying location-specific factors such as temperature, fish spawning patterns, and the arrival or presence of weather systems. As such, EPA and state regulatory staff cannot typically tell if a firm is in violation of its pollution permits by viewing its annual emissions quantities (i.e. without performing an on-site inspection).[15] In addition, even if regulators *could* immediately determine whether a plant has

[14]ECHO is a collection of data sets covering compliance activities for various programs including the Clean Air Act (CAA), the National Pollutant Elimination Discharge System (NPDES), NPDES Biosolids, and the Integrated Compliance Information System for Federal Civil Enforcement Case Data (ICIS FE&C). We combine all of the data sets available in ECHO to construct our final data set.

[15]For example, "EPA's enforcement program depends heavily upon inspections by regional or state enforce-

exceeded its permitted level of pollution, firms would not face regulatory consequences unless regulators pursued enforcement actions, an outcome that EPA and state inspectors have applied unevenly across regions and time.[16]

2.2 District and Elections Data

To construct our main data set, we merge the TRI and ECHO data with Congressional boundary definitions from Lewis, DeVine, Pitcher, and Martis (2013) and Congressional district election results from the MIT Election Data + Science Lab. We then construct an indicator variable, *Democrat Win*, that equals one if a plant is located in a district that was won by a Democratic Party candidate in its most recent election, and equals zero otherwise.

2.3 Health Data

Our main source of data for health-related variables is the Center for Medicare and Medicaid Services (CMS), which is part of the U.S. Department of Health and Human Services. CMS provides a data set containing quantity and average price (payment) data related to many common medical procedures performed at more than 4,000 inpatient hospitals starting from 2011 for all Medicare and Medicaid recipients. We obtain this data for 622 Diagnosis Related Groups (DRGs), which we aggregate at the Major Diagnostic Category (MDC) level. There are 25 mutually-exclusive MDCs in the CMS taxonomy, with each MDC covering a broad diagnostic area such as the eyes, the respiratory system, the digestive system, or the skin.

Consistent with the literature on pollution and local health outcomes (see, e.g., Schwartz, 1996 and Hoek, Krishnan, Beelen, Peters, Ostro, Brunekreef, and Kaufman, 2013), our tests focus on MDC 4, which captures issues with the respiratory system. We also construct data for a "placebo" group of MDCs (18–22) which covers illnesses such as infectious diseases and mental health issues that

ment staff as the primary means of detecting violations and evaluating overall facility compliance. Thus, the quality and the content of the agency's and states' inspections, and the number of inspections undertaken to ensure adequate coverage, are important indicators of the enforcement program's effectiveness." Source: https://www.govinfo.gov/content/pkg/GAOREPORTS-GAO-06-840T/html/GAOREPORTS-GAO-06-840T.htm.

[16] For example, "[GAO] found variations in regional [enforcement] actions reflected in the (1) number of inspections EPA and state enforcement personnel conducted at facilities discharging pollutants within a region, (2) number and type of enforcement actions taken, and (3) the size of the penalties assessed and the criteria used in determining the penalties assessed." Ibid.

are unlikely to be caused by pollution from local plants. Some tests also utilize health outcome and payments data spanning all MDC codes in the CMS data set.

To create our main data set, we merge our CMS data set with our emissions, compliance, and Congressional district data set at the Zip code level. To ensure that we accurately map health outcomes to Congressional districts, we drop all Zip codes spanning two or more Congressional districts. Since most Zip codes do not contain a hospital and most people travel outside of their Zip code to receive hospital care, we aggregate all health and plant data at the three-digit Zip code-district level. This level of aggregation corresponds roughly to a small metropolitan area or county, though large and mid-sized metropolitan areas often have multiple three-digit Zip codes.

2.4 Other Data Sources

We also use data from a number of other sources. We obtain political ideology scores from VoteView and the League of Conservation Voters, data on public environmental opinion from Yale Climate Opinion Maps, and data on state and federal environmental budgets from the Environmental Council of the States (ECOS). Data on campaign contributions to Congressional candidates are sourced from the Federal Election Commission. We also obtain data on cost of goods sold from Compustat, which we hand-match with the TRI data based on the name of the firm.

2.5 Summary Statistics

Table 1 reports summary statistics for our main variables on emissions, compliance, elections, and health. Our sample consists of 37,369 distinct plants during the period 1991-2016. Emission variables are defined at the plant-chemical-year level, while compliance-related variables are defined at the plant-year level. The average facility in our sample releases 30,846 pounds per chemical per year, experiences 0.8 inspections per year, and is subject to 0.15 enforcement actions per year, including both formal and informal actions. The average percentage margin of victory for Democratic Congressional candidates is approximately 2.7%, indicating that the average district in our sample has a slight Democratic tilt. Table 1 also shows that there are on average 54 respiratory-related hospital visits per Zip3-district-year costing around $485,000 in total.

3 Empirical Framework

Identifying the causal effect of politicians' ideologies on firm outcomes is challenging for a number of reasons. First, it is difficult to measure a politician's ideology. Second, it is difficult to find settings in which politicians' ideologies can be directly traced to measurable firm outcomes. Third, politicians are not elected randomly, and there are many potential omitted variables (both within and outside of districts) that could be associated with both a politician's election victory and firm outcomes in the politician's district. Fourth, firm decisions could themselves affect the politician's ideology or election results (reverse causality). Finally, attributes of a politician other than ideology (for example, seniority) may directly affect firm outcomes as well.

To overcome these challenges, our main tests combine a regression discontinuity (RD) design around close elections with detailed plant-chemical-time level microdata on firms' pollution and production decisions. Close-election RD designs are common in the political economy literature (see, e.g., Ferreira and Gyourko, 2009; Akey, 2015) because elections (and particularly two-party elections) are well-suited for RD tests: there is a clear vote share at which point a candidate is declared the winner, and treatment – particularly right around the threshold – often depends on plausibly exogenous factors such as the weather, traffic, or other relatively minor factors that can affect voter turnout at the margins.

Our main tests use a candidate's political party as a proxy for their ideology regarding the environment. As shown in Figure 1, Democrats and Republicans on average have very different views about the environment, and this is reflected in their legislative voting records, especially in recent years. We also examine intraparty variation to help confirm that our results are capturing political ideology and not some other factor that is specific to the two political parties themselves.

To implement our close-election RD design, we define *Win Margin* as the difference in the vote share of the Democratic candidate minus the vote share of the Republican candidate. We are interested in whether there is a discontinuity in pollution when *Win Margin* = 0. To examine this question, we first estimate the local linear RD equation:

$$Y_{ic(jd)t} = \beta_1 \text{Democrat Win}_{dt} + \theta f(\text{Win Margin}_{dt}) + \delta \text{Democrat Win}_{dt} \times f(\text{Win Margin}_{dt}) + \mu_c + \epsilon_{ict} \,, \quad (1)$$

where the main dependent variable is (log) pollution of chemical c at establishment i owned by firm j in Congressional district d at time t, Democrat Win$_{dt}$ is an indicator for a Democrat winning the most recent election, f(Win Margin$_{dt}$) are polynomials of different order of the variable Win Margin$_{dt}$, and μ_c is a chemical fixed effect. Importantly, Democrat Win$_{dt}$ $\times$ f(Win Margin$_{dt}$) allows the estimation of β_1 to be identified when the win margin is equal to zero. In line with Akey (2015), we restrict the sample to elections with an absolute vote margin less than 5%.

Local linear RD regressions face a well-known trade-off between sample bandwidth size around the RD threshold and bias in the estimates of the RD coefficients. As such, we also report the results of a non-parametric RD estimation procedure that attempts to give relatively more weight to observations around the cutoff without sacrificing precision (see, e.g., Calonico, Cattaneo, and Titiunik, 2014; Lowes and Montero, 2021). This procedure allows the econometrician to specify a weighting method for each observation in the sample (i.e., a kernel) and a (possibly non-linear) functional form for the relationship between the outcome variable and the running variable on each side of the cutoff. The procedure jointly estimates the RD parameter of interest, its optimal bias-corrected standard error, and the optimal sample bandwidth around the cutoff (Calonico, Cattaneo, and Titiunik, 2014). The exact specification for these tests is:

$$Y_{ic(jd)t} = \beta_1 \text{Democrat Win}_{dt} + \theta g(\text{Win Margin}_{dt}) + \epsilon_{ict} \ , \tag{2}$$

where g(Win Margin$_{dt}$) is now the RD polynomial. Our baseline specification is a local polynomial of order one in the vote margin estimated separately on each side of the zero margin cutoff. We use a triangular weighting kernel and calculate the optimal bandwidth by using the MSE-minimizing procedure suggested by Cattaneo, Idrobo, and Titiunik (2019). We also estimate the regression specifications with different polynomials and kernel definitions.

In some cases, it is not possible to use RD estimation techniques due to the data structure or the specific hypothesis being tested. In those cases, we estimate panel regressions of the form:

$$Y_{ic(jd)t} = \beta_1 \text{Democrat Win}_{dt} + \beta_{FE} + \epsilon_{ict} \ , \tag{3}$$

where, thanks to the granularity of our data, we are able to employ a variety of (often stringent) fixed effects including year fixed effects, establishment fixed effects, establishment $\times$ chemical fixed effects, district fixed effects, district $\times$ chemical $\times$ year fixed effects, firm $\times$ chemical $\times$ year fixed effects, state $\times$ year fixed effects, and state $\times$ year $\times$ chemical fixed effects, depending on the test. The multidimensional nature of these fixed effects allows us to isolate very specific sources of variation, such as (for example) variation in pollution for a given chemical across plants owned by the same firm at the same point in time.

4 Results

4.1 Main Result: Pollution

We use a regression discontinuity design to examine the effects of district political affiliation on plant-level emissions in a close-election setting. As described in Section 3, identification in this setting relies on quasi-random assignment of a plant's district to different political parties. In other words, we compare the emissions of plants located in districts where Democrats win an election by a very small margin, and plants located in districts where Republicans win an election by a very small margin.

Figure 2 presents our main regression discontinuity result. We first rank district-year observations in our sample by their Democrat win margin in the most recent electoral college election.[17] We restrict the sample to a narrow ±5% Democrat win margin window, and we construct 18 equally-spaced bins on either side of the zero win margin cutoff.[18] In Figure 2, we report the average log-emissions in each Democrat win margin bin, as well as the fitted values and 95% confidence intervals of a local polynomial regression on each side of the cutoff. Figure 2 shows an economically and statistically significant drop in emissions for plants located in districts that are won by closely-elected Democrats. This drop in emissions is roughly constant away from the zero win cutoff, suggesting that our result is not driven by outlying observations just above or below the zero cutoff.

In Table 2, we formally test the visual evidence presented in Figure 2. In Columns (1)-(3), we again

[17]For example, a 100% (-100%) Democrat win margin implies that the district was won by Democrats (Republicans) with a 100% margin, and a 1% Democrat win margin implies that the district was won by Democrats with a 1% margin.

[18]In Appendix Figure A1, we plot the same figure using a linear polynomial fit over the ±5% Democrat win margin window.

focus on a narrow 5% window around the zero margin cutoff, and regress the natural logarithm of plant-level emissions on a dummy equal to one if the district where the plant is located was won by a Democrat in its most recent election and equal to zero otherwise (Column (1)), as well as on an interaction term between this indicator and the Democrat win margin (Columns (2) and (3)). These local OLS specifications confirm the visual evidence from Figure 2. Plants located in districts that are just-won by Democrats have on average 21.3% to 39.7% higher emissions than plants located in districts that are just-won by Republicans—the election of a Democrat representative causes firms to reduce pollution by up to 39.7% under our RDD identifying assumptions.

Columns (4)-(7) report results using non-parametric local polynomial RD specifications (Calonico, Cattaneo, and Titiunik, 2014; Lowes and Montero, 2021). Each column contains a different combination of polynomial functional form (linear versus quadratic) and kernel weighting method (triangular versus Epanechnikov). Columns (4)-(7) show that our results are robust to the Calonico, Cattaneo, and Titiunik (2014) estimation technique and various polynomial and kernel combinations: as in the first three columns, we find that Democratic close election victories are associated with an average 35% reduction in plant-level emissions.

The magnitudes documented in Table 2 are large. The 35.5% reduction in emissions implied by our non-parametric specification (4) entails a reduction in firm-level emissions of approximately 10 thousand pounds relative to the unconditional sample mean of 30,846 pounds per plant-chemical, and approximately 130 pounds relative to the unconditional median of 369 pounds per plant-chemical. These results are quantitatively similar when we focus only on the 5% close election sample. In this sample, the mean level of emissions is 30,675 pounds, and the median level of emissions is 455 pounds. Overall, the results of Figure 2 and Table 2 provide strong empirical evidence that district-level affiliation to the Democratic Party is associated with economically large reductions in toxic emissions.

4.2 Robustness

4.2.1 Covariate Balance

One concern with our results in Table 2 is that other factors such as local economic activity might correlate with both close election victories and firms' subsequent pollution decisions. However, Figure A2 confirms that there are no discontinuities related to district-level GDP growth, the district-level unemployment rate, or district-level credit growth around the 50% voting threshold.[19] Hence, districts in our close-election sample seem similar along observable economic dimensions.

We also provide evidence that districts on both sides of the cutoff share similar views about the environment. Figure A3 uses data from the Yale Climate Opinion Maps project for 2020 to show that residents of districts just won by Democrats in the 2018 election share similar views about the environment as residents of districts just lost by Democrats in 2018. While this test represents a single cross-section, the results support the idea that there are no significant differences in environmental viewpoints between districts just won or just lost by Democrats. Figure A4 also shows that the elections in our sample are spread out across 48 of the 50 states and show very little correlation across regions.[20]

4.2.2 Residualized RD

To further rule out the possibility that our results could be driven by a confounding factor, we follow Lowes and Montero (2021) and perform an RD analysis on a residualized version of our main emissions variable after removing most variation that could plausibly be driven by confounding factors. We first regress emissions on Congressional district fixed effects as well as a state $\times$ chemical $\times$ year fixed effect. We then perform our baseline RD tests on this residualized outcome variable. This test helps to rule out confounding stories that rely on variation across districts, variation at the state-time

[19] We include employment because politicians' ideologies might affect employment at local plants, with possible effects on emissions. We include credit growth because politicians' partisan ideologies may lead to changes in local firms' credit conditions, which in turn might indirectly affect their abatement decisions (Xu and Kim, 2021). We measure credit growth using the (log) number of mortgage originations from HMDA and the number of consumer and small-business loan originations made under the Community Reinvestment Act.

[20] For example, the seven states with the largest number of close elections per Congressional district in our sample are Connecticut, Kansas, Maine, Nebraska, Nevada, New Hampshire, and Washington. These states have vastly different economic, social, and demographic profiles. During our sample period, there were no close elections in Mississippi or Vermont.

level, or variation at the chemical-time level.[21] In the interest of space, in the rest of the paper we keep only two specifications from Table 2: a local linear regression in the $\pm 5\%$ win margin window, and a non-parametric RD estimate using a linear polynomial, a triangular kernel, and the optimal sample bandwidth selection method of Calonico, Cattaneo, and Titiunik (2014). Our results are robust to alternative specifications.

Table A1 shows that our main results survive this stringent robustness test. In all columns except column (1) (a simple difference in means), we still find economically and statistically significant reductions in pollution when a close Democrat is elected. While magnitudes are lower than in Table 2, they are still quite sizable; for example, we find pollution reductions of approximately 4% and 7% in columns (4) and (6), which use non-parametric specifications with a triangular kernel. These tests suggest that even after removing most of the variation in pollution across geography, chemicals, and time, politicians' ideologies still have significant effects on firms' emission decisions.

4.2.3 Governors and State Regulatory Agencies

We also examine whether politicians' impact on pollution differs depending on the political party of their governor. Beland and Boucher (2015) find that firm pollution is lower under Democratic governors, raising questions about whether our findings are simply capturing a governor effect. More broadly, since most EPA laws are enforced by states, and since state governors generally appoint the heads of the agencies responsible for the enforcement of environmental regulation, it is natural to think that the magnitudes of our effect might depend on the political party of the governor.[22] In addition, splitting the sample by the party of the governor allows us to determine whether we observe effects for governors of both parties, or whether the effect is exclusively concentrated among Democratic governors.

Figure A5 and Table A2 show that our main results hold regardless of the political party of the governor. For example, in column (7) of Table A2, the effect is large and highly statistically significant

[21] For example, these tests rule out the possibility that our pollution effects can be explained by (1) state-level economic conditions, (2) the governor, state agencies, and state-level regulations, (3) variation in plant makeup across districts, or (4) state-level supply or demand shocks.

[22] In particular, consistent with Beland and Boucher (2015), we hypothesize that the effects would be larger when a Democrat is governor, since a Democratic governor will be more likely to appoint agency heads who care about the enforcement of environmental regulations, and since agencies under a Democratic governor might be more receptive to input and requests from members of Congress that relate to the enforcement of environmental regulations.

for both Democratic and Republican governors. However, the figure and table also show that the effect is quantitatively larger for Democratic governors. This is most apparent in Figure A5, where the blue line represents the effect of close election victories by Democrats in states represented by Democratic governors, and the red line represents the same test but in states represented by Republican governors. The figure shows that the size of the discontinuity is much larger for the blue line than the red line, confirming that pollution reductions following close Democratic Congressional victories are stronger in states with Democratic governors.

4.2.4 McCrary Test

Another concern is that the distribution of election margins may not be continuous at the 50% threshold, suggesting that the assignment variable could potentially be manipulated. Figure A6 presents the results of a McCrary (2008) density test. The figure shows that the distribution of the assignment variable is smooth across the threshold, confirming that it is unlikely that the assignment variable (election outcomes) was systematically manipulated.

4.2.5 Additional Robustness

We also report the results of five additional robustness tests. First, in Appendix Table A3 we show that our local OLS specification in Table 2 produces statistically-similar results when we cluster our standard errors at the facility level or using 97 distinct vote bins around the zero vote margin (Lee and Card (2008)).[23] Second, we present the results of two placebo tests in Figure A7 that show that our results are not spuriously caused by sample selection or other issues. Third, in Table A4 we show that our results are almost identical when we run Poisson regressions on the level of emissions instead of OLS regressions and non-parametric regressions on the natural logarithm of the level of emissions, reducing concerns that our results may be driven by the distribution of emissions (Cohn, Liu, and Wardlaw, 2021)). Fourth, Table A5 confirms that the results in Table 2 hold after excluding power plants (NAICS two-digit code of 22) from our sample. Since power plant "production" is largely determined by economic activity in the region, this test provides additional evidence that differences

[23]The Lee and Card (2008) clustering is motivated by the presence of small mass points in the distribution of the outcome variable around the zero win margin cutoff.

in economic activity across districts are unlikely to explain our findings. Finally, Table A6 shows that district-level emissions growth rates do not predict the outcomes of subsequent elections, suggesting that Democratic close-election victories are not driven by pre-election changes in emissions levels.

4.3 Production, Abatement, and Post-Production Recycling Activities

We now dig deeper into the pollution and production decisions made by firms following the close election of a Democratic representative. Table 2 shows that plant-level emissions decline following the close election of a Democratic representative. There are at least three non-mutually exclusive ways in which firms can reduce pollution at a plant. First, the firm can simply reduce production at the plant. This would keep the number of units of pollution per unit of production constant, but would lead to lower overall pollution. Second, the firm could invest in new abatement technologies to reduce the emissions occurring during the production process. Third, the firm could increase its post-production treatment and recycling activity.

We first examine the link between firms' pollution and production decisions. In particular, we utilize the EPA's data on production, which is available at the facility-chemical-year level, to examine whether pollution *per unit of production* also falls after a plant is represented by a closely-elected Democrat. Since output is only available as an annual growth rate, we follow Akey and Appel (2019, 2021) and construct a contemporaneous measure of plant emissions relative to production for each plant-chemical-year as

$$\begin{aligned} \log\left(\text{Cumulative Emissions/Production}\right)_{ijt} &= \log\left(\prod_{\tau=2}^{t} \frac{1}{\text{Prod. Growth}_{ij\tau}} \times \frac{\text{Emissions}_{ij\tau}}{\text{Emissions}_{ij\tau-1}}\right), \\ &= \log\left(\frac{\text{Emissions}_{ijt}}{\text{Production}_{ijt}}\right) - K_{ij}, \end{aligned} \tag{4}$$

where Emissions_{ijt} are the emissions of chemical j by plant i in year t, $\text{Prod. Growth}_{ijt}$ is the ratio of year t's output and year $t-1$'s output associated with the production of chemical j in plant i (directly available from the EPA data), and K_{ij} is a plant-chemical constant.

In Table 3, we show that plant emissions in blue districts decrease even relative to production. In the first column of the table, we show that emissions decrease by around 9.3% relative to production when the district where the plant is located is just-won by a Democrat. In Column (2), we confirm that this result holds economically and statistically using a non-parametric specification and a flexible RD bandwidth choice. In Appendix Table A7, we also document no effects on plant-level production when a district is just-won by a Democrat politician.[24] Hence, while plant-level emissions clearly decrease following a close Democratic election, production at the same factories does not decrease.

How can pollution go up or down if production remains unchanged? In Table 4, we examine whether firms invest in new abatement technologies and/or change their post-production recycling behavior in order to reduce pollution following a close Democrat win. Columns (1)–(2) of Table 4 show that firms indeed increase their investment in abatement activities following close Democrat wins. The magnitudes are large: the unconditional average number of abatement activities at the plant-chemical-year level is 0.06, so our estimates imply a 25% increase in abatement activities following a Democrat win.

In Columns (3)-(4), we examine whether firms reduce emissions through their post-production treatment, recycling, and energy recovery activities. The dependent variable in this panel is the post-production activity ratio, which is the sum of emissions reduced through treatment, recycling, and energy recovery activities divided by the total gross waste of a plant.[25] Columns (3)-(4) show that firms increase their post-production emission reduction activities after a Democrat win. Since the unconditional mean of the post-production activity ratio is 0.5, our estimates imply a 5.8% increase in the post-production ratio following a Democrat win. Collectively, these results suggest that firms increase both their production abatement and their post-production recycling activities following a Democrat win.[26]

[24]Similar to (4), we compute cumulative plant-level production related to chemical j as

$$\log\left(\text{Cumulative Production}\right)_{ijt} = \log\left(\prod_{\tau=2}^{t}\text{Prod. Growth}_{ij\tau}\right) = \log\left(\text{Production}_{ijt}\right) - K'_{ij}, \tag{5}$$

with K'_{jt} another plant-chemical-specific constant.

[25]We define total gross waste as the sum of total actual releases after post-production activities and the emissions that are reduced through treatment, recycling, and energy recovery activities. The TRI emissions data that we use in our main tests excludes emissions reduced through post-production activities (Li, Xu, and Zhu, 2021).

[26]In addition to investing in abatement technologies and post-production emission reduction activities, firms may also reduce pollution by "turning up" their existing abatement devices, as shown by Buntaine, Greenstone, He, Liu, Wang, and Zhang (2021) using detailed electricity consumption data from China. While our data does not allow us to isolate this channel, it would be consistent with (and complementary to) the results documented in Table 4.

4.4 Reallocation

Given the results in Table 2, a natural question is whether firms with plants in multiple Congressional districts reallocate pollution to other plants that are represented by Republicans following the close election of a Democrat. All else equal, a firm that has plants located in areas represented by a Democrat and a Republican may prefer for pollution to occur at the Republican plants, since less abatement and post-production investment might be needed at these plants.

To test this hypothesis, we first examine the allocation of pollution across a firm's different plants. For these tests, we switch to a sample containing data from all elections (not just close elections), as this provides us with the ability to add varying degrees of fixed effects that are not possible in the RD setting. Specifically, we regress the natural logarithm of plant-chemical-level emissions on an indicator equal to one if the district politician is a Democrat and equal to zero otherwise, and on different combinations of fixed effects.

Table 5 presents the results. First, column (1) confirms that our main RD results in Table 2 continue to hold within a broader sample. In columns (2)–(5) we add a firm $\times$ chemical $\times$ year fixed effect, thereby transforming the analysis into a purely within-firm analysis. Column (2) shows that *within-firm* plant-level emissions decline by approximately 4% following a Democratic victory, even after accounting for any systematic differences in emissions profiles among Congressional districts (as redefined each decade) using a Congressional district $\times$ chemical fixed effect.[27] This suggests that, even relative to a firm's other plants in other Congressional districts, pollution at the focal firm falls following a Democratic victory. Column (3) replaces the Congressional district $\times$ chemical fixed effect with an even more stringent facility $\times$ chemical fixed effect, and finds that pollution still falls at the focal plant relative to the firm's other plants. Columns (4) and (5) include state $\times$ year and state $\times$ chemical $\times$ year fixed effects, respectively, thereby absorbing any variation caused by (say) changes in state laws, state politicians, or state economic conditions, even those that have differential effects on different chemicals. The results show that, even after removing nearly all variation in emissions, pollution still falls at the focal plant relative to other plants owned by the same firm producing the same chemical in the same year in the same state (but a different Congressional district).

[27] This specification also helps to rule out Congressional redistricting as a driver of our results, since we observe similar results even after including district-decade ($\times$ chemical) fixed effects.

We now examine whether firms reallocate pollution between facilities following a shock to the political ideology of one of their Congressional representatives. To do so, we follow Giroud and Mueller (2019) and construct, for each plant, a measure of the political ideology of the politicians representing a firm's *other* plants producing the same chemical at the same point in time. For each firm-facility-chemical-year observation, we define *Other Facilities' Democrat Share* as the fraction of other facilities (excluding the focal facility) owned by the same firm producing the same chemical at the same point in time that are located in districts represented by Democrats. This strategy also has parallels to the empirical strategy developed by Bertrand and Mullainathan (2003), though we use an average of other plants' representation by Democrats instead of isolating plants with owners headquartered in different locations. We also construct an indicator variable, *High Democrat Share*, that equals one when the *Other Facilities' Democrat Share* variable exceeds the median level, and equals zero otherwise. Finally, we include a variable, *Local Democrat*, that is analogous to the *Democrat Win* variable from Table 5. We then regress emissions on these variables.

The results are reported in Table 6. Columns (1)–(2) report results for the *Other Facilities' Democrat Share* variable, while columns (3)–(4) report results for the *High Democrat Share* variable. Columns (1) and (3) include chemical $\times$ year and facility $\times$ chemical fixed effects, while columns (2) and (4) include facility $\times$ chemical and district $\times$ chemical $\times$ year fixed effects (which absorb the *Local Democrat* variable). Columns (1) and (3) show that, while pollution falls when a facility is represented by a local Democrat, this effect is smaller when the firm's other facilities are located in districts represented by Democrats. Columns (2) and (4) show that, even after completely absorbing time-varying factors at the local district level (including the local representative), pollution is higher at the local facility by as much as 3–6% when the firm's *other* facilities are represented by Democrats.

Figure 3 depicts these results visually. The figure plots pollution at a plant located in a given district as a function of the share of other facilities owned by the same firm in other Congressional districts that are represented by Democrats. Figure 3 shows that pollution in a given district is strongly increasing in the degree to which the same firms' other plants are represented by Democrats.[28] The intuition is that, all else equal, a given plant (represented by either a Democrat or Republican) will

[28] Figure A8 shows that the pattern in Figure 3 holds when we look at pollution per unit of production rather than the level of pollution itself.

pollute more if the firm's other plants are owned by Democrats, since the firm on average may attempt to reallocate more pollution to the focal plant.[29]

While reallocation tests are complicated to execute in an RD design, Figure 4 contains the results of RD tests as similar as possible in spirit to the tests in Table 6. Specifically, we examine pollution differences across facilities after first sorting facilities on the fraction of other facilities belonging to the same company that are represented by Democrats. To ease interpretation, the running variable in these tests is the Republican win margin. Figure 4 shows that the jump in emissions when a district changes from a Democrat to a Republican representative is larger if the firm operates a larger share of its *other plants* in Democratic districts. This result is consistent with the idea that if the other plants owned by the firm are mostly located in Democrat (Republican) districts, the demand for pollution reallocation from these districts to the focal district is higher (lower), thereby leading to higher (lower) pollution changes in the focal district. This result provides yet another piece of evidence supporting the idea that firms reallocate pollution across plants due to the ideology of the politicians representing each plant.

Finally, we attempt to better understand how firms reallocate pollution across plants. In Figure 5, we repeat the same exercise from Figure 3 and plot the post-production activities of a plant as a function of the share of blue plants owned by the same firm. We focus on post-production activities because, unlike abatement investment, these activities are easier to "turn up" and "turn down" at different facilities (see, e.g., Buntaine, Greenstone, He, Liu, Wang, and Zhang, 2021). As in our previous tests, we normalize these activities by the total gross emissions. Figure 5 shows that a firm's post-production activities are *decreasing* in the share of the firms' other plants represented by Democrats, suggesting that firms reallocate pollution by reallocating their (costly) post-production recycling, treatment, and energy recovery activities.[30]

[29]The same pattern should hold regardless of whether the focal plant is represented by a Democrat or Republican, but all else equal, pollution levels should be higher *conditional on Democrat Share* if the plant is represented by a Republican. Figure A9 confirms that this is indeed the case.

[30]In contrast, abatement investment is arguably less likely to be reallocated, as it is very costly to implement, longer-term in nature, and more likely to be irreversible.

4.5 Firm-Level Effects

We now ask whether emission reduction activities (such as those documented in Table 4) result in higher overall costs for firms with plants in Democrat districts, despite firms' best efforts to reallocate pollution to other plants. To examine this question, we begin by analyzing whether firms' COGS rise if they are represented by a closely-elected Democrat versus a closely-elected Republican.[31] To do so, we aggregate our data to the firm-time level for each chemical.[32] To capture the firm's exposure to political ideology, we construct a variable, *Democrat Share*, that equals the fraction of a firm's total plants operating in a Democratic district for a given chemical at a given point in time. We also construct a weighted version of *Democrat Share* that assigns higher weights to plants producing more of a given chemical. We then assess whether a firm's COGS increases when more of its plants are represented by Democrats. Our tests also include the equivalent of firm and time fixed effects – in our setting, these are firm $\times$ chemical and chemical $\times$ year fixed effects.

Table 7 presents the results of these tests. Columns (1) and (2) confirm that our main pollution result continues to hold at the firm-chemical-time level using the *Democrat Share* and weighted *Democrat Share* measures. Columns (3) and (4) examine COGS. When more of a firm's plants are represented by Democrats (and hence, when firm pollution per unit of production falls), we indeed find that the firm's COGS is higher. The magnitudes are large: raising the Democrat share from zero to one would cause the firm's COGS to rise by approximately 4%. This finding suggests that reducing pollution has real costs for the firm, and potentially for the firm's shareholders.

We next look at firms' M/B ratios and Tobin's Q.[33] If firms' COGS is expected to decline for at least a few years, one might expect firm value to also decline. Table 7 confirms this hypothesis: raising the Democrat share from zero to one would cause M/B ratios to fall by approximately 4% (columns (5) and (6)) and would cause Tobin's Q to decline by approximately 1% (columns (7) and (8)). Thus,

[31] Abatement and recycling costs are accounted for as cost of goods sold (COGS) on firms' income statements if they can be imputed to specific production processes (as in the case of our chemicals), and as either other operating expenses or capital expenditures otherwise. See, e.g., page 314 of BP's 2019 environmental report (https://www.bp.com/content/dam/bp/business-sites/en/global/corporate/pdfs/investors/bp-annual-report-and-form-20f-2019.pdf).

[32] Aggregating data across chemicals is challenging due to differences in the relative weight and toxicity of each chemical.

[33] The M/B ratio is defined as the market value of equity divided by the book value of equity. We use the definition provided on Ken French's website and restrict the sample to nonnegative observations. We define Tobin's Q as total assets plus market equity minus book equity. Both definitions use data from Compustat.

complying with the ideologically-driven demands of local politicians can have a material affect on the value of constituent firms.

4.6 Real Effects on Public Health

We now examine whether differences in emissions induced by politicians' differing environmental ideologies have real effects on local health outcomes in politicians' districts. To do so, we merge the Zip code-level CMS panel of health outcomes with our data on emissions and elections. We then compare how health outcomes change when districts are represented by closely-elected Democrats versus closely-elected Republicans.

To directly link our tests to pollution-related health outcomes (as opposed to general health policies for which different parties may have different preferences), we study how, within the same district and year, health outcomes change in Zip codes with high pollution exposure (i.e., a relatively high number of plants), and in Zip codes with low pollution exposure (i..e, a relatively low number of plants) when Democrats win the district. As described in Section 2, we focus only on health outcomes related to respiratory diseases (CMS Major Diagnostic Category 4), since these health outcomes are more sensitive to emissions. We also conduct a placebo test using diseases that are less likely to be caused by pollution exposure (CMS MDC categories 18 to 21), such as health problems related to infectious diseases, mental health, and drug issues).[34]

In Panel A of Table 8, we study the effect of a Democrat win on respiratory health outcomes. We construct an indicator variable that is equal to one if the Zip code-level number of plants in a given year is above the sample median in that year and zero otherwise. The interaction between the Democrat win indicator and the high number of plants indicator captures the incremental change in respiratory health outcomes in emission-sensitive (versus less-sensitive) areas when a district is won by a Democrat (versus a Republican).

In the first three columns of Table 8, our dependent variable is the number of clinical discharges related to respiratory diseases at the three-digit Zip code (Zip3) level. The columns show two key findings. First, areas with a high number of plants have 18.8%–32.5% more respiratory-related discharges than areas with a low number of plants, even within a given district and year. Hence, high-

[34] In Appendix Table A8, we also show that our results hold in the full CMS sample.

emissions areas are generally associated with higher levels of respiratory illness, regardless of the political party of the area's U.S. representative. However, columns (1)–(3) also show that this baseline effect decreases by up to one-third when the district is won by a Democrat. In specification (3), where we exploit cross-sectional variation between Zip codes located in the same district in the same year, we find that areas with a high number of plants have 18.8% more discharges when the district representative is a Republican, but only 12.2% more discharges when the district representative is a Democrat, relative to areas with a low number of plants.[35] This translates into a difference of approximately 67 discharges per district per year, which is sizable: if all Congressional seats were to flip from Democrat to Republican, this would result in an additional 58,290 hospital discharges per election cycle.[36]

In Columns (4)-(6) of Panel A, we repeat the same experiment using Zip3-district-year payments for respiratory-related discharges as our outcome variable. The results of these tests confirm that the negative health effects of pollution are lower in areas that are pollution-sensitive when the area is represented by a Democrat. For example, areas with a high number of plants have 18.9% higher respiratory-related payments when the district is red, but only 11.6% higher payments when the district is blue. The economic magnitude of this difference is again large: approximately $628,000 per district per year, which translates into a hypothetical cost of more than $546 million per election cycle if all Congressional seats were to flip from Democrat to Republican.

In Panel B of Table 8, we conduct a placebo test using health outcomes that are less likely to be directly related to pollution, such as mental health issues and infectious diseases. This test helps to alleviate concerns that health outcomes broadly improve in areas represented by Democrats for reasons other than decreased pollution. If this were true, we would expect improvements in health outcomes across many categories of illnesses, and not only for respiratory diseases. However, Panel B shows that there are no incremental effects on our placebo health outcomes in pollution-sensitive areas when the district politician is a Democrat. These results suggest that our main findings in Panel A are indeed related to the politically-motivated changes in local pollution documented by our main

[35] As described in Section 2, a single Zip3 area can span multiple Congressional districts, which allows us to identify Zip-district fixed effects.

[36] The difference in magnitudes is 6.6%, and on average there are 727 discharges per high-plant 3-digit Zip code per year and 1.4 high-plant Zip codes per district. Hence, the expected district-wide effect is 6.6% $\times$ 727 $\times$ 1.4 = 67 discharges.

tests.

4.6.1 Reallocation

We also examine whether there is, in effect, a reallocation of public health costs that mirrors firms' reallocation of pollution across plants (Table 6). As in Table 6, for each firm-plant-time triad, we compute the fraction of the firm's *other* plants that are represented by Democrats at that point in time. Since health outcomes are measured at the Zip3 level, we compute the average of this fraction across all plants within a given Zip3 area. We then assess whether respiratory illnesses in a given area are higher in cases where the plants in that area are owned by firms whose *other* plants are in areas represented by Democrats.

Figure 6 shows that adverse respiratory health effects are indeed stronger in Zip3 areas where plants are owned by firms whose other plants are primarily represented by Democrats. As a placebo test, we also examine whether adverse health effects for non-respiratory diseases also increase in these areas. The answer is no, as shown in Figure A10: if anything, non-respiratory illnesses drop in these areas on a relative basis.

4.6.2 Firm-Level Effects

Finally, we roll up health outcomes at the firm level and assess whether aggregate respiratory discharges and payments decrease at the firm level following Democrat wins. Aggregating health outcomes is complicated by the fact that health outcomes cannot be traced to a specific firm or plant. In addition, unlike Table 8, we cannot feasibly compare high-plant versus low-plant areas since most firms do not own plants in both high-plant and low-plant areas within the same district. As such, it is not possible to calculate the precise firm-level health effects associated with changes in districts' Congressional representation.

However, it is possible to provide a very rough estimate of these effects. To partially overcome the challenges above, we aggregate all annual respiratory discharges and payments at the three-digit Zip code level and then assign these aggregate levels to each plant within the area. A firm's total and average annual respiratory discharges/payments are then defined as the sum (average) of all three-digit Zip discharges/payments associated with the firm's various plant locations. As in Table 7, we relate these firm-level health effects to *Democrat Share* and *Emissions-Weighted Democrat Share*, which capture the fraction of the firm's plants that are represented by Democrats.

Table A9 contains the results of these tests. Columns (1)–(4) examine total discharges and average discharges for all firms in the sample, while columns (5)–(8) examine total discharges and average discharges at multi-plant firms. Columns (1)–(4) show that there is a statistically noisy but economically sizable relationship between firm-level discharges and *Democrat Share*. For example, column (3) shows that moving the share of a firm's plants represented by Democrats from zero to one would be associated with a 4.4% decline in the firm's average discharges (though this result is not statistically significant). Columns (5)–(8) show that these effects are much larger at multi-plant firms: for example, column (7) shows that average discharges drop by more than 9% when *Democrat Share* is moved from zero to one. Collectively, these results – while speculative – indicate that even though firms do their best to reallocate illnesses, the net effects of Democratic victories on respiratory illnesses in their districts are material.

4.7 Mechanism: Increased Regulatory Oversight

Why do plants reduce pollution in a district following a close Democratic victory? We argue that politicians lean on regulators to increase environmental inspections and enforcement. Given an expected increase in inspections and enforcement, plants that are at risk of over-polluting should reduce pollution provided that the cost of reducing pollution is lower than the expected pecuniary and non-pecuniary penalties from over-polluting.

A necessary condition for this hypothesis to be true is that firms are indeed over-polluting (or have a higher risk of over-polluting) prior to a Democrat winning a close election. While it is not possible to directly measure whether firms are over-polluting, the narrative above yields a simple prediction: all else equal, when a Democrat is closely elected, we would expect larger reductions in pollution at plants with high *prior* pollution, since these are the plants that were most likely to be over-polluting prior to the election. Figure A11 confirms that this is indeed the case: the drop in emissions is significantly larger at firms with above-median pollution within a given state-chemical-year triad. Hence, the largest drops in pollution following a close Democratic win occur at the plants with the highest level of pre-election pollution.

We next study the effect of close Democratic wins on EPA-related inspections at the plant-year level. In the first two columns of Table 9, we focus on the total (intensive and extensive margin) effects of close elections on regulatory inspections. We find that close election victories by Democrats are associated with a 6.8%-7.8% increase in overall inspection volumes, which is significant. We next examine the extensive margin. In columns (3) and (4), we show that district wins by Democrats lead to a 2.2% increase in the likelihood of getting at least one inspection. This number is large, corresponding to a 6.7% increase relative to the unconditional probability of 32.64% of receiving at least one inspection for the average plant in our sample. We then examine the intensive margin. We find that close district wins by Democrats are systematically associated with a 17.7% to 21.4% increase in inspections for plants that are already subject to inspections (i.e., plants with non-zero annual inspections). Figure 7 displays this pattern graphically. To put the magnitudes in perspective, conditional on receiving at least one inspection, the average plant in our sample receives 2.44 inspections per year. A 20% increase in inspections—as implied by our estimates when a Democrat wins—leads to an extra 0.49 annual inspections relative to the mean. Overall, the results of Table 9 provide strong evidence that Democrat district affiliation results in more EPA inspections, suggesting that Democrat representatives may induce environmental agencies to monitor firms' emissions more closely.

Does increased monitoring also result in stricter enforcement when a district is won by Democrats? In the absence of frictions, it is not clear that realized enforcement actions should change significantly: firms should optimally reduce pollution once the expected cost of over-polluting goes up. Hence, the expected effects of increased monitoring on realized enforcement penalties are unclear. Nonetheless, in the presence of frictions such as asymmetric information about inspection thoroughness, it seems reasonable to think that, even as firms are reducing pollution, there may still be a greater number of enforcement actions per inspection due to inspectors writing up firms for minor infractions that would not have been penalized under Republican representatives.

In Table 10, we study enforcement actions and pecuniary penalties at the plant-year level. In Panel A, we start from the intensive margin of enforcement. Columns (1) and (2) show that the probability of an enforcement action (either formal or informal) increases by around 6.4% when the district where the plant is located is just-won by a Democrat. Figure 8 presents this pattern graphically. Again, this estimated effect implies a large increase in enforcement actions, given that the unconditional probability of an enforcement following an inspection is equal to 21.98%. In other words, Democrat wins increase the probability of an enforcement by 29.11% following an inspection.

Importantly, in Columns (3)-(6) of Panel A, we show that the main effects from Columns (1) and (2) come primarily from an increase in *informal* enforcement (e.g., cease and desist letters) as opposed to formal enforcement (e.g., civil legal actions). Close Democrat wins are associated with a 7.7% increase in the probability of an informal enforcement action (an increase of 47.65% relative to the unconditional probability of 16.16% of an informal enforcement after an inspection), and only with a 2.7% increase in the probability of a formal action (an increase of 24.59% relative to the unconditional probability of 10.98% of a formal enforcement after an inspection). Consistent with these estimates, in the last two columns of Panel A we also confirm that the probability of a monetary penalty increases by around 2.2% following a close Democratic win.

In Panel B of Table 10, we confirm that our enforcement results also hold on the intensive margin—enforcement actions per inspection increase by around 0.05 (a 27% increase relative to the sample mean) and informal enforcement actions per inspection increase by around 0.055 (a 52% increase relative to the sample mean) when a Democrat representative just-wins the district. On the other hand, formal enforcement actions per inspection and penalties per inspection do not experience statistically significant changes when a Democrat gains control of the local district.

The EPA delegates most of the enforcement of federal environmental protection laws to state regulatory agencies.[37] Consistent with the idea that state regulators are the primary agencies responsible for enforcing EPA regulations, Table A10 shows that our results on inspections and enforcement are mostly driven by state (as opposed to federal) regulators, though the main results hold for federal regulators as well. This suggests that, to the extent that politicians are actually interfering with regulatory agencies, such political interference appears to mostly happen at the state rather than the federal level in our sample.

If Democratic representatives are causally affecting the number of inspections carried out by state

[37]Generally speaking, if a state has more stringent environmental protection laws than the federal EPA laws, then the EPA usually delegates inspection and enforcement authority to the state.

regulators, we would also expect the budgets of state agencies responsible for enforcing federal environmental laws to be an increasing fraction of the number of districts represented by Democrats (regardless of which party holds the governor's seat). Consistent with this conjecture, Figure A12 uses data from the Environmental Council of States to show that both a state's total environmental agency budget and the component of the environmental budget funded by the Federal government are increasing in the fraction of districts represented by Democrats. While this test is only suggestive, it supports the idea that representatives are playing an important role in the enforcement of environmental regulations within their home states.

4.8 Additional Robustness

4.8.1 Within-party Variation

Our main hypothesis is that the ideology of politicians causes them to take actions to affect pollution in their home districts. By sorting politicians into groups based on their political party, our tests implicitly assume that political party memberships capture meaningful differences in the personal ideologies of politicians. Figure 1 provides evidence supporting this assumption: the figure shows that the amount of inter-party variation in LCV scores is many times larger than the amount of intra-party variation in representatives' environmental voting records. Nonetheless, it is important to verify more systematically that politicians' actions are driven by their ideological views about the environment and not by some other factor that systematically differs between Democrats and Republicans.

To do so, we exploit *within-party* ideological differences to see if, for example, firms pollute less in districts just won by Democrats with strongly pro-environment voting records relative to firms in other districts just won by Democrats with weaker environmental voting records. This test allows us to confirm that it is the ideology of the politician, rather than the politician's party, that is causing the changes in observed pollution levels at constituent firms.

We measure ideology in two ways. First, we obtain Member Ideology scores for each representative from the VoteView database. These scores are calculated based on politicians' voting records using the DW-NOMINATE methodology. Second, we utilize the same annual LCV environmental scorecards that we used to construct Figure 1. LCV reports a score ranging from 0 to 100 for each representative based on their voting record on environment-related bills, with 100 representing a perfect pro-environment voting record.

The results of this test are reported in Figure 9. The figure shows that the reductions in firm pollution are much stronger in districts just won by "deep blue" (more pro-environment) Democrats than in districts just won by "light blue" Democrats. This result provides further evidence that the reductions in pollution documented in Table 2 are caused by differences in political ideology between Democrats and Republicans rather than other factors that happen to be correlated with political party membership.

4.8.2 Seat Pickups

If partisan ideology is a key driver of politicians' influence over emissions in their district, we would also expect to see strong effects on emissions when a district switches from being represented by a Democrat to being represented by a Republican (and vice versa; often known as a "pickup" for the winning party). To test this hypothesis, we start with all facilities that were represented by Republicans in the year prior to an election. We then break up these facilities into those that were represented by a Democrat after the election, and those that were represented by a Republican. We perform a similar exercise for facilities initially represented by a Democrat.

Table A11 confirms that seat pickups are associated with strong effects on local firms' pollution. Columns (1) and (2) show that, after a district moves from Republican to Democratic representation, relative emissions at facilities in that district decline by approximately 6%. Columns (3) and (4) show that, after a district moves from Democratic to Republican representation, relative emissions at facilities in that district rise by approximately 3%. Figure 10 displays these patterns graphically. Collectively, these findings support the idea that partisan ideological differences are at least partially responsible for the stark changes in emissions in red versus blue districts during our sample period.

4.8.3 Reelection

We also show that changes in firms' emissions do not affect politicians' reelection probabilities. In Table A12, we use district-level emissions growth rates to predict whether an incumbent politician will be reelected. We define *Reelected* as equal to one if a sitting politician is reelected and equal to zero otherwise. We then interact the *Democrat Win* variable (from the previous election) with the district-level emissions growth rate during the politician's latest term (just prior to reelection). If Democratic politicians' preference for low emissions is a response to career considerations (such as shifts in voter preferences in their districts), then Democrats should be more likely to win reelection when the growth rate of emissions at constituent firms is low during their terms. However, the interaction term in all columns of Table A12 is statistically and economically insignificant, providing further support that career incentives and changes in voter preferences are unlikely to explain our results.

4.8.4 Political Power

All else equal, greater political power should translate into a greater ability to influence regulators. Hence, we might expect our results to be stronger for powerful politicians such as the chair or ranking member of House committees. In addition, all else equal, politicians with stronger ideological views should have a higher probability of influencing regulators. Thus, we might expect our results to be strongest for the *interaction* of politicians' ideologies and political power.

To examine this hypothesis, we perform a triple-difference analysis that interacts our main *Democrat Win* variable with a committee chair dummy variable and another dummy variable related to a politician's ideology. We construct a dummy variable that equals one if a member is a committee chair, and takes the value of zero otherwise. We also construct a second variable that captures the strength of House members' political ideologies. This variable takes the value of one if a politician has a strong ideology (ideology score in the top quartile of the distribution) in either direction and takes the value of zero otherwise. We then interact these variables with each other and with our main *Democrat Win* variable.

The results are presented in Table 11. We find three results. First, there is still a reduction in pollution in districts represented by non-committee-chair, less-ideological Democrats. Second, this result is not stronger (and is if anything weaker) for districts represented by less-ideological *committee chairs*, suggesting that political power alone is not a major contributing factor to our results. Third, and most importantly, in columns (3)–(5), we find very strong effects coming from ideological Democratic committee chairs – the loading of -0.249 for the *Low Id. Score* $\times$ *Democrat Win* $\times$ *Committee Chair* variable in column (5) is more than 10 times larger than the loading on the main effect in the same column. This suggests that powerful committee chairs with strong ideologies may be most adept at influencing state environmental regulators and/or influencing pollution decisions at firms in the districts they represent.

4.8.5 Political Connections

Finally, a natural concern is that our findings are simply capturing the effects of politically connected firms, who may alter their pollution behavior for reasons other than the politician's partisan ideology (such as, for example, to help the politician win election or reelection to office). This explanation seems unlikely for a number of reasons; for example, it is not clear why these effects would be concentrated amongst the most ideological representatives from both parties, and it is not clear why inspections and enforcement would change. Nonetheless, to rule out this explanation, we use campaign contribution data from the FEC to split firms each year into those who donated to the (winning) local representative in the most recent election cycle (connected firms), and those that did not (unconnected firms). We then restrict the sample to only include plants owned by unconnected firms. Figure A13 confirms that our main results are unchanged when we focus solely on plants owned by firms that are not connected to their local U.S. representative. This reinforces the central point that our main results appear to be capturing the effect of *political ideology* on regulatory and firm outcomes.

5 Conclusion

How do politicians' partisan beliefs translate into changes in firm behavior? In this paper, we provide causal evidence that politicians' ideology affects constituent firms' industrial pollution decisions. We focus on pollution decisions because of the availability of detailed, facility-level pollution and production data, and because politicians are strongly ideologically polarized on the issue of pollution.

Using a regression discontinuity design involving election outcomes in close U.S. congressional races, we find that plants pollute less when they are represented by a closely-elected Democrat than when they are represented by a closely-elected Republican. The decline in pollution stems from costly increases in abatement investment and post-production treatment activities, not from reduced production. We also show that multi-plant firms appear to reallocate pollution across plants after a change in one plant's political representation: using Giroud and Mueller (2019)-style tests, we show that a firm's individual plants pollute more and recycle less when more of the firm's *other* plants are represented by Democrats. Our results survive a battery of robustness tests and are stronger within party for more ideological representatives, confirming ideology as the main driver behind the wedge we observe in politicians' pollution postures.

Since we measure firms' compliance with federal environmental laws (that apply equally all over the country), our setting allows us to largely abstract from changes in legislation or rule-making. As such, we focus on politically-motivated regulatory interference as a plausible potential mechanism. Consistent with this mechanism, we show that facility inspections by environmental regulators increase by approximately 20% and informal enforcement actions rise significantly after a Democratic close election win.

Finally, we show that pollution differences caused by politicians' partisan ideologies can have meaningful impacts on the health of local communities. Hospital discharges and payments for respiratory diseases decrease around plants in Congressional districts represented by Democrats, whereas discharges and payments for illnesses plausibly unrelated to pollution do not change. In addition, we show that there is a reallocation of community health costs after a Democrat wins, with pollution – and health costs – being reallocated to other plants that are not represented by Democrats. Collectively, our results confirm that the AOC-Amazon dispute highlighted in the introduction is part of a larger trend: U.S. politicians routinely impart their partisan ideological beliefs on constituent firms in an extralegal fashion, and these outcomes can have significant consequences for the health of local communities.

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Figure 1

Environmental Polarization Over Time

This figure plots the median annual League of Conservation Voters (LCV) scores of Democrats and Republicans in the U.S. House of Representatives from 1991 to 2020. The LCV computes scores based on politicians' voting records on legislation related to the environment. A higher LCV score indicates that a politician voted in favor of a higher number of pro-environment law proposals. The data was retrieved from the LCV website.

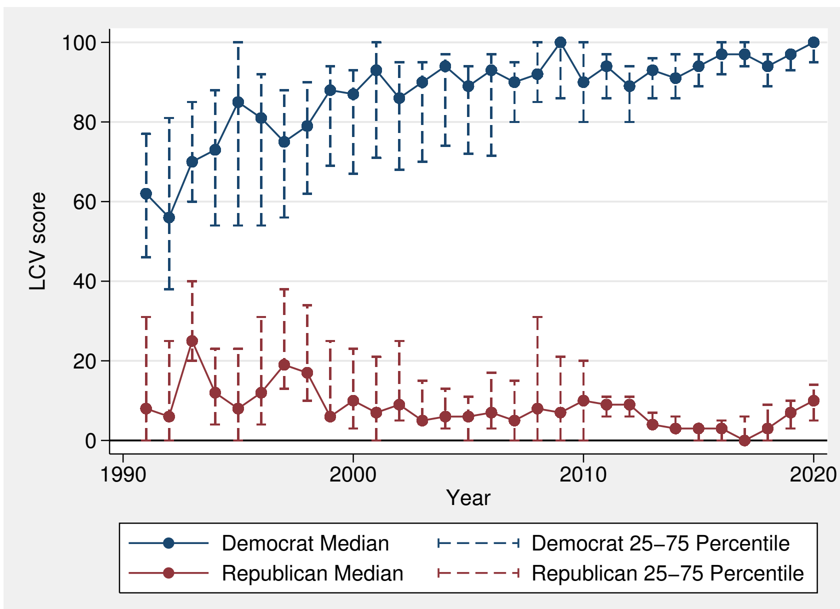

Figure 2

RD using Close Elections: Emissions

The figure plots the natural logarithm of facility-chemical-level toxic emissions in the two years following Congressional elections as a function of the vote share margin of a Democratic candidate in a congressional district. The vote share margin is the percentage by which a candidate won (lost) the election in a given district, and the sample uses elections won or lost by a margin of 5% or less. In the figure, we plot average emissions in the two years following a district election for 36 bins of the election win margin distribution, as well as fitted values and 95% confidence intervals of local polynomial regressions fitted on each side of the zero win margin threshold. The data on emissions is available at the facility-chemical-year level from the EPA's Toxics Release Inventory (TRI) database. The sample period is 1991-2016.

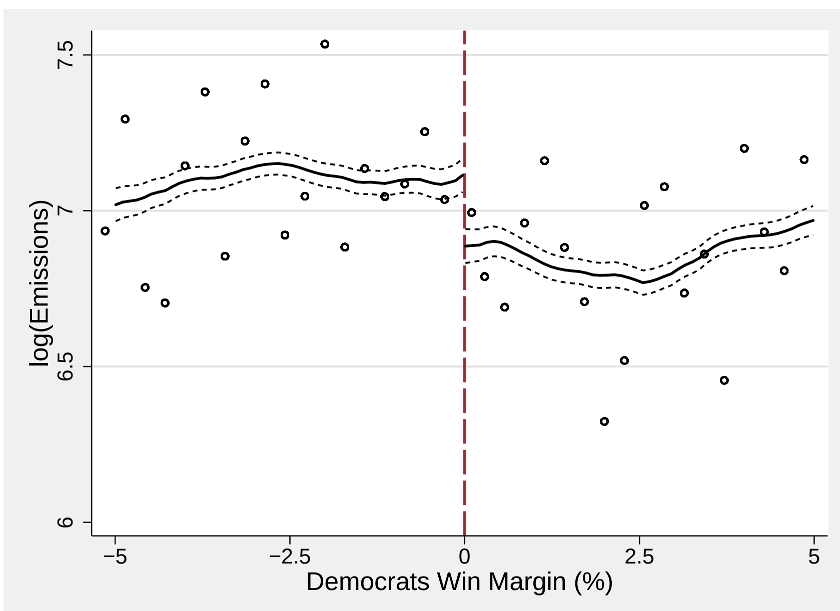

Figure 3

Within-Firm Reallocation of Toxic Emissions

This figure plots the relationship between a plant's emissions and the share of the other plants of the same firm that are represented by Democrats. To produce this figure, we first remove any time-invariant differences in the total level of emissions for each chemical by regressing facility-level emissions on chemical fixed effects. We drop single-plant firms from the sample, and we construct a plant-level variable representing the share of the same firm's *other plants* that are represented by Democrats. We call this plant-level variable "Other Facilities' Democrat Share." In the figure, we plot average emissions in 25 bins of the "Other Facilities' Democrat Share" distribution. All the variables are defined as in Table 1, and the sample period is 1991-2016.

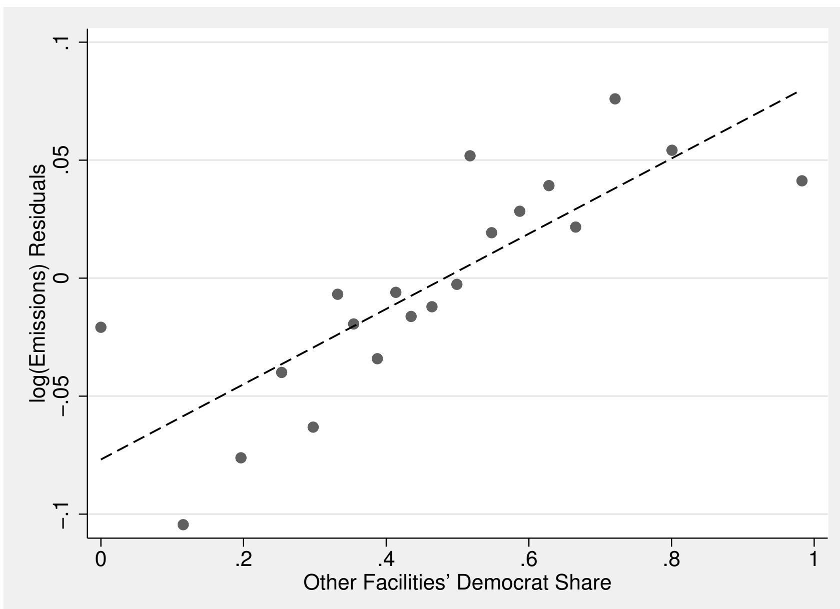

Figure 4

Reallocation of Toxic Emissions: RD Evidence

In this figure, we repeat the same exercise as in Figure 2, but we split the sample into plants that have above- and below-median values of the "Other Facilities' Democrat Share" variable. This variable captures, for each plant-chemical-year triad, the share of the plant owner's *other* plants that are represented by Democrats. For ease of interpretation, we report our results as a function of the Republican win margin. As in Figure 3, to produce this figure we only keep firms that have plants in more than one district. All the variables are defined as in Table 1, and the sample period is 1991-2016.

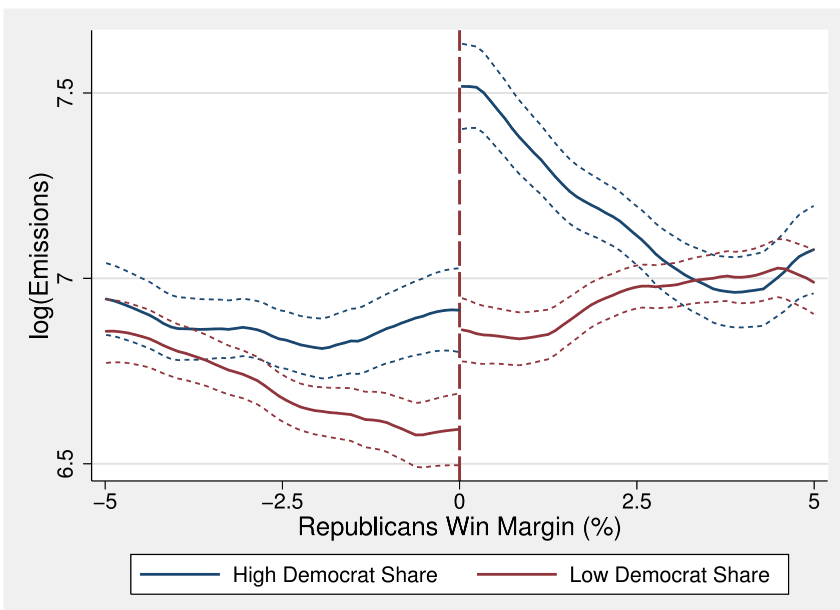

Figure 5

Within-Firm Reallocation of Post-Production Activities

This figure plots post-production recycling activities as functions of the share of the other plants of the same firm that are represented by Democrats. To produce this figure, we follow the same procedure as in Figure 3 by first removing time-invariant chemical fixed effects from the recycling levels and then plotting the residuals in 25 bins of the "Other Facilities' Democrat Share" distribution. The post-production activity ratio is the ratio of emissions reduced through post-production treatment, recycling, and energy recovery activities to the total gross waste of a plant. The total gross waste of a plant is the sum of total actual releases and the emissions that are reduced through treatment, recycling, and energy recovery activities. All variables are defined as in Table 1, and the sample period is 1991-2016.

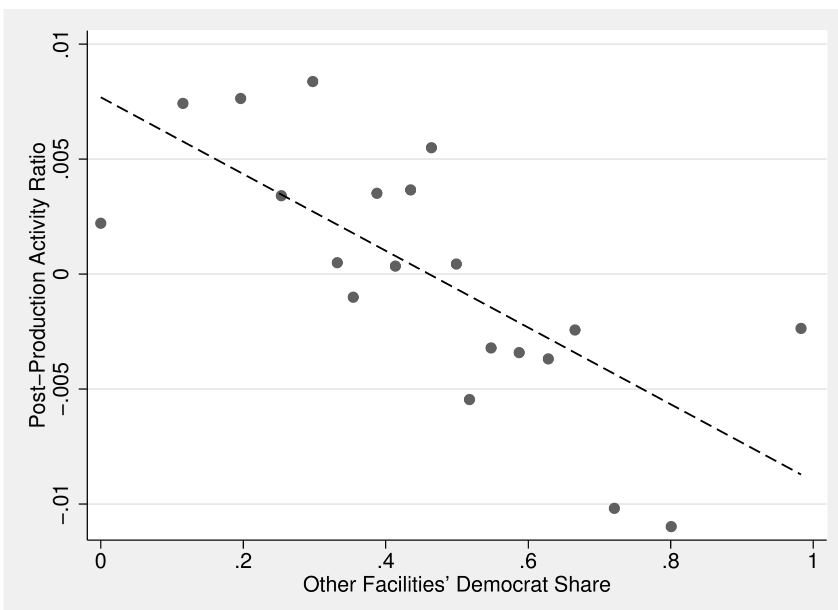

Figure 6

Reallocation Tests: Respiratory Diseases

This figure plots the relationship between the number of patient discharges related to respiratory diseases in an area, and the average value of "Other Facilities' Democrat Share" across plants located in that area. The procedure we follow to produce this figure is similar to that described in Figure 3, but the horizontal axes in this figure represent *average* values of "Other Facilities' Democrat Share" for all plants located in an area. Panel A includes Zip codes that contain a number of establishments higher than the median in our sample, and Panel B includes Zip codes with a number of establishments lower than the median. The data on patient discharges is described in Table 1. All variables are defined as in Table 1, and the sample period is 2011-2016.

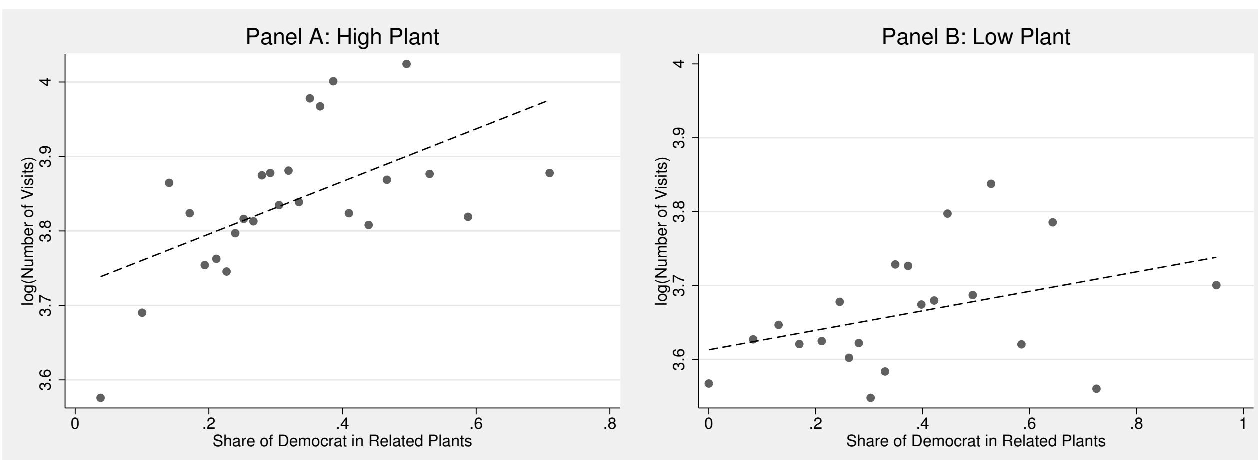

Figure 7

RD using Close Elections: Inspections

The figure plots the natural logarithm of facility inspections in the two years following Congressional elections as a function of the vote share margin of a Democratic candidate in a congressional district. Inspection data comes from the EPA's ECHO data set. The figure is identical to Figure 2 except for the outcome variable. All variables are defined as in Table 1, and the sample period is 1991-2016.

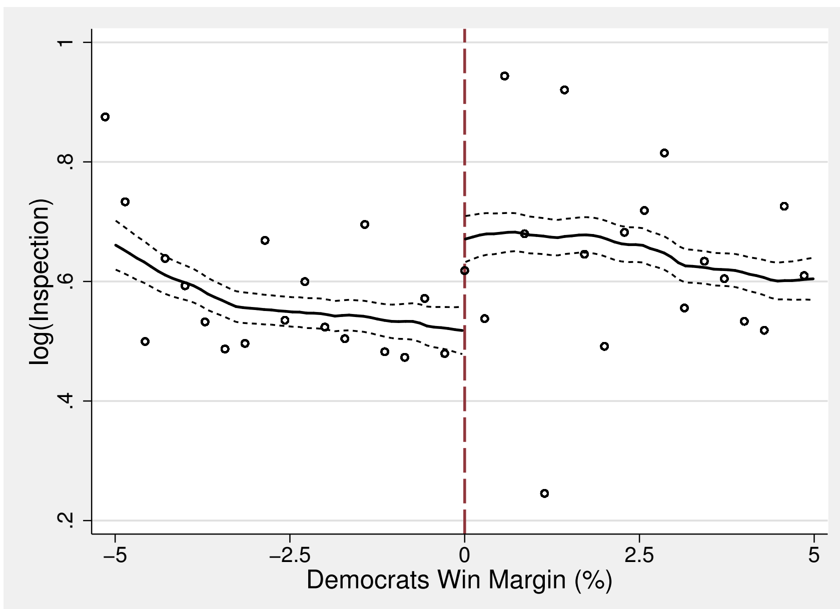

Figure 8

RD using Close Elections: Enforcement

The figure plots the natural logarithm of facility inspections in the two years following Congressional elections as a function of the vote share margin of a Democratic candidate in a congressional district. The figure is identical to Figures 2 and 7 except for the outcome variable. All variables are defined as in Table 1, and the sample period is 1991-2016.

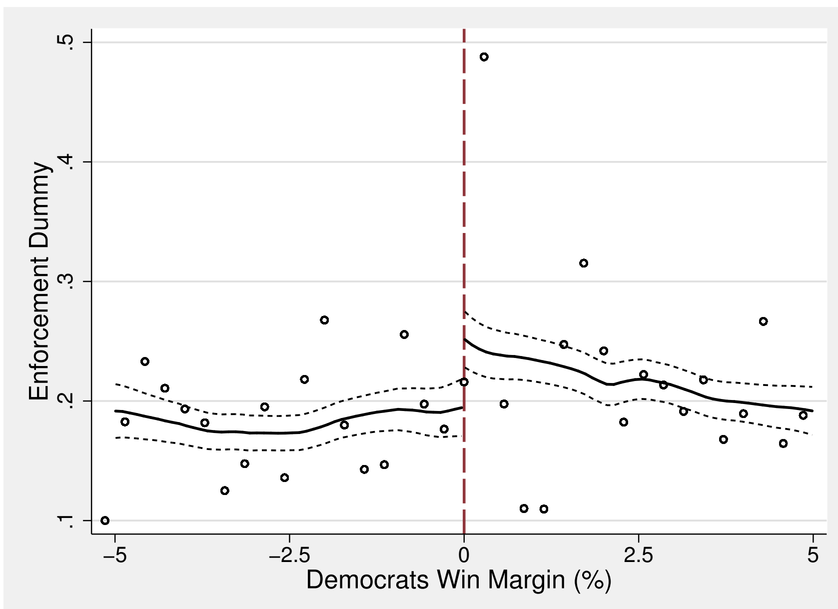

Figure 9

The Effects of Ideology

In this figure, we split the sample of close elections based on Democrats' ideology using two measures of ideological variation: ideology scores from the VoteView database of voting records, and environmental scorecards from the League of Conservation Voters (LCV). As in Figure 2, the figure plots the natural logarithm of toxic emissions at the facility-chemical-year level in the two years following Congressional elections as a function of the vote share margin of a Democratic candidate in the congressional district. In Panel A, our measure of ideology is the politician's ideology score from VoteView (updated annually). The deep blue line represents marginal wins by Democrats in the 25th percentile of the Democrat ideology distribution, while the light blue line represents marginal Democrat wins by all other Democrats. In Panel B, our measure of ideology is the politician's annual LCV score. The deep blue line represents marginal wins by Democrats in the 75th percentile of the Democrat LCV score distribution, while the light blue line represents marginal Democrat wins by all other Democrats. The LCV scores come from the LCV website. Democrat win margin is the percentage by which a Democrat candidate won or lost the election. The sample uses elections won or lost by a margin of 5% or less.

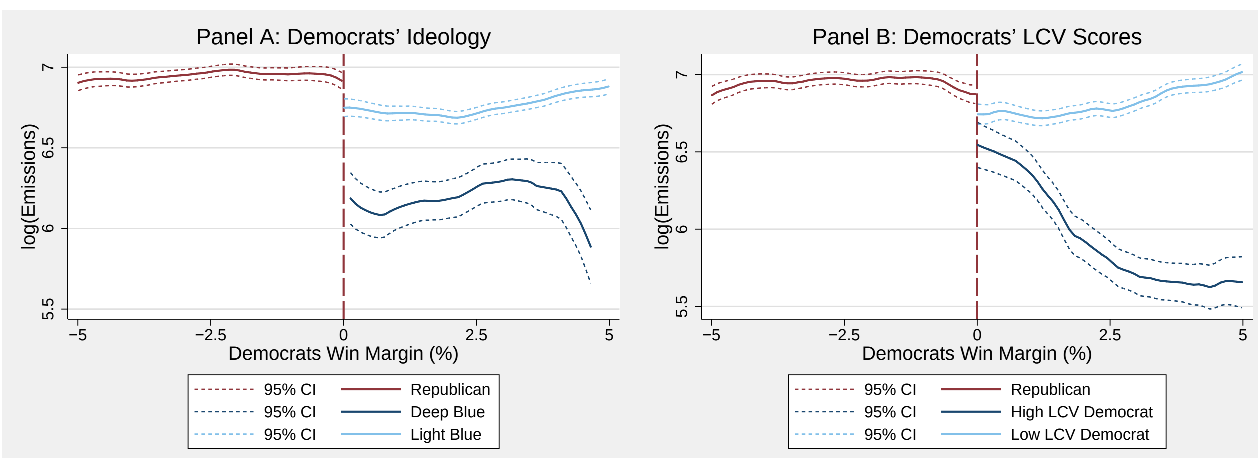

Figure 10

Examining "Switchers"

The figure shows the difference in emissions for facilities located in areas that switch from a Democratic to a Republican representative, and vice versa. In Panel A, we average emissions across all facilities represented by Democrats in a given election cycle, and then compute the average difference in emissions for districts that switch to a Republican representative in the next election cycle and those that keep a Democrat representative in the next election cycle. In Panel B, we average emissions across all facilities represented by Republicans in a given election cycle, and then compute the average difference in emissions for districts that switch to a Democrat representative in the next election cycle and those that keep a Republican representative in the next election cycle. In the figure, we report average differences as well as 95% confidence intervals around these averages, and we normalize emission differences to equal zero in the year of the (November) election. All the variables are defined as in Table 1, and the sample period is 1991-2016.

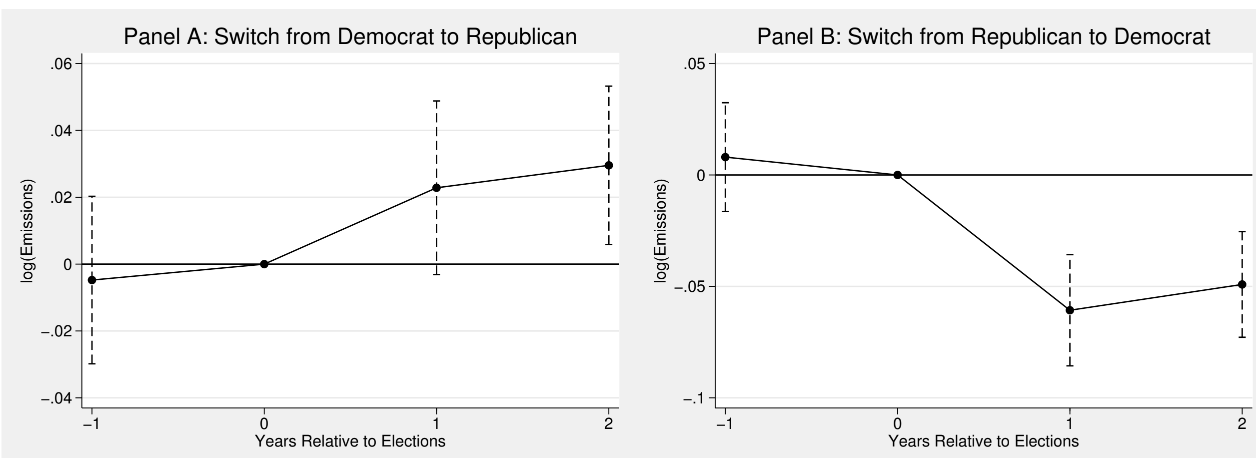

Table 1

Summary Statistics

This table presents summary statistics for the main variables in the paper. Emissions are annual toxic chemical releases (in pounds) at the facility-chemical-year level over the period 1991-2016, available on the U.S. Environmental Protection Agency's (EPA) website. Congressional election data are from the MIT Election Data and Science Lab. Abatement is the number of source reduction activites at the facility-chemical-year level over the period 1991-2016 reported in the EPA's Pollution Prevention (P2) database. The post-production reduction ratio is the ratio of emissions reduced through post-production treatment, recycling, and energy recovery activities to the total gross waste of a plant over the period 1991-2016, available from the EPA TRI database. Cost of goods sold, Market-Book ratio and Tobin's Q are from Compustat, which we hand-match with the TRI data based on the name of the firm. Health data, including the number of discharges and total payments (in millions of US dollars) for respiratory diseases and non-pollution related diseases are from the Center for Medicare & Medicaid Services (CMS) over the period 2011-2016. Environmental regulation compliance data including inspections, enforcement actions, and penalties, are from the EPA's Enforcement and Compliance History Online (ECHO) dataset over the period 1991-2016. All data is publicly-available.

	Mean	SD	p10	p50	p90	Facilities	Observations
Emissions	30845.79	177340.99	0.00	369.00	43486.00	37,369	1,784,978
Democrats Win Margin	2.67	36.88	-41.26	0.96	50.43	.	5,304
Source Reduction Abatement	0.26	0.77	0.00	0.00	1.00	36,262	1,589,601
Post-production Reduction Ratio	0.50	0.45	0.00	0.55	1.00	37,369	1,535,051
log(COGS)	6.83	1.82	4.50	6.83	9.10	.	19,578
Market-Book Ratio	3.12	3.19	0.94	2.25	5.70	.	15,991
Tobin's Q	1.67	0.79	0.99	1.43	2.65	.	16,814
Discharges (Respiratory)	54.45	58.33	13.00	34.00	121.00	.	60,352
Total Payment (Respiratory)	0.48	0.54	0.10	0.30	1.10	.	60,352
Discharges (Placebo)	82.25	138.20	12.00	32.00	205.00	.	28,282
Total Payment (Placebo)	1.06	1.76	0.09	0.43	2.71	.	28,282
Inspections	0.80	1.67	0.00	0.00	2.00	37,333	438,272
Enforcement	0.15	0.53	0.00	0.00	0.00	37,333	438,272
Formal Enforcement	0.06	0.30	0.00	0.00	0.00	37,333	438,272
Informal Enforcement	0.09	0.35	0.00	0.00	0.00	37,333	438,272
Penalty	277.89	1889.76	0.00	0.00	0.00	37,333	438,272

Table 2

Representatives' Political Ideologies and Toxic Emissions

In this table, we study the effect of marginal district wins by Democratic Party candidates on emissions by local plants. In column (1), we regress the natural logarithm of plant-level emissions on a dummy equal to one if the district where the plant is located was won by a Democrat in its most recent election, and equal to zero otherwise. In columns (2)-(3), we augment this specification with a linear interaction term between the dummy and Democrat margin votes in a local OLS regression framework. In columns (4)-(7), we use non-parametric local polynomial RD estimators (Calonico, Cattaneo, and Titiunik, 2014), experimenting with linear and quadratic polynomials and triangular and Epanechnikov kernels. In columns (1)-(3), we report standard errors clustered at the district-year level. In columns (4)-(7), we report robust bias-corrected standard errors as in Calonico, Cattaneo, and Titiunik (2014). The dependent variable is defined as in Table 1, and the sample contains all district elections during the period 1991-2016. In columns (1)-(3), we restrict the sample to district elections with an absolute vote margin of less than 5% during the same period.

	Dep. Variable: log(Emissions)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Democrat Win	-0.213**	-0.397**	-0.305***	-0.355***	-0.349***	-0.353***	-0.355***
	(0.08)	(0.16)	(0.12)	(0.03)	(0.03)	(0.04)	(0.04)
Method	Local OLS	Local OLS	Local OLS	NP	NP	NP	NP
Polynomial	Zero	Linear	Linear	Linear	Linear	Quadratic	Quadratic
Kernel	–	–	–	Tri.	Epa.	Tri.	Epa.
Chemical FE	No	No	Yes	–	–	–	–
Observations	94,140	94,140	94,111	1,329,508	1,329,508	1,329,508	1,329,508

Note: Standard errors in parentheses. ***, **, and * respectively denote statistical significance at the 1%, 5%, and 10% levels.

Table 3

Emissions and Plant Production

In this table, we study the effect of marginal district wins by Democratic Party candidates on emissions per unit of production. The dependent variable is the natural logarithm of cumulative emissions per production at the plant-chemical level, as described in Equation (4). In column (1), we regress this outcome variable on a dummy equal to one if the district where the plant is located is marginally won by a Democrat, together with a linear interaction term between the dummy and the Democrat vote margin in a local linear OLS framework. In column (2), we use the non-parametric local polynomial RD estimator of Calonico et al. (2014), specifying a linear polynomial and a triangular kernel. We report standard errors clustered at the district-year level for the local linear OLS regression and robust bias-corrected standard errors as in Calonico et al. (2014) for the non-parametric regression. The sample contains all district elections during the period 1991-2016. In column (1), we restrict the sample to district elections with an absolute vote margin of less than 5% during the same period.

	log(Cumulative Emissions/Production)	
	(1)	(2)
Democrat Win	-0.093*	-0.057***
	(0.06)	(0.02)
Method	Local OLS	NP
Polynomial	Linear	Linear
Kernel	–	Tri.
Chemical FE	Yes	–
Observations	84,306	1,178,073

Note: Standard errors in parentheses. ***, **, and * respectively denote statistical significance at the 1%, 5%, and 10% levels.

Table 4

Abatement and Post-Production Activity Tests

In this table, we study the effect of marginal district wins by Democratic Party candidates on source abatement investment and on post-production treatment, recycling, and energy recovery activities. In columns (1)-(2), the dependent variable is the natural logarithm of 1 + the total number of plant-level abatement activities for a specific chemical in a year. The dependent variable in columns (3)-(4) is the ratio of emissions reduced through post-production treatment, recycling, and energy recovery activities to the total gross waste of a plant—the sum of the plant's total actual releases and the emissions that are reduced through treatment, recycling, and energy recovery activities. The specifications mimic those in Table 3. The dependent variable is defined as in Table 1, and the sample contains all district elections during the period 1991-2016.

	Log(1+Abatement)		Post-Production Reduction Ratio	
	(1)	(2)	(3)	(4)
Democrat Win	0.033*	0.018***	0.029**	0.023***
	(0.02)	(0.00)	(0.01)	(0.00)
Method	Local OLS	NP	Local OLS	NP
Polynomial	Linear	Linear	Linear	Linear
Kernel	–	Tri.	–	Tri.
Chemical FE	Yes	–	Yes	–
Observations	104,915	1,491,554	102,529	1,438,871

Note: Standard errors in parentheses. ***, **, and * respectively denote statistical significance at the 1%, 5%, and 10% levels.

Table 5

Political Ideology and Within-firm Emissions

This table uses OLS panel regressions to examine the relationship between a plant's toxic emissions and the political affiliation of the local representative. In this table, the dependent variable is the natural logarithm of emissions at the plant-chemical-year level in the two years following a district election. Democrat Win is an indicator that takes the value of one if a candidate from the Democratic party won the last election in the district where the plant is located. Standard errors are clustered at the district-year level. The sample period is 1991-2016.

	Dep. Variable: log(Emissions)				
	(1)	(2)	(3)	(4)	(5)
Democrat Win	-0.059***	-0.042***	-0.020**	-0.018*	-0.020*
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Census District FE	Yes	No	No	No	No
Year FE	Yes	No	No	No	No
Firm × Chemical × Year FE	No	Yes	Yes	Yes	Yes
Census District × Chemical FE	No	Yes	No	No	No
Facility × Chemical FE	No	No	Yes	Yes	Yes
State × Year FE	No	No	No	Yes	No
State × Year × Chemical FE	No	No	No	No	Yes
R-Squared	0.076	0.850	0.929	0.929	0.938
Observations	1,329,508	790,904	782,632	782,632	739,229

Note: Standard errors in parentheses. ***, **, and * respectively denote statistical significance at the 1%, 5%, and 10% levels.

Table 6

Reallocation of Toxic Emissions

This table examines how a facility's pollution depends on the political party representation of the firm's other facilities. In columns (1) and (2), we regress annual plant-chemical-level toxic emissions on the share of plants owned by the same firm at the same time that are represented by a Democrat, which we refer to as "Other Facilities' Democrat Share," as in Figure 3. In columns (3) and (4), we regress emissions on an indicator for whether this share is above the median in our sample. Standard errors are clustered at the district-year level. The dependent variable is defined as in Table 1, and the sample contains all district elections during the period 1991-2016.

	Log(Emissions)			
	(1)	(2)	(3)	(4)
Other Facilities' Democrat Share	0.028**	0.063***		
	(0.01)	(0.01)		
Local Democrat	-0.018*		-0.017*	
	(0.01)		(0.01)	
High Other Facilities' Democrat Share			0.015**	0.027***
			(0.01)	(0.01)
District × Chemical FE	Yes	Yes	Yes	Yes
Chemical × Year FE	Yes	Yes	Yes	Yes
Facility × Chemical FE	Yes	Yes	Yes	Yes
District × Chemical × Year FE	No	Yes	No	Yes
R-Squared	0.890	0.922	0.890	0.922
Observations	1,128,556	897,686	1,128,556	897,686

Note: Standard errors in parentheses. ***, **, and * respectively denote statistical significance at the 1%, 5%, and 10% levels.

Table 7

Firm-Level Pollution and Financial Outcomes

In this table, we examine the firm-level financial effects of changes in environmental pollution. The unit of observation is a firm-chemical-year. We examine firms' costs of goods sold (COGS), market-to-book ratios (M/B) and Tobin's Q. COGS should include any changes in the cost of abatement, while the M/B ratio should capture the cumulative expected financial effects of a change in firms' pollution profiles. To obtain firm-level COGS, we manually match each firm name in the EPA-TRI dataset with firm names in Compustat. The variable Democrat share in columns (1), (3), (5) and (7) is the fraction of a firm's total plants operating in a Democrat district. In columns (2), (4), (6) and (8), we weigh each plant-chemical-year observation by its total emission levels, such that plant-chemical Democrat Share observations associated with higher emissions receive more weight. The dependent variable in columns (1)-(2) is the natural logarithm of firm-level emissions. The dependent variable in columns (3)-(4) is the natural logarithm of firm-level costs of goods sold (COGS). The dependent variable in columns (5)-(6) is the firm-level M/B ratio, censored at zero. The dependent variable in columns (7)-(8) is the firm-level tobin's Q. Standard errors are clustered at the district-year level, and the sample period is 1991-2016.

	log(Emissions)		log(COGS)		Market-Book Ratio		Tobin's Q	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Democrat Share	-0.040*		0.048***		-0.132*		-0.022*	
	(0.02)		(0.01)		(0.07)		(0.01)	
Emissions-Weighted Democrat Share		-0.062***		0.037***		-0.139**		-0.020**
		(0.02)		(0.01)		(0.06)		(0.01)
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.863	0.864	0.951	0.951	0.519	0.519	0.668	0.668
Observations	189,858	189,858	189,313	189,313	155,413	155,413	162,633	162,633

Note: Standard errors in parentheses. ***, **, and * respectively denote statistical significance at the 1%, 5%, and 10% levels.

Table 8

Real Effects: Local Health Outcomes

This table uses OLS regressions to examine the relationship between local health outcomes and political affiliations. The dependent variables are the natural logarithm of discharges and total payments for respiratory diseases (Panel A) and for pollution-unrelated diseases (Panel B). Democrat Win is an indicator that takes the value of one if a Democratic candidate won the last election in the district where the plant is located. High Num. Plants is an indicator that takes the value of one if the number of plants in the area is above median. ZIP is the three-digit Zip code. MDC is major diagnostic category code that divides all possible principal diagnoses into 25 mutually exclusive diagnosis areas. Standard errors are clustered at district-year level. The sample period is 2011-2016.

Panel A: Respiratory Diseases

	log(Number of Discharges)			log(Total Payments)		
	(1)	(2)	(3)	(4)	(5)	(6)
Democrat Win	0.014	0.007		0.101***	0.021	
	(0.02)	(0.02)		(0.02)	(0.02)	
High Num. Plants	0.325***	0.288***	0.188***	0.350***	0.301***	0.189***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Democrat Win × High Num. Plants	-0.082***	-0.071**	-0.066**	-0.126***	-0.075**	-0.073**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
ZIP FE	Yes	Yes	No	Yes	Yes	No
Census District FE	No	Yes	No	No	Yes	No
Year FE	Yes	Yes	No	Yes	Yes	No
District × Year FE	No	No	Yes	No	No	Yes
ZIP × District FE	No	No	Yes	No	No	Yes
R-Squared	0.187	0.239	0.273	0.207	0.264	0.299
Observations	60,351	60,349	60,336	60,351	60,349	60,336

Panel B: Placebo, Pollution-Unrelated Diseases

	log(Number of Discharges)			log(Total Payments)		
	(1)	(2)	(3)	(4)	(5)	(6)
Democrat Win	0.023	-0.012		0.131***	-0.041	
	(0.02)	(0.04)		(0.03)	(0.04)	
High Num. Plants	0.212***	0.149***	0.112***	0.259***	0.167***	0.124***
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Democrat Win × High Num. Plants	0.035	0.060*	0.004	-0.041	0.053	0.004
	(0.03)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)
ZIP FE	Yes	Yes	No	Yes	Yes	No
Census District FE	No	Yes	No	No	Yes	No
Year FE	Yes	Yes	No	Yes	Yes	No
District × Year FE	No	No	Yes	No	No	Yes
ZIP × District FE	No	No	Yes	No	No	Yes
MDC FE	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.216	0.249	0.275	0.431	0.469	0.493
Observations	28,276	28,273	28,227	28,276	28,273	28,227

Note: Standard errors in parentheses. ***, **, and * respectively denote statistical significance at the 1%, 5%, and 10% levels.

Table 9

Mechanism: Regulatory Inspections

In this table, we study the effect of marginal district wins by Democratic Party candidates on inspections by the EPA. The dependent variable in columns (1)-(2) is the natural logarithm of 1 + plant inspections in a given year. The dependent variable in columns (3)-(4) is an indicator variable that takes the value of one if a plant gets EPA inspection in a year, and zero otherwise, pinning down the extensive margin of inspections. The dependent variable in columns (5)-(6) is the natural logarithm of plant inspections, pinning down the extensive margin of inspections. In columns (1), (3) and (5), we estimate our regressions using a local OLS specification, while in columns (2), (4) and (6) we use a non-parametric local polynomial RD estimator (Calonico et al., 2014), specifying a linear polynomial and a triangular kernel. We report standard errors clustered at the district-year level for local linear OLS regressions, and robust bias-corrected standard errors as in Calonico et al. (2014) for non-parametric regressions. The sample contains all district elections during the period 1991-2016. In columns (1), (3), and (5) we restrict the sample to district elections with an absolute vote margin of less than 5% during the same period.

	log(1+Inspections)		Inspection Dummy		log(Inspections)	
	(1)	(2)	(3)	(4)	(5)	(6)
Democrat Win	0.078*	0.068***	0.029	0.022***	0.214***	0.177***
	(0.04)	(0.01)	(0.03)	(0.01)	(0.07)	(0.02)
Method	Local OLS	NP	Local OLS	NP	Local OLS	NP
Polynomial	Linear	Linear	Linear	Linear	Linear	Linear
Kernel	–	Tri.	–	Tri.	–	Tri.
Observations	30,773	414,343	30,773	414,343	9,419	132,990

Note: Standard errors in parentheses. ***, **, and * respectively denote statistical significance at the 1%, 5%, and 10% levels.

Table 10

Mechanism: Regulatory Enforcement

In this table, we study the effect of marginal district wins by Democratic Party candidates on EPA enforcement and penalties. The dependent variables in Panel A are indicator variables equal to one if the plant gets an EPA enforcement, an informal enforcement, a formal enforcement, or a penalty, and equal to zero otherwise. The dependent variables in Panel B represents the number of enforcement actions, informal enforcement actions, formal enforcement actions, and penalties relative to inspections. The specifications in this table mimic those in Tables 3 and 9.

Panel A: Enforcement Dummies

	Enforcement		Informal Enf.		Formal Enf.		Penalty	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Democrat Win	0.064*	0.068***	0.080**	0.077***	0.003	0.027***	0.005	0.022***
	(0.03)	(0.01)	(0.03)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Method	Local OLS	NP	Local OLS	NP	Local OLS	NP	Local OLS	NP
Polynomial	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear
Kernel	–	Tri.	–	Tri.	–	Tri.	–	Tri.
Observations	9,419	132,989	9,419	132,989	9,419	132,989	9,419	132,989

Panel B: Enforcement per Inspection

	$\frac{\text{Enforcement}}{\text{Inspections}}$		$\frac{\text{Informal Enf.}}{\text{Inspections}}$		$\frac{\text{Formal Enf.}}{\text{Inspections}}$		$\frac{\text{Penalties}}{\text{Inspections}}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Democrat Win	0.050	0.055***	0.058**	0.055***	-0.005	0.009*	-47.603	28.617
	(0.04)	(0.01)	(0.03)	(0.01)	(0.02)	(0.00)	(61.21)	(23.84)
Method	Local OLS	NP	Local OLS	NP	Local OLS	NP	Local OLS	NP
Polynomial	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear
Kernel	–	Tri.	–	Tri.	–	Tri.	–	Tri.
Observations	9,419	132,989	9,419	132,989	9,419	132,989	9,419	132,989

Note: Standard errors in parentheses. ***, **, and * respectively denote statistical significance at the 1%, 5%, and 10% levels.

Table 11

Affiliation, Power, and Ideology

This table uses OLS panel regressions to examine the relationship between plant toxic emissions and politicians' party affiliations, their power, and their ideology. The dependent variable is the natural logarithm of emissions at the plant-chemical-year level. Democrat Win is an indicator equal to one if a candidate from the Democratic party won the last election in the district where the plant is located, and equal to zero otherwise. Committee Chair is an indicator equal to one if a candidate is the chair of a committee in Congress, and equal to zero otherwise. Ideological is an indicator equal to one if a candidate has an ideology score lower than the 25th percentile of the ideology distribution within the Democratic Party or higher than the 75th percentile of the distribution within the Republican Party, and equal to zero otherwise. Ideology scores are from VoteView. Standard errors are clustered at the district-year level. The sample period is 1991-2016.

	Dep. Variable: log(Emissions)				
	(1)	(2)	(3)	(4)	(5)
Democrat Win	-0.047**	-0.035**	-0.026**	-0.020*	-0.020*
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Democrat × Chair	0.047	-0.002	0.039	0.017	0.016
	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
Ideological × Democrat × Chair	0.032	-0.006	-0.143**	-0.168**	-0.222***
	(0.09)	(0.11)	(0.07)	(0.07)	(0.07)
Lower Order Terms	Yes	Yes	Yes	Yes	Yes
Census District FE	Yes	No	No	No	No
Year FE	Yes	No	No	No	No
Firm × Chemical × Year FE	No	Yes	Yes	Yes	Yes
Census District × Chemical FE	No	Yes	No	No	No
Facility × Chemical FE	No	No	Yes	Yes	Yes
State × Year FE	No	No	No	Yes	No
State × Year × Chemical FE	No	No	No	No	Yes
R-Squared	0.077	0.850	0.929	0.930	0.938
Observations	1,300,744	770,151	761,731	761,731	718,698

Note: Standard errors in parentheses. ***, **, and * respectively denote statistical significance at the 1%, 5%, and 10% levels.

Appendix: For Online Publication

Figure A1

Emissions RD using Close Elections: Linear Fit

This figure re-plots the main results from Figure 2 using linear fits on both sides of the margin of victory threshold. The figure is otherwise identical to 2.

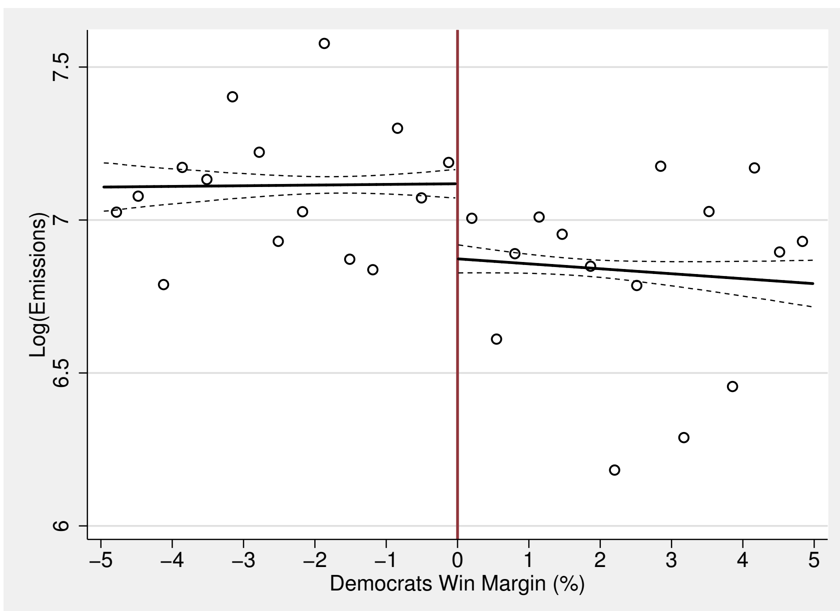

Figure A2

Covariate Balance Tests

The figures show the results of covariate balance tests in the close elections in our sample. Panels A to D respectively plot the natural logarithm of district-level GDP, the percentage unemployment rate, the natural logarithm of the number of CRA originations, and the natural logarithm of the number of HMDA originations in the two years following Congressional elections as functions of the vote share margin of a Democratic candidate in a congressional district. Democrat win margin is the percentage by which a Democrat candidate won or lost the election. The sample uses elections won or lost by a margin of 5% or less. The sample period is 1991-2016.

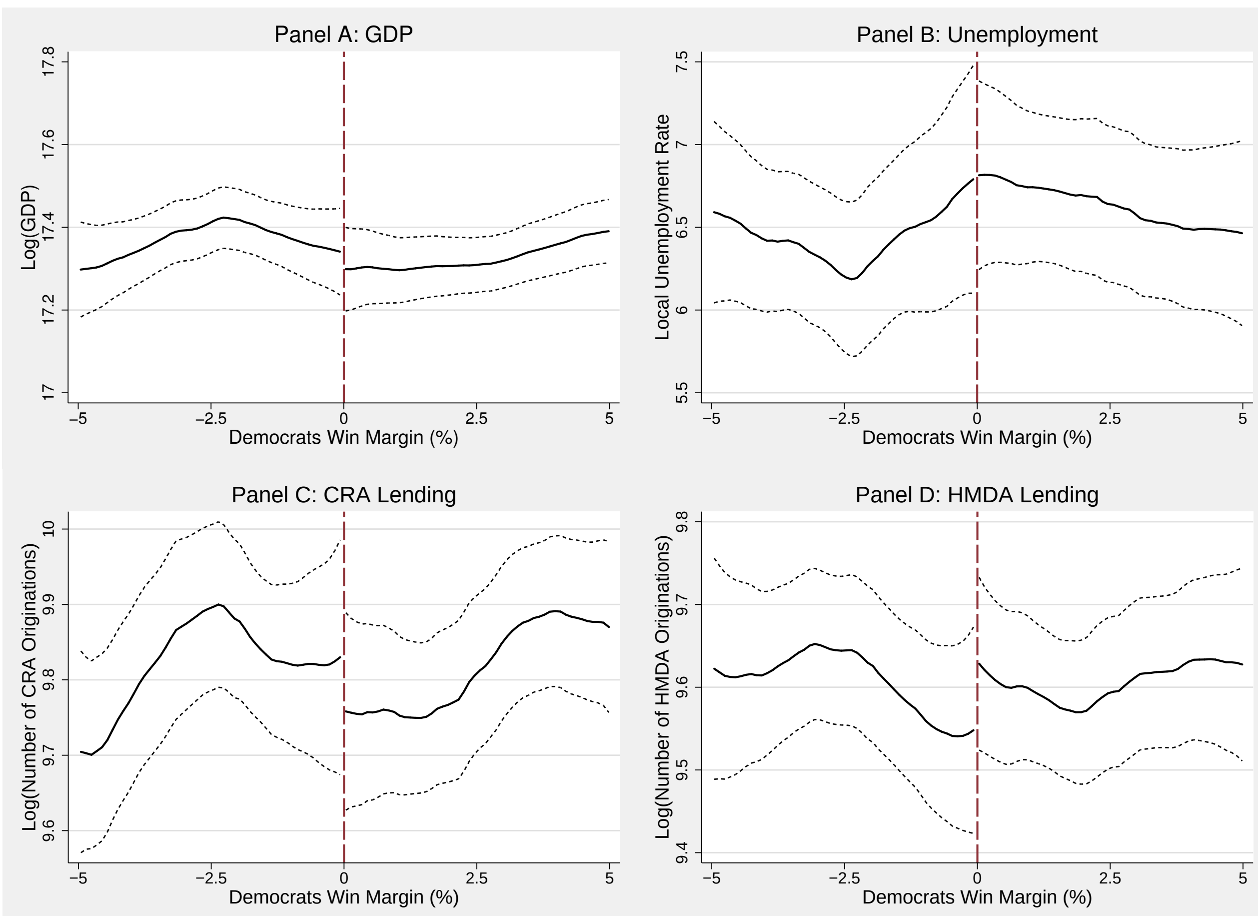

Figure A3

Opinion on the Environment

This figure reports congressional district residents' opinion on the environment in 2020 as a function of the vote share margin of the local Democratic candidate in the 2018 Congressional election. The vertical axis represents the percentage of local residents who think Congress should be doing more or much more to address environmental issues. The data is obtained from the Yale Climate Opinion Maps (YCOM) and is only available for 2020. Democrat win margin is the percentage by which a Democrat candidate won or lost the election. The sample uses elections won or lost by a margin of 5% or less.

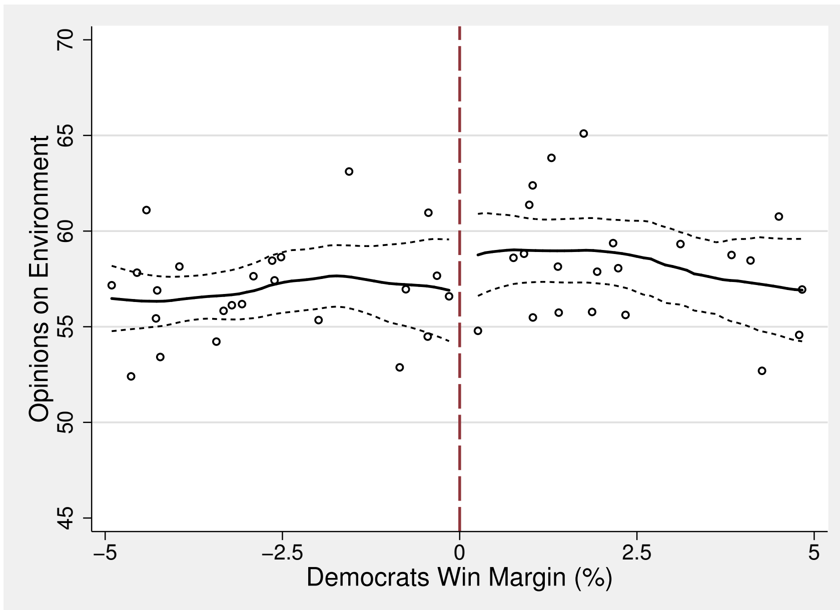

Figure A4

Close Elections Around the US

The figure plots the total number of close elections normalized by the number of districts in each US State from 1991 to 2016.

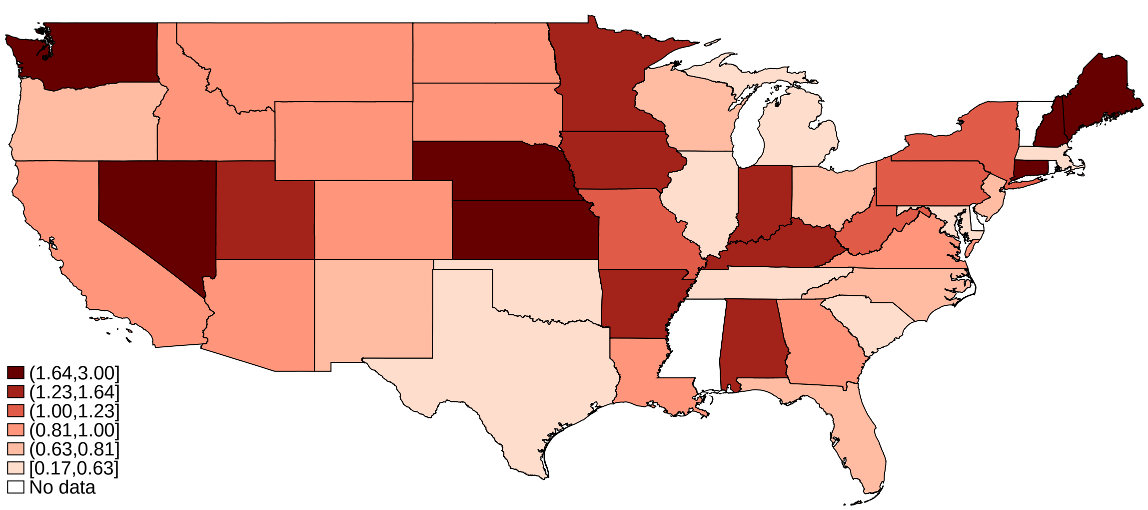

Figure A5

Emissions RD based on Governor's Political Party

The figure splits the sample of close elections by the political party affiliation of the state governor. As in our main Figure 2, we plot the natural logarithm of facility-chemical-level toxic emissions in the two years following Congressional elections as a function of the vote share margin of a Democratic candidate in a congressional district. The red line indicates states with a Republican governor and the blue line indicates states with a Democratic governor. Vote share margin is the percentage by which a candidate won (lost) the election. The sample uses elections won or lost by a margin of 5% or less.

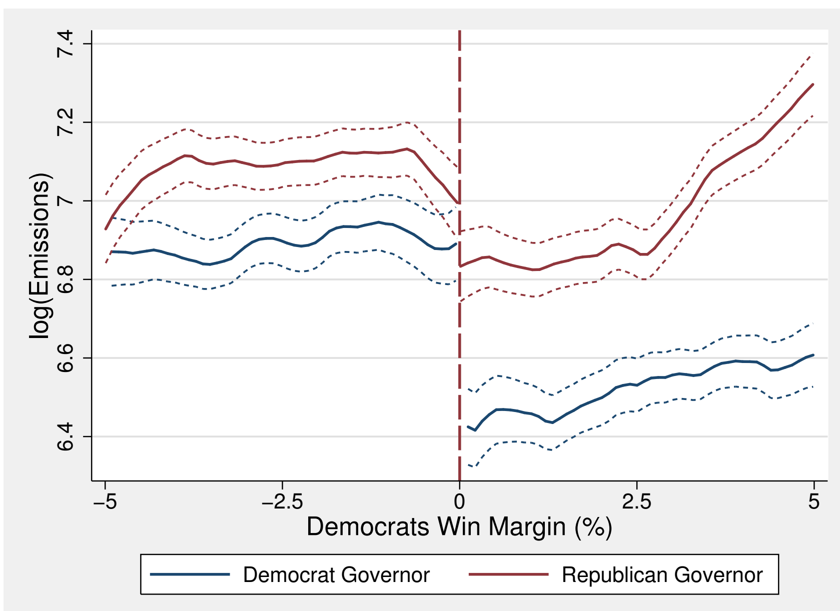

Figure A6

McCrary Test

The figures plots the results of a McCrary (2008) density test of the null hypothesis that the distribution of close election does not feature discontinuities around the zero Democrat margin vote cutoff. The sample includes the universe of US congressional elections from 1991 to 2016.

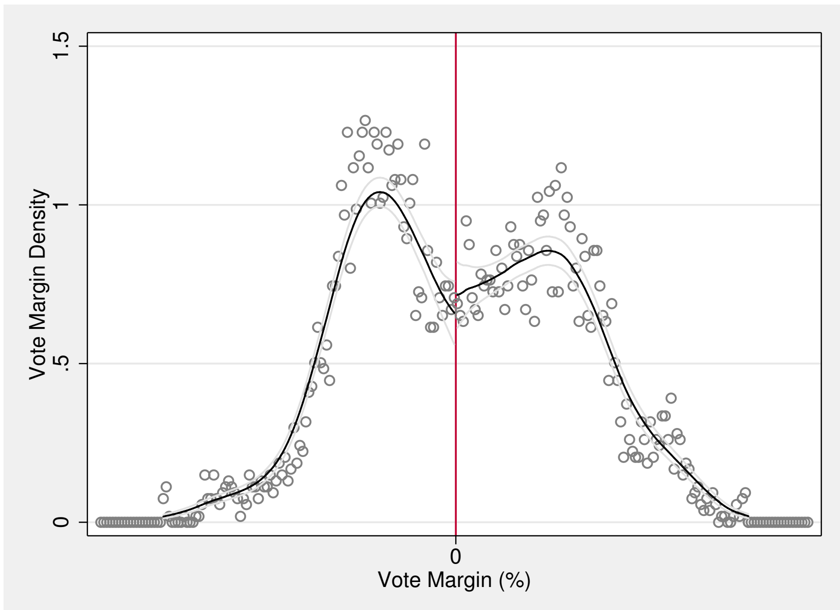

Figure A7

Placebo Tests

Both figures show placebo tests for the nonparametric specifications in Table 2, column (4). Panel A shows the distribution of coefficients from estimating 10,000 specifications where the Democrat margin of victory is uniformly randomly assigned across districts in our sample and all other data is left unchanged. Panel B shows the distribution of coefficients from estimating 10,000 specifications where the political party is uniformly randomly assigned across district politicians in our sample and all other data is left unchanged. In panels, we report our actual coefficient from Table 2, column (4), for comparison.

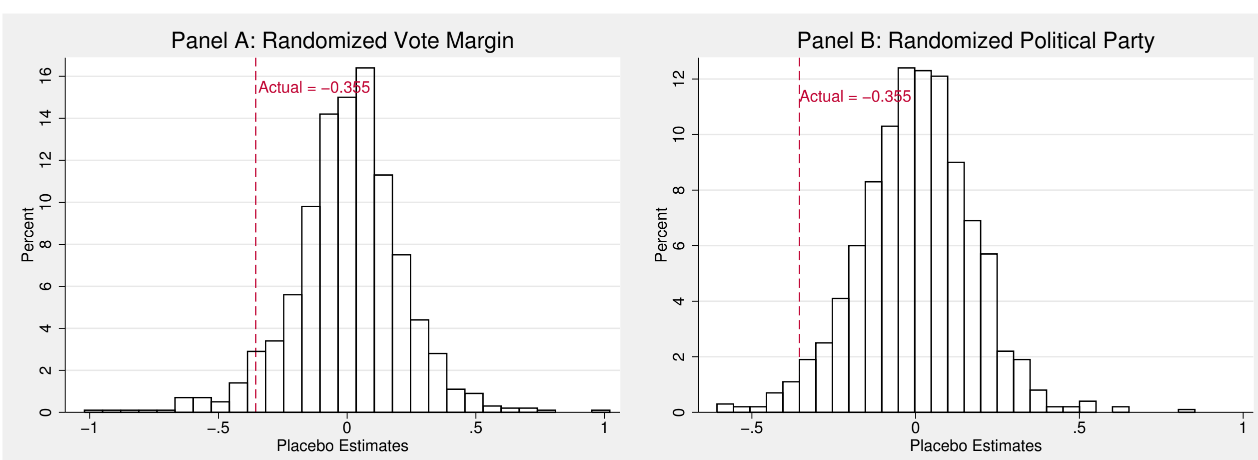

Figure A8

Reallocation of Pollution Per Unit of Production

This figure is identical to Figure 3, but instead of plotting pollution as the outcome variable, we plot pollution per unit of production. All other details are identical to Figure 3.

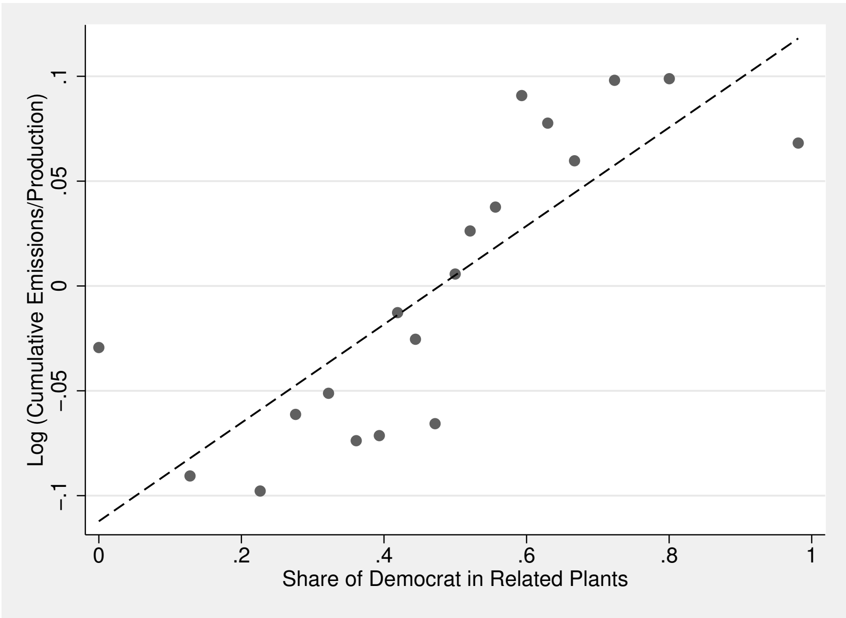

Figure A9

Political Affiliation and Reallocation

In this figure, we split the sample in Figure 3 into observations where the focal plant is represented by a Democrat (blue) versus a Republican (red). All other details are identical to Figure 3.

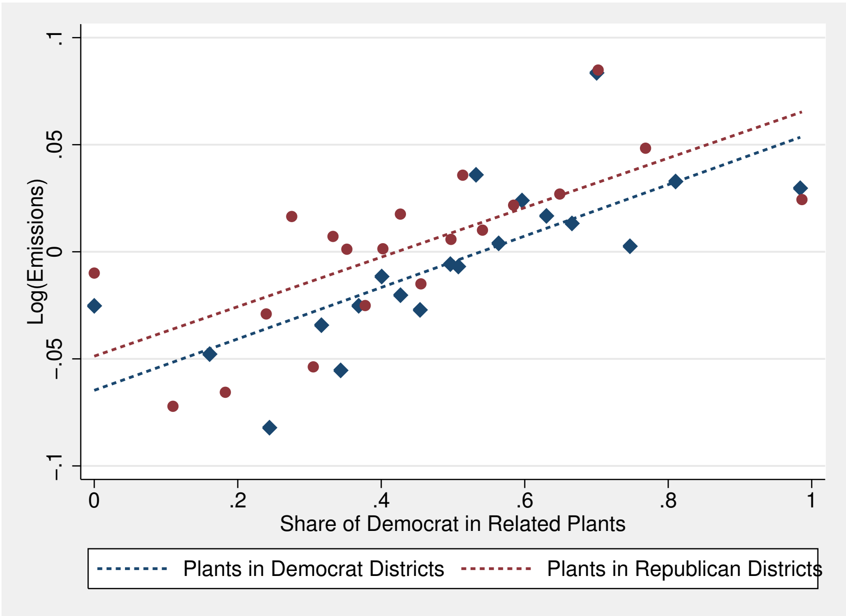

Figure A10

Reallocation Tests: Placebo on Non-Respiratory Diseases

This Figure provides a placebo test on the results of Figure 6, by showing that the data shows no evidence of reallocation of public health costs for non-respiratory diseases. The procedure we follow to produce this figure is identical that of Figure 6.

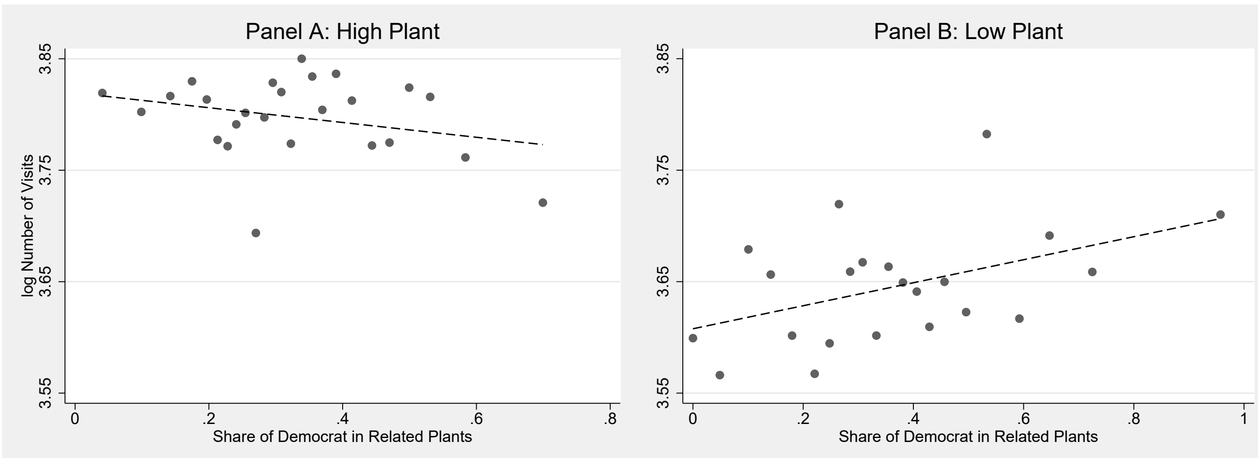

Figure A11

High Ex-ante Pollution Plants

In this figure, we split the sample from Figure 2 into plants that are *ex ante* high polluters and low polluters and plot the resulting emissions for plants in each group around close Congressional elections. Plants are sorted into high- or low-pollution groups in year t based on whether their emissions are above or below the median level of pollution at the state-chemical level in year $t-1$. All other details are identical to Figure 2.

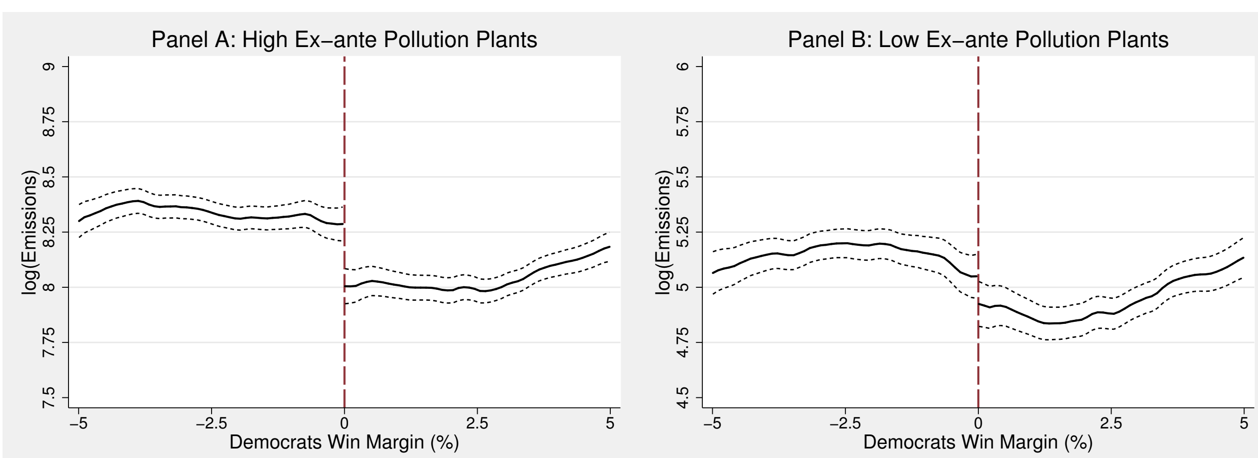

Figure A12

State Environmental Agency Budgets

This figure shows a positive correlation between the total budget of a State's environmental agency and the fraction of its districts controlled by Democrats (Panel A), as well as a positive correlation between the environmental agency's budget coming from the federal government and the fraction of its districts controlled by Democrats (Panel B). The data on total budgets and federal budgets comes from the Environmental Council of the States (ECOS) Green Reports for the years 2009-2011, 2012-2013, 2013-2015, and 2016-2019. The resulting state-year panel contains all US States with reported budgets during the period 2009-2019.

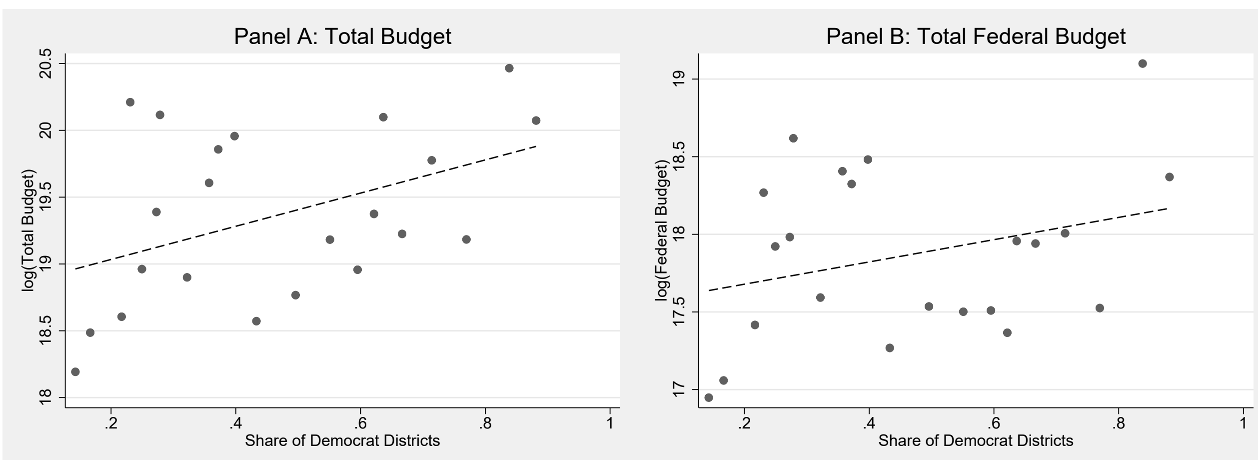

Figure A13

Politically-Unconnected Firms

This figure shows a similar pattern to Figure 2 in the sample of firms that are *not* politically connected to a local politician. The data on political connections comes from the the Federal Election Commission (FEC). We define a firm to be politically connected if it donated to the winning district politician over the last election cycle. The procedure we follow to construct this figure is identical to that of Figure 2.

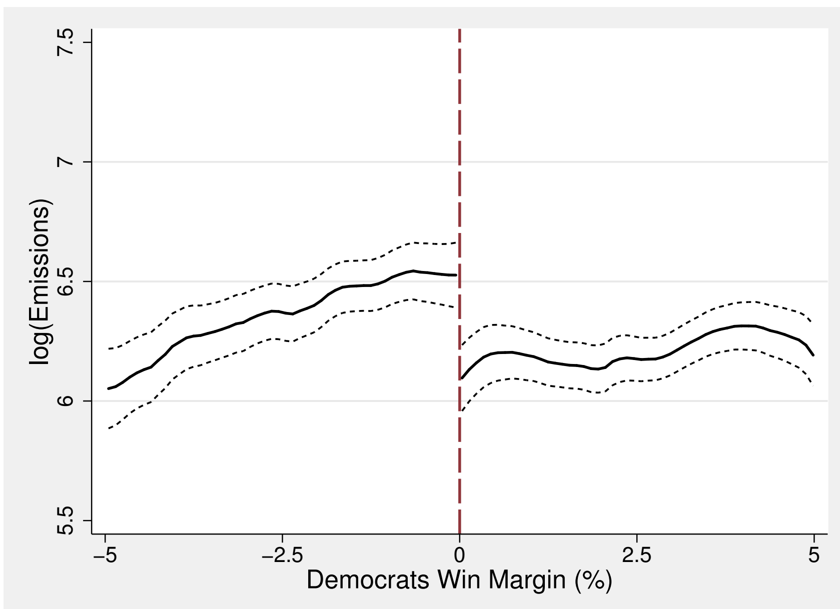

Table A1

RD Results: Residuals

This table presents the results of a robustness test to our main test in Table 2, where we orthogonalize the natural logarithm of plant-chemical-year emissions with respect to different combinations of fixed effects. The dependent variable in columns (1)–(2) is the residual of an OLS regression of the natural logarithm of plant-chemical-year emissions on state $\times$ year $\times$ chemical fixed effects. The dependent variable in columns (3)-(4) is the residual of an OLS regression of the natural logarithm of plant-chemical-year emissions on firm $\times$ year $\times$ chemical fixed effects.

	Dep. Variable: log(Emissions) Residuals			
	(1)	(2)	(3)	(4)
Democrat Win	-0.145**	-0.031*	-0.034	-0.052***
	(0.07)	(0.02)	(0.07)	(0.02)
Method	Local OLS	NP	Local OLS	NP
Polynomial	Linear	Linear	Linear	Linear
Kernel	–	Tri.	–	Tri.
Chemical FE	Yes	–	Yes	–
Observations	90,555	1,281,479	57,320	811,995

Note: Standard errors in parentheses. ***, **, and * respectively denote statistical significance at the 1%, 5%, and 10% levels.

Table A2

RD Split on Governors' Political Parties

This table runs the same regressions as in Table 2, but splits the sample between close elections in states represented by Democrat and Republican governors. Governors' political affiliations are obtained from Congressional Quarterly (CQ) Press U.S. Political Stats.

Panel A: Democratic Governors

	Dep. Variable: log(Emissions)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Democrat Win	-0.353***	-0.438*	-0.341*	-0.406***	-0.471***	-0.348***	-0.370***
	(0.13)	(0.26)	(0.19)	(0.05)	(0.04)	(0.07)	(0.08)
Method	Local OLS	Local OLS	Local OLS	NP	NP	NP	NP
Polynomial	Zero	Linear	Linear	Linear	Linear	Quadratic	Quadratic
Kernel	–	–	–	Tri.	Epa.	Tri.	Epa.
Chemical FE	No	No	Yes	–	–	–	–
Observations	45,446	45,446	45,404	551,241	551,241	551,241	551,241

Panel B: Republican Governors

	Dep. Variable: log(Emissions)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Democrat Win	-0.089	-0.389**	-0.302**	-0.325***	-0.342***	-0.308***	-0.291***
	(0.11)	(0.19)	(0.14)	(0.05)	(0.05)	(0.05)	(0.05)
Method	Local OLS	Local OLS	Local OLS	NP	NP	NP	NP
Polynomial	Zero	Linear	Linear	Linear	Linear	Quadratic	Quadratic
Kernel	–	–	–	Tri.	Epa.	Tri.	Epa.
Chemical FE	No	No	Yes	–	–	–	–
Observations	48,694	48,694	48,666	778,267	778,267	778,267	778,267

Note: Standard errors in parentheses. ***, **, and * respectively denote statistical significance at the 1%, 5%, and 10% levels.

Table A3

Robustness: OLS Standard Error Clustering

In this table, we conduct robustness on the OLS results from Table 2 with additional clustering at the facility level and using 1% equally-spaced bins (Lee and Card, 2008). In columns (1) and (4), we regress the natural logarithm of plant-level emissions on a dummy equal to one if the district where the plant is located was won by a democrat in its most recent election, and equal to zero otherwise. In columns (2)-(3) and (5)-(6), we augment the specification with a linear interaction term between the dummy and democrat margin votes in a local OLS regression framework. The sample contains district elections with an absolute vote margin of less than 5% during the period 1991-2016.

	Dep. Variable: log(Emissions)					
	(1)	(2)	(3)	(4)	(5)	(6)
Democrat Win	-0.213***	-0.397***	-0.305***	-0.213*	-0.397*	-0.305*
	(0.06)	(0.12)	(0.11)	(0.12)	(0.23)	(0.17)
Method	Local OLS	Local OLS	Local OLS	Local OLS	Local OLS	Local OLS
Polynomial	Zero	Linear	Linear	Zero	Linear	Linear
Chemical FE	No	No	Yes	No	No	Yes
SE Clustering	Facility	Facility	Facility	L-C Bins	L-C Bins	L-C Bins
Observations	94,140	94,140	94,111	94,140	94,140	94,111

Note: Standard errors in parentheses. ***, **, and * respectively denote statistical significance at the 1%, 5%, and 10% levels.

Table A4

Robustness: Poisson Regressions

In this table, we conduct additional robustness on the OLS results from Table 2 using Poisson regression specifications. We regress the raw number of plant-level emissions on a dummy equal to one if the district where the plant is located was won by a democrat in its most recent election, and equal to zero otherwise. In columns (2)-(3), we augment the specification with a linear interaction term between the dummy and democrat margin votes. In column (3), we add chemical fixed effects. The sample contains district elections with an absolute vote margin of less than 5% during the period 1991-2016.

	Dep. Variable: Emissions (Pounds)		
	(1)	(2)	(3)
Democrat Win	-0.184***	-0.340***	-0.348***
	(0.07)	(0.13)	(0.12)
Method	Poisson	Poisson	Poisson
Polynomial	Zero	Linear	Linear
Chemical FE	No	No	Yes
Observations	118,698	118,698	118,698

Note: Standard errors in parentheses. ***, **, and * respectively denote statistical significance at the 1%, 5%, and 10% levels.

Table A5

Robustness: Excluding Power Plants

This table runs the same regressions as in Table 2 after excluding power plants from the sample. Power plants are defined by their NAICS code (22; Utilities industry).

	Dep. Variable: log(Emissions)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Democrat Win	-0.203**	-0.271*	-0.160	-0.308***	-0.319***	-0.348***	-0.289***
	(0.09)	(0.16)	(0.11)	(0.03)	(0.04)	(0.03)	(0.04)
Method	Local OLS	Local OLS	Local OLS	NP	NP	NP	NP
Polynomial	Zero	Linear	Linear	Linear	Linear	Quadratic	Quadratic
Kernel	–	–	–	Tri.	Epa.	Tri.	Epa.
Chemical FE	No	No	Yes	–	–	–	–
Observations	87,245	87,245	87,214	1,237,932	1,237,932	1,237,932	1,237,932

Note: Standard errors in parentheses. ***, **, and * respectively denote statistical significance at the 1%, 5%, and 10% levels.

Table A6

Robustness: Predicting Election Results

This table examines whether pre-election pollution growth rates can predict subsequent election results. The dependent variable is the *Democrat win* dummy variable used in previous tables. The independent variable is the district-level emissions growth rate from election cycle t-2 to election cycle t-1 (which we use to predict elections in cycle t). Columns (1) and (2) use logit and probit specifications, respectively, while columns (3) – (5) use OLS. Columns (1) to (4) restrict the sample to close elections, while column (5) includes all elections. The sample period is 1991-2016.

	Democrat Win				
	(1)	(2)	(3)	(4)	(5)
Pre-Election Emissions Growth	-0.090	-0.055	-0.022	-0.026	0.001
	(0.10)	(0.06)	(0.02)	(0.02)	(0.00)
Method	Logit	Probit	OLS	OLS	OLS
Sample	Close Elections	Close Elections	Close Elections	Close Elections	All Elections
Year FE	No	No	No	Yes	Yes
R-squared			0.002	0.011	0.007
Observations	610	610	610	610	9,318

Note: Standard errors in parentheses. ***, **, and * respectively denote statistical significance at the 1%, 5%, and 10% levels.

Table A7

Cumulative Plant Production

In this table, we study the effects of close Democratic Congressional victories on plant production. The dependent variable is the natural logarithm of cumulative production (the cumulative product of the production ratio at the plant-chemical level, as defined in Equation (5)). The production ratio is the ratio of the quantity of output that uses a specific chemical in any given year relative to the quantity of output that used the same chemical in the previous year. The specifications in the table mimic those in Table 3.

	log(Cumulative Production)	
	(1)	(2)
Democrat Win	0.022	0.007
	(0.02)	(0.01)
Method	Local OLS	NP
Polynomial	Linear	Linear
Kernel	–	Tri.
Chemical FE	46,618	630,875

Note: Standard errors in parentheses. ***, **, and * respectively denote statistical significance at the 1%, 5%, and 10% levels.

Table A8

CMS Inpatient Data, Full Sample

This table uses OLS regressions to examine the relationship between local health outcomes and political affiliations. The dependent variable is the natural logarithm of discharges and total payments for all types of procedures. Democrat Win is an indicator that takes the value of one if a Democrat won the most recent Congressional election in the district of the plant. High Num. Plants is an indicator that takes the value of one if the number of plants in the area is above median. ZIP is the three-digit Zip code. MDC is major diagnostic category code that divides all possible principal diagnoses into 25 mutually exclusive diagnosis areas. Standard errors are clustered at district-year level, and the sample period is 2011-2016.

	log(Number of Discharges)			log(Total Payments)		
	(1)	(2)	(3)	(4)	(5)	(6)
Democrat Win	0.021	-0.007		0.113***	-0.000	
	(0.02)	(0.02)		(0.02)	(0.02)	
High Num. Plants	0.215***	0.183***	0.121***	0.240***	0.202***	0.127***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Democrat Win × High Num. Plants	-0.039*	-0.036*	-0.043*	-0.084***	-0.044*	-0.041*
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
ZIP FE	Yes	Yes	No	Yes	Yes	No
Census District FE	No	Yes	No	No	Yes	No
Year FE	Yes	Yes	No	Yes	Yes	No
District × Year FE	No	No	Yes	No	No	Yes
ZIP × District FE	No	No	Yes	No	No	Yes
MDC FE	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.174	0.208	0.226	0.267	0.306	0.323
Observations	369,610	369,609	369,606	369,610	369,609	369,606

Note: Standard errors in parentheses. ***, **, and * respectively denote statistical significance at the 1%, 5%, and 10% levels.

Table A9

Firm-level Health Effects

This table uses OLS regressions to examine the firm-level, aggregate health effects of reduced pollution following Congressional election victories by Democrats. The dependent variable is the natural logarithm of total discharges and average discharges at the firm level. These quantities are computed by aggregating discharges in all three-digit Zip codes where the firm's plants are located. Democrat Win is an indicator that takes the value of one if a Democrat won the most recent Congressional election in the district of the plant. High Num. Plants is an indicator that takes the value of one if the number of plants in the area is above median. ZIP is the three-digit Zip code. MDC is major diagnostic category code that divides all possible principal diagnoses into 25 mutually exclusive diagnosis areas. Standard errors are clustered at district-year level, and the sample period is 2011-2016.

	log(Total Discharges)				log(Average Discharges)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Democrat Share	-0.019		-0.085		-0.044		-0.092*	
	(0.06)		(0.07)		(0.05)		(0.05)	
Emissions-Weighted Democrat Share		-0.050		-0.107**		-0.046		-0.082**
		(0.05)		(0.05)		(0.04)		(0.04)
Chemical × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Full Sample	Yes	Yes	No	No	Yes	Yes	No	No
Multi-plant Firms	No	No	Yes	Yes	No	No	Yes	Yes
R-Squared	0.897	0.898	0.897	0.897	0.866	0.866	0.861	0.861
Observations	41,791	41,791	36,476	36,476	41,791	41,791	36,476	36,476

Note: Standard errors in parentheses. ***, **, and * respectively denote statistical significance at the 1%, 5%, and 10% levels.

Table A10

Inspections and Enforcement by State and Federal Regulators

In this table, we study the effect of marginal district wins by Democratic Party candidates on inspections and enforcements led by state and federal regulators. The dependent variable in columns (1)-(2) is the natural logarithm of total plant inspections in a year. The dependent variable in columns (3)-(4) is an indicator variable that takes the value of one if a plant gets an EPA inspection in that year, and zero otherwise. The dependent variable in columns (5)-(6) is an indicator variable that takes the value of one if a plant receives an EPA enforcement, and zero otherwise. The dependent variable in columns (7)-(8) is the number of enforcements per inspection. Columns (1), (3), (5), and (7) of both panels report results for our favorite linear OLS specifications. Columns (2), (4), (6), and (8) report results for non-parametric local polynomial RD estimators with linear polynomials and triangular kernels. We report standard errors clustered at the district-year level for local linear OLS regressions, and robust bias-corrected standard errors as in Calonico et al. (2014) for non-parametric regressions. The sample contains all district elections during the period 1991-2016. In columns (1), (3), (5) and (7), we restrict the sample to district elections with an absolute vote margin of less than 5% during the same period.

Panel A: State Regulators

	log(Inspections)		Insp. Dummy		Enf. Dummy		$\frac{\text{Enforcement}}{\text{Inspections}}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Democrat Win	0.071*	0.058***	0.030	0.021***	0.084**	0.077***	0.063**	0.058***
	(0.04)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)
Method	Local OLS	NP	Local OLS	NP	Local OLS	NP	Local OLS	NP
Polynomial	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear
Kernel	–	Tri.	–	Tri.	–	Tri.	–	Tri.
Observations	30,773	414,341	30,773	414,341	9,418	132,987	9,418	132,987

Panel B: Federal Regulators

	log(Inspections)		Insp. Dummy		Enf. Dummy		$\frac{\text{Enforcement}}{\text{Inspections}}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Democrat Win	0.008	0.007***	0.011	0.010***	-0.014	-0.007	-0.010	-0.005
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
Method	Local OLS	NP	Local OLS	NP	Local OLS	NP	Local OLS	NP
Polynomial	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear
Kernel	–	Tri.	–	Tri.	–	Tri.	–	Tri.
Observations	30,773	414,341	30,773	414,341	9,418	132,987	9,418	132,987

Note: Standard errors in parentheses. ***, **, and * respectively denote statistical significance at the 1%, 5%, and 10% levels.

Table A11

Emissions and Seat Pickups

This table splits our full sample into four groups around election periods. In group 1, we focus on cases where a Democrat held the seat before and after the election. In group 2, we focus on cases where a Democrat held the seat before the election but a Republican held the seat after the election. In group 3, we focus on cases where a Republican held the seat before and after the election. In group 4, we focus on cases where a Republican held the seat before the election and a Democrat held the seat after the election. In the first two columns of the table, we keep the sub-sample of groups 1 and 2, and we define "Switchers" as an indicator for plant-chemical observations in group 2. In column (1), we interact the "Switchers" indicator with a post-election indicator, and in column (2) we interact the "Switchers" indicator with individual year-level indicators, keeping the election year as a baseline. In the last two columns of the table, we keep the sub-sample of groups 3 and 4, and we define "Switchers" as an indicator for plant-chemical observations in group 4. In column (3), we interact the "Switchers" indicator with a post-election indicator, and in column (4) we interact the "Switchers" indicator with individual year-level indicators, keeping the election year as a baseline. The dependent variable is log(emissions), as in Table 2. Standard errors are clustered at the district-year level, and the sample period is 1991-2016.

	log(Emissions): R-D Switchers		log(Emissions): D-R Switchers	
	(1)	(2)	(3)	(4)
Switchers × Post Election	-0.059***		0.029***	
	(0.01)		(0.01)	
Switchers × Election Year -1		0.008		-0.005
		(0.01)		(0.01)
Switchers × Election Year +1		-0.061***		0.023*
		(0.01)		(0.01)
Switchers × Election Year +2		-0.049***		0.030**
		(0.01)		(0.01)
Low-Order Terms	Yes	Yes	Yes	Yes
District × Election Year FE	Yes	Yes	Yes	Yes
Facility × Chemical FE	Yes	Yes	Yes	Yes
R-squared	0.892	0.892	0.890	0.890
Observations	1,516,595	1,516,595	1,407,224	1,407,224

Note: Standard errors in parentheses. ***, **, and * respectively denote statistical significance at the 1%, 5%, and 10% levels.

Table A12

Emissions and Reelections

This table examines whether district-level pollution growth rates affects politicians' likelihood of being reelected. We report results from regressing lagged district-level emissions growth rates on the *Democrat win* dummy variable used in previous tables. Columns (1) and (2) use logit and probit models, respectively, while columns (3) – (6) use OLS regressions with various fixed effects. The sample period is 1991-2016.

	Reelected					
	(1)	(2)	(3)	(4)	(5)	(6)
Democrat Win	-0.022	-0.012	-0.004	-0.002	-0.077***	-0.075***
	(0.05)	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)
Emissions Growth Rate	0.034	0.019	0.005	-0.000	0.006	0.001
	(0.04)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Democrat Win × Emissions Growth Rate	0.007	0.005	0.001	0.001	0.000	0.001
	(0.05)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Method	Logit	Probit	OLS	OLS	OLS	OLS
Year FE	No	No	No	Yes	No	Yes
District FE	No	No	No	No	Yes	Yes
R-squared			0.000	0.053	0.099	0.151
Observations	10,229	10,229	10,229	10,229	10,229	10,229

Note: Standard errors in parentheses. ***, **, and * respectively denote statistical significance at the 1%, 5%, and 10% levels.