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Abstract

We investigate how the government, as a customer, affects a supplier's environmental policies. We find that government contractors have significantly lower levels of toxic pollution. Exploring the mechanisms, we show that government contractors reduce pollution by strengthening internal environmental governance and increasing investments in pollution abatement. Further analysis rules out alternative explanations related to reduced economic activities and financial constraints. Overall, our results highlight the government's important role in disciplining corporate environmental misbehavior.

I. Introduction

A growing literature examines how corporate environmental behavior can be influenced by various stakeholders, such as equity investors (Akey and Appel (2019), Kim, Wan, Wang, and Yang (2019), and Bellon (2025)), financial analysts (Jing, Keasey, Lim, and Xu (2024)), local media (Heese, Pérez-Cavazos, and Peter (2022)), banks (Bellon (2021)), and social rating agencies (Chatterji and Toffel (2010)). Among various monitoring forces, the government represents a formal institution that profoundly impacts firms' environmental policies through regulatory oversight (e.g., the Environmental Protection Agency (EPA)) and environmental regulations (e.g., the Clean Air Act) (Gray and Shimshack (2011)).[1]

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[1]Survey evidence suggests that regulators and legislators influence U.S. corporate environmental performance more than communities, activist groups, or the media (Delmas and Toffel (2008)).

Importantly, government agencies can act as customers and constitute a pivotal part of the U.S. economy.[2] While the implications of government procurement for corporate outcomes have attracted widespread attention from the public, media, and policymakers (Cohen, Li, Li, and Lou (2022)), little is known about the role of the government as a customer in shaping corporate environmental policies. We fill this gap by investigating how government procurement affects a firm's toxic pollution.

Government customers, including agencies and departments that purchase on behalf of the federal government, have strong incentives to monitor corporate environmental policies. They are required by various federal regulations to achieve sustainable procurement with a particular focus on reducing the toxic pollution of their contractors (i.e., suppliers). Specifically, Federal Acquisition Regulation (FAR) Part 23 promotes sustainable acquisition by requiring federal agencies to prioritize products and services that reduce risks to human health and the environment, particularly those related to toxic pollution. Contractors are subject to standards that emphasize pollution prevention, the safe handling of hazardous materials, and the use of environmentally preferable products. Additionally, under FAR Part 52, contractors may be required to implement programs to reduce waste and toxic substances, as specified in their contracts. Executive Order 12969, issued by President Clinton in 1995, requires government contractors to comply with toxic chemical release reporting requirements throughout the contract duration (see https://www.govinfo.gov/content/pkg/FR-1995-08-10/pdf/95-19972.pdf). According to FAR Part 42, environmental compliance is evaluated through the Contract Performance Assessment Reporting System, and contracting officers are responsible for monitoring "the contractor's environmental practices for adverse impact on contract performance or contract cost, and for compliance with environmental requirements specified in the contract."[3]

From a contractor's perspective, violating federal contractual requirements likely leads to more severe losses than violating private-sector contractual requirements (Engstrom (2012)), suggesting higher ex ante expected costs of violations in the presence of government customers. When the government detects a contractor's noncompliance, it may initiate a lawsuit that entails monetary penalties and impose stricter contract terms (Heese and Pérez-Cavazos (2019), Samuels (2021), Cohen et al. (2022)). Contractors with poor environmental performance are considered irresponsible, potentially leading to suspension or termination of government business relationships. To promote accountability, the government formally discloses environmental violations and procurement-related sanctions through enforcement actions, particularly under the False Claims Act. For instance, in 2016, Lockheed Martin paid a 5-million-USD penalty to settle allegations of violating hazardous waste laws and knowingly submitting false claims to the Department of Energy. The company was accused of misrepresenting its

[2]The U.S. federal government, the nation's largest buyer of goods and services, is a major revenue source for many firms (Samuels (2021), Ngo and Stanfield (2022)).

[3]Contracting officers are responsible for: i) requesting environmental technical assistance if needed, ii) monitoring contractor compliance with requirements for environmentally preferable, energy-efficient, biobased products, and those containing recovered materials, and iii) ensuring that contractors meet reporting requirements on recovered material content (FAR, 42.3).

compliance with the Resource Conservation and Recovery Act and failing to properly manage, report, and dispose of hazardous waste (see https://www.justice.gov/opa/pr/lockheed-martin-agrees-pay-5-million-settle-alleged-violations-false-claims-act-and-resource). Such enforcement outcomes are often publicized through the Department of Justice press releases and official reports. Penalties and public disclosure serve as a deterrent to potential violators and reinforce the government's commitment to environmental sustainability. Thus, we hypothesize that contractor firms under government scrutiny are incentivized to improve their environmental performance to avoid the severe consequences of environmental misbehavior.

To estimate the effect of government customers on corporate environmental policies, we obtain federal government contract data from the USAspending.gov website. Following prior studies (e.g., Mills, Nutter, and Schwab (2013), Hadley (2019), and Samuels (2021)), we measure government contracting by the number of a firm's federal government contracts in a year and the ratio of total contract value to firm sales in a year. To measure corporate toxic pollution, we use Toxics Release Inventory (TRI) data on the amount of toxic emissions released by the registered plants of U.S. firms. Our final sample consists of 9,438 firm-year observations for 793 unique public firms (with at least one plant in the TRI database) over the period of 2001–2019. We find that government contractor firms have significantly lower levels of toxic pollution. Specifically, a 1% increase in the number of government contracts is associated with a 0.086% and 0.091% decrease in the total toxic pollution and sales-scaled toxic emissions of contractor firms, respectively. The results hold across a comprehensive set of robustness tests, providing strong support for our hypothesis that monitoring by government customers significantly reduces corporate pollution.

To substantiate the argument that government customers play an external governance role in reducing corporate pollution, we perform cross-sectional analyses. First, the negative effect of government customers on corporate pollution is stronger for firms with longer-duration contracts, echoing the view that more interactions between the government and its contractors over longer contracting horizons facilitate monitoring. Furthermore, government customers have a greater effect on corporate pollution reduction for firms that rely more on government contracts and for firms without political connections, because such firms are more incentivized to maintain business relationships with government customers. Collectively, the cross-sectional evidence suggests that the mitigating effect on pollution is, on average, more than twice as large in subsets of firms facing greater government scrutiny, highlighting the monitoring role of government customers in curbing supplier pollution.

However, the relationship between having government customers and corporate environmental policies could be spurious. Unobserved heterogeneity correlated with both government contracting and corporate environmental policies could bias the results. To allay potential endogeneity concerns, following prior studies (Cohen, Coval, and Malloy (2011), Cohen and Malloy (2016), Kong (2020), and Cohen et al. (2022)), we use turnovers in congressional committee chairmanships as an exogenous shock to state-level federal government expenditures. The rationale is that government procurement often experiences a substantial increase for firms headquartered in states represented by a new powerful chair (Cohen et al. (2011)).

Our difference-in-differences (DiD) analysis provides consistent evidence that suppliers experiencing a plausibly exogenous increase in federal government procurement significantly reduce corporate pollution. Specifically, congressional chairman turnovers are associated with a 29.7% reduction in both the total toxic pollution and sales-scaled toxic emissions of treated firms, relative to control firms.

Next, we explore two channels through which government customers shape their contractor firms' environmental policies. The first channel pertains to internal environmental governance, with a particular focus on building human capital through the appointment of sustainability directors and the provision of environmental training to employees. We find that, on average, a 1-unit increase in the sales-scaled value of government contracts is associated with a 1.26 percentage point increase in the likelihood of appointing a sustainability director and a 3.35 percentage point increase in the likelihood of providing environmental management training, respectively. The second channel is more direct as it focuses on firm pollution abatement investments aimed at preventing pollution at its source. Our analysis shows that a 1-unit increase in the sales-scaled value of government contracts is associated with a 2.18 percentage point higher likelihood of making environmental investments, and with a 0.95 and 0.78 percentage point higher likelihood of investing in operations-related and production-related pollution prevention practices, respectively. Moreover, the corresponding DiD analyses based on congressional chairman turnovers provide largely consistent evidence. The DiD results indicate that turnovers are associated with increases of 10.6 percentage points in the likelihood of environmental management training, 11.67 in environmental investments, 6.67 in operations-related pollution prevention investments, and 7.95 in production-related pollution prevention investments among treated firms, relative to control firms.

Further, we assess two alternative explanations for our findings. First, we examine whether the lower pollution in government contractor firms is driven by a reduction in firms' economic activities. The results provide little support for this conjecture. Using production volume and employment growth as proxies for economic activities (Akey and Appel (2021)), the relationship between government customers and overall firm economic activities is statistically insignificant. Second, we consider whether government contracting alleviates the financial constraints of contractor firms, thereby allowing more investment in pollution abatement. Inconsistent with this explanation, we observe an insignificant effect of government customers on their contractors' financial constraints. Ruling out these alternative explanations reinforces our interpretation that the external governance provided by government customers shapes corporate environmental policies and performance.

In the final part of our analysis, we explore the consequences of firm environmental misbehavior. While our main analysis focuses on the government's ex post monitoring role, environmental performance may influence the ex ante selection of contractors (Flammer (2018)). We test this ex ante effect by examining the impact of firms' environmental violations on procurement outcomes. We find that environmental violations in the past 5 years significantly reduce both the number and value of government contracts awarded to violators, suggesting that government customers consider environmental records when selecting suppliers. In addition, our analysis of corporate pollution around first-time government contract awards (Samuels (2021)) confirms the presence of both ex ante selection and ex post monitoring effects. Taken together, our study reveals that government customers promote corporate environmental sustainability through both selection and monitoring.

Our article makes two main contributions. First, it adds to the literature on the determinants of corporate environmental policies. One line of this research focuses on various corporate and managerial characteristics, such as organizational form (Akey and Appel (2021)), financing capacity (Cohn and Deryugina (2018), Levine, Lin, Wang, and Xie (2018), Xu and Kim (2022), and Bartram, Hou, and Kim (2022)), executive incentives (Berrone and Gomez-Mejia (2009), Flammer, Hong, and Minor (2019)), ownership structure (Berrone, Cruz, Gomez-Mejia, and Larraza-Kintana (2010), Shive and Forster (2020)), and segment disclosure (Jing, Xu, and Zuo (2025)). More relevant to us, another line of research explores the roles of various stakeholders, including local institutional investors (Kim et al. (2019)), hedge funds (Akey and Appel (2019), Chu and Zhao (2019), Naaraayanan, Sachdeva, and Sharma (2021)), private equity (Bellon (2025)), financial analysts (Jing et al. (2024)), banks (Bellon (2021)), corporate customers (Chen, Su, Tian, Xu, and Zuo (2025)), and local media (Heese et al. (2022)). Our study sheds light on this inquiry by highlighting the important role of government customers in determining corporate environmental policies.

Second, our article contributes to the literature on the microeconomic outcomes of government spending.[4] The extant literature on the real effects of government procurement shows that government contractors tend to have favorable loan contract terms (Cohen et al. (2022)), higher stability and profitability (Goldman (2020), Cohen and Li (2020)), less corporate innovation (Kong (2020)), and a lower cost of equity (Dhaliwal, Judd, Serfling, and Shaikh (2016)). A closely related strand of literature exploring the implications of government customers' monitoring of their contractors shows that such monitoring helps enhance contractors' financial reporting quality and transparency (Samuels (2021)) and reduces federal tax avoidance (Mills et al. (2013)). Complementing these studies, we document an important and underexplored impact of government spending on corporate environmental policies: government monitoring significantly improves the supplier firm's environmental performance and reduces its environmentally irresponsible behavior.

II. Data, Empirical Model, and Descriptive Statistics

A. Pollution Data

We obtain data on corporate pollution from the TRI database of the EPA. The database has been widely used in previous literature to assess corporate environmental

[4]Prior studies focus on the macroeconomic impact of government spending on consumption (Galí, López-Salido, and Vallés (2007), Ramey (2011)), employment (Chodorow-Reich, Feiveson, Liscow, and Woolston (2012), Nakamura and Steinsson (2014)), and output (Blanchard and Perotti (2002), Hall (2009), Nakamura and Steinsson (2014)).

performance (e.g., Klassen and McLaughlin (1996), King and Lenox (2002), Berrone et al. (2010), Akey and Appel (2021), Xu and Kim (2022), Hsu, Li, and Tsou (2023)). Since 1987, the TRI program has required U.S. plants to report toxic emissions information if a facility: i) manufactures, processes, or uses 1 of over 700 TRI-listed chemicals; ii) has 10 or more full-time employees; and iii) operates in 1 of the approximately 400 industries covered by the program.[5] One unique feature of the TRI database is that it provides detailed information on plants with toxic emissions, including facility name, parent company name, reporting year, and the quantity of toxic pollution released into the environment.

We supplement the TRI data with the financial information of U.S. public firms from the Compustat database. Since there is no common identifier for firms across the two data sets, following previous studies (e.g., Akey and Appel (2019), Akey and Appel (2021), Xu and Kim (2022), and Jing et al. (2024)), we conduct both fuzzy matching and manual checks. Specifically, we first apply a fuzzy string-matching algorithm to match the parent company names in the TRI database with the company names in Compustat. We then manually check the matched firms based on company address, company website, and the DUNS number to ensure matching accuracy.[6] Following Akey and Appel (2019), (2021) and Chu and Zhao (2019), we exclude plants with zero toxic pollution. This procedure leaves us with 6,918 plants across 793 unique firms over the period of 2001–2019.[7] Since the explanatory variables are lagged by 1 year relative to the firm-level pollution variables in our main analysis, the pollution data span from 2002 to 2020.

The toxic emissions data from the TRI data set are at the chemical-facility-year level. To capture a firm's environmental performance, we aggregate the amount of all chemical emissions across its facilities to construct two firm-level measures of toxic pollution (e.g., Chatterji and Toffel (2010), Chu and Zhao (2019), Bartram et al. (2022), and Jing et al. (2024)). *LN(POLLUTION)* is the natural logarithm of toxic pollution. *LN(POLLUTION/SALES)* is the natural logarithm of toxic pollution scaled by total sales. One justification for the sales-scaled measure is that it captures pollution intensity by measuring the level of pollution per unit of output (Konar and Cohen (1997), (2001), Clarkson, Li, Richardson, and Vasvari (2008), and Shive and Forster (2020)).

B. Government Procurement Data

We collect data on federal government contracts from the USAspending.gov website, developed in compliance with the Federal Funding Accountability and Transparency Act. This database is widely used in prior studies (e.g., Goldman, Rocholl, and So (2013), Mills et al. (2013), Flammer (2018), Brogaard, Denes, and Duchin (2021), Hebous and Zimmermann (2021), and Samuels (2021)). It provides detailed information on all contracts awarded by U.S. federal government agencies

[5]The TRI toxic chemical list contains 775 chemicals from 33 chemical categories. The full list can be found at https://www.epa.gov/toxics-release-inventory-tri-program/tri-listed-chemicals.

[6]The TRI database provides DUNS numbers of parent companies. For Compustat firms, we use Dun & Bradstreet to check their DUNS numbers.

[7]The sample starts in 2001 because the government procurement data are available from 2001 onward.

with a transaction value over 3,000 USD. Such information includes contract obligated amount, award date, contract-awarding agency, duration, and award recipient characteristics. Each contract may consist of several transactions, including the initial contract award and subsequent modifications, and firms can have multiple contracts that span several years (Samuels (2021)). Following Hebous and Zimmermann (2021) and Boland and Godsell (2021), we exclude contract awards below the 3,000 USD threshold and those using other than full and open competition procedures. These contracts are less regulated because they are insulated from numerous competitive procedures and reporting requirements (Warren (2014)).[8]

Motivated by prior literature (e.g., Goldman et al. (2013), Mills et al. (2013), Hebous and Zimmermann (2021), and Samuels (2021)), we construct two measures of government contracting by aggregating the amount of contract awards for each firm-fiscal year. *LN(CONTRACT_N)* is the natural logarithm of the number of federal government contracts a firm has in a year plus 1. *CONTRACT/SALES* is the amount of federal award dollars scaled by the firm's sales in a year, indicating how reliant the firm is on government customers.

We then merge the government contracting data with our pollution sample. As before, we use a fuzzy string-matching algorithm to match the parent company name of each contract award with the company names in our pollution sample and manually check the accuracy of each match. All variables are winsorized at the 1st and 99th percentiles to mitigate the effect of outliers. Our final sample consists of 793 unique U.S. public firms and 9,438 firm-year observations, of which 472 unique firms and 4,367 firm-year observations have the government as a customer, with a total of 1,750,290 federal government contracts.[9]

C. Empirical Model

We examine the effect of government customers on corporate environmental policies using the following model specification:

$$(1) \qquad POLLUTION_{i,t+1} = \alpha + \beta_1 GOV\_CONTRACT_{i,t} + \delta X_{i,t} + \eta_i + \mu_t + \varepsilon_{i,t},$$

where i indexes firms and t indexes fiscal years. The dependent variable captures corporate environmental policies, proxied by total toxic pollution, *LN(POLLUTION)*, and output-adjusted toxic emissions, *LN(POLLUTION/SALES). GOV_CONTRACT* is our main explanatory variable of interest, and our two measures of government contracting are the natural logarithm of the number of government contracts plus 1, *LN(CONTRACT_N)*, and the fraction of sales to government customers, *CONTRACT/SALES.* Our coefficient of interest β_1 captures the effect of government customers on corporate environmental policies.

$X_{i,t}$ denotes a vector of firm-specific control variables commonly used in prior studies (e.g., Shive and Forster (2020), Samuels (2021), Xu and Kim (2022)),

[8]The reporting threshold is 25,000 USD prior to 2004 and decreases to 3,000 USD in 2004. Our results are robust when excluding contract awards under 25,000 USD.

[9]The proportion of government contractor firms in our sample is higher than that in other studies (e.g., Hebous and Zimmermann (2021), Samuels (2021)) because our pollution sample is dominated by manufacturing firms, which are major recipients of federal contracts.

including firm size (*SIZE*), the market-to-book ratio (*MTB*), tangibility (*TANGIBILITY*), dividend (*DIVIDEND*), capital expenditure (*CAPEX*), cash holdings (*CASH*), book leverage (*LEVERAGE*), return on assets (*ROA*), and research and development expenditure (*R&D*). All the explanatory variables in equation (1) are lagged by 1 year, as it takes time for firms to respond to government monitoring. We include firm (η_i) and year (μ_t) fixed effects to account for any unobserved time-invariant firm characteristics and time-varying aggregate trends that might influence corporate environmental policies. Standard errors are clustered at the firm level.

D. Descriptive Statistics

Table 1 reports the descriptive statistics of government contract awards by year and industry, respectively. Panel A reports, for each year, the number of contracts, total contract value, the number of government contractor firms, and the proportion of government contractor firms. Our sample firms receive the lowest number of

TABLE 1

Distribution of Government Contract Awards

Table 1 reports descriptive statistics on government contract awards, including the number of contracts, total contract value, number of observations with government contracts, and the proportion of government contractor firms, presented by year in Panel A and by industry in Panel B.

Panel A. Government Contract Award Distribution by Year

Year	Contract_N	Total Contract Value (Billion)	No. of Obs. with Contracts	Percentage of Obs. with Contracts in Each Year
2001	32,053	21.220	237	44.13%
2002	41,623	32.369	245	46.49%
2003	52,625	35.844	257	49.14%
2004	60,789	38.219	272	51.61%
2005	83,985	33.984	276	53.08%
2006	81,750	46.100	265	51.36%
2007	91,730	47.743	271	53.14%
2008	100,599	57.163	276	54.01%
2009	96,311	51.821	267	52.77%
2010	142,702	55.301	262	51.88%
2011	140,656	58.285	235	46.17%
2012	119,017	61.625	229	45.71%
2013	118,553	48.647	205	41.75%
2014	129,830	48.643	198	41.51%
2015	121,182	41.567	187	39.87%
2016	93,485	42.959	180	38.96%
2017	82,390	36.764	173	37.12%
2018	84,711	33.357	169	37.64%
2019	76,299	27.711	163	37.73%

Panel B. Government contract award Distribution by Industry

Industry	Contract_N	Total Contract Value (Billion)	No. of Obs. with Contracts	Percentage of Obs. with Contracts in Each Industry
Business Equipment	224,218	163.054	623	51.23%
Chemicals	20,610	1.574	263	28.56%
Consumer Durables	138,700	33.123	293	40.92%
Consumer Non-Durables	15,302	8.752	319	49.77%
Health Care	115,573	28.160	369	71.51%
Manufacturing	426,333	493.094	1,520	46.12%
Oil and Gas	9,436	24.681	165	45.08%
Mines, Construction, and Transportation	75,846	42.908	299	47.76%
Utilities	3,767	1.945	313	45.49%
Retail	720,486	22.029	194	52.86%

Industries with fewer than 10 firm-year observations in our sample (finance, telephone, and television) are not reported.

government contracts (32,053 contracts) in 2001 and the highest number (142,702 contracts) in 2010. Notably, both the number and value of contracts increase after the 2007–2008 financial crisis, indicating that sales to government customers are not adversely affected by the crisis. The prevalence of government contracts varies across years. The number of firms with government contracts ranges from 163 in 2019 to 276 in 2005 and 2008. The percentage of firms with government contracts in a year ranges from 37.12% in 2017 to 54.01% in 2008.

Panel B of Table 1 reports, for each Fama–French 12 industry (except the industries with fewer than 10 observations—namely, finance and telephone and television), the number of contracts, total contract value, the number of government contractor firms, and the proportion of government contractor firms. The two most prevalent industries in terms of contract number, contract value, and the number of firms with government contracts are manufacturing and business equipment. For the majority of industries, the proportion of government contractor firms is between 40% and 53%. The industries with the lowest and the highest percentage of government contractor firms are chemicals (28.56%) and health care (71.51%), respectively.

Panel A1 of Table 2 presents the descriptive statistics of the firm-level pollution measures, government contracting measures, and firm financial variables for the full sample. In our sample, the firm-year average value of government contracts is 50.22 million USD, with a standard deviation of 247.82 million USD. The average level of pollution is 1,783.705 thousand pounds, with a standard deviation of 6,587.818 thousand pounds. The log-transformed sales-scaled measure of pollution has an average of −11.426 and a standard deviation of 3.747. The standardized pollution measure has a mean of 0 and a standard deviation of 1.

In Panel A2 of Table 2, we report the descriptive statistics of the government contracting measures for the subsample of firm-year observations with government contracts. 46.3% of the firm-year observations have government contracts. In this subsample, the firm-year average value of government contracts is 108.54 million USD, with a standard deviation of 355.55 million USD. The 5th percentile, 25th percentile, median, 75th percentile, and 95th percentile values of the firm-year government contract awards are 0.015 million, 0.356 million, 3.317 million, 23.709 million, and 698.477 million USD, respectively, indicating that the distribution of government contract values is right-skewed, with a small number of very high contract values. This pattern is largely in line with that documented by Samuels (2021).[10]

In Panel B of Table 2, we present the decomposition of the standard deviations of our government contracting variables. The within-firm standard deviations of *CONTRACT_N* and *CONTRACT/SALES* are 161.846 and 1.003, respectively, whereas their corresponding between-firm standard deviations are 275.470 and 1.828. These statistics suggest that government contracting is fairly dynamic during our sample period, which allows us to exploit the within-firm variation in the

[10]Samuels (2021) reports the mean, median, 75th percentile, and 95th percentile of government contract values (in million USD) as 124, 0.628, 6.727, and 192, respectively. Similar to our study, the distribution of contract values is heavily right-skewed. The main difference is that our sample is limited to firms with pollution data from the EPA, while Samuels (2021) includes the CRSP-Compustat firms.

TABLE 2

Descriptive Statistics

Table 2 reports summary statistics for the main variables used in our analysis. Panel A presents summary statistics on pollution, government contracting, and financial variables for the full sample (in Panel A1) and government contracting variables for the subsample of firm-year observations with government contracts (in Panel A2). Panel B reports the within-firm and between-firm standard deviations of the government contracting variables. Refer to the Appendix for variable definitions.

Panel A. Summary Statistics on Pollution, Government Contracting, and Financial Variables

Variable	No. of Obs.	Mean	Median	Std. Dev.	5th	25th	75th	95th
Panel A1. Full Sample								
CONTRACT_VALUE (MILLION)	9,438	50.222	0.000	247.820	0.000	0.000	2.391	165.446
CONTRACT_N	9,438	99.261	0.000	358.696	0.000	0.000	19.000	505.000
LN(CONTRACT_N)	9,438	1.592	0.000	2.207	0.000	0.000	2.996	6.227
CONTRACT/SALES	9,438	0.550	0.000	2.162	0.000	0.000	0.080	2.638
HAVE_CONTRACT	9,438	0.463	0.000	0.499	0.000	0.000	1.000	1.000
POLLUTION (THOUSAND)	9,438	1,783.705	44.091	6,587.818	0.009	2.905	432.268	8,932.823
LN(POLLUTION)	9,438	10.165	10.694	4.054	2.197	7.974	12.977	16.005
LN(POLLUTION/SALE)	9,438	−11.426	−10.887	3.747	−18.934	−13.418	−8.765	−6.225
LN(POLLUTION/AT)	9,438	−11.564	−11.013	3.706	−18.973	−13.633	−8.837	−6.645
LN(POLLUTION/COGS)	9,438	−11.022	−10.430	3.703	−18.590	−12.899	−8.406	−5.932
STANDARDIZED_POLLUTION	9,246	0.000	−0.309	1.000	−0.706	−0.400	−0.145	2.215
SIZE	9,438	7.852	7.778	1.766	4.889	6.663	9.008	10.829
MTB	9,438	2.730	2.074	3.794	0.513	1.377	3.331	7.820
TANGIBILITY	9,438	0.304	0.252	0.192	0.079	0.156	0.410	0.708
DIVIDEND	9,438	0.016	0.011	0.021	0.000	0.000	0.023	0.057
CAPEX	9,438	0.043	0.035	0.030	0.011	0.022	0.056	0.102
CASH	9,438	0.097	0.064	0.099	0.004	0.024	0.138	0.305
LEVERAGE	9,438	0.270	0.263	0.164	0.002	0.156	0.371	0.561
ROA	9,438	0.042	0.046	0.073	−0.079	0.018	0.078	0.142
R&D	9,438	0.018	0.007	0.029	0.000	0.000	0.024	0.078
Panel A2. Subsample (Firm-Years with Government Contracts)								
CONTRACT_VALUE (MILLION)	4,367	108.540	3.317	355.549	0.015	0.356	23.709	698.477
CONTRACT_N	4,367	214.524	25.000	503.358	1.000	4.000	153.000	1,315.000
LN(CONTRACT_N)	4,367	3.440	3.258	2.042	0.693	1.609	5.037	7.182
CONTRACT/SALES	4,367	1.189	0.105	3.056	0.000	0.012	0.641	7.678

Panel B. Decomposing the Standard Deviations of Government Contracting Variables

	No. of Obs.	Within-Firm Std. Dev.	Between-Firm Std. Dev.
CONTRACT_VALUE (MILLION)	9,438	97.756	190.794
CONTRACT_N	9,438	161.846	275.470
LN(CONTRACT_N)	9,438	0.771	1.942
CONTRACT/SALES	9,438	1.003	1.828
HAVE_CONTRACT	9,438	0.271	0.427

presence of government customers to study its impact on corporate environmental policies.

III. Main Results

A. Government Customers and Corporate Pollution

Table 3 reports the baseline estimation results of the impact of government customers on corporate pollution. The dependent variable is the toxic pollution, *LN (POLLUTION)*, in columns 1 and 2, and sales-adjusted toxic pollution, *LN(POLLUTION/SALES)*, in columns 3 and 4. The measure for government contracting is *LN(CONTRACT_N)* in columns 1 and 3, and *CONTRACT/SALES* in columns 2 and 4. Across all specifications, the coefficients on both *LN(CONTRACT_N)* and

TABLE 3

Government Contracting and Corporate Pollution

Table 3 reports the baseline regressions of corporate pollution on government contracting. We use the OLS estimator. The dependent variable is *LN(POLLUTION)* in columns 1 and 2 and *LN(POLLUTION/SALES)* in columns 3 and 4. *LN(POLLUTION)* is the natural logarithm of the amount of toxic pollution. *LN(POLLUTION/SALES)* is the natural logarithm of sales-adjusted toxic pollution. The main explanatory variables are two measures of government contracting. *LN(CONTRACT_N)* is the natural logarithm of the number of government contracts plus 1. *CONTRACT/SALES* is the amount of federal award dollars scaled by total sales revenue. Refer to the Appendix for variable definitions. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	LN(POLLUTION)		*LN(POLLUTION/SALES)*	
	1	2	3	4
LN(CONTRACT_N)	−0.086***		−0.091***	
	(−2.92)		(−3.04)	
CONTRACT/SALES		−0.050***		−0.059***
		(−2.58)		(−3.13)
SIZE	0.628***	0.598***	−0.005	−0.038
	(5.64)	(5.46)	(−0.05)	(−0.35)
MTB	0.012**	0.012**	0.009	0.009
	(2.12)	(2.11)	(1.63)	(1.62)
TANGIBILITY	0.229	0.216	0.924*	0.910*
	(0.46)	(0.43)	(1.88)	(1.85)
DIVIDEND	1.826	1.840	1.438	1.453
	(0.93)	(0.94)	(0.72)	(0.73)
CAPEX	0.059	0.075	−0.509	−0.497
	(0.05)	(0.06)	(−0.46)	(−0.45)
CASH	−0.563	−0.586	−0.155	−0.177
	(−1.18)	(−1.23)	(−0.32)	(−0.36)
LEVERAGE	0.030	0.020	0.093	0.081
	(0.08)	(0.06)	(0.25)	(0.22)
ROA	0.938*	0.945*	0.390	0.398
	(1.72)	(1.73)	(0.72)	(0.74)
R&D	0.500	0.393	−3.237	−3.362
	(0.12)	(0.10)	(−0.81)	(−0.87)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	9,438	9,438	9,438	9,438
Adj. R^2	0.873	0.873	0.854	0.854

CONTRACT/SALES are negative and statistically significant at the 1% level, suggesting that firms significantly reduce toxic pollution in the presence of government customers. The effect is economically significant. As shown in columns 1 and 3, a 1% increase in the number of government contracts reduces the total toxic pollution and sales-scaled toxic emissions of contractor firms by 0.086% and 0.091%, respectively. Overall, the baseline results are consistent with our hypothesis that, when facing scrutiny from government customers, contractor firms improve environmental performance by reducing toxic pollution.

B. Cross-Sectional Analysis

Next, we explore the cross-sectional heterogeneity in the effect of government customers on corporate pollution. To the extent that government customers play an external governance role, we expect their effect on corporate pollution to be i) more pronounced when the government has stronger incentives to engage in monitoring, ii) stronger when firms rely more on government customers and are therefore more incentivized to comply with their environmental requirements, and iii) weaker when firms are politically connected.

We test cross-sectional heterogeneity in the effect of government procurement using the following specification.

$$(2) \qquad POLLUTION_{i,t+1} = \alpha + \beta_1 CONTRACT_{D1\,i,t} + \beta_2 CONTRACT_{D0\,i,t} + \delta X_{i,t} + \eta_i + \mu_t + \varepsilon_{i,t},$$

where we divide firms with government contracts into two groups denoted as *CONTRACT_D1* and *CONTRACT_D0*, and then test whether the coefficients on these two subgroup indicators (i.e., β_1 and β_2) are statistically different from each other.

Based on equation (2), we first examine the effect of contract duration on the relationship between government customers and supplier pollution. Contracts with longer durations typically require more commitment from government agencies and impose more stringent procurement-related requirements on contractors (Samuels (2021)). Additionally, over longer contract periods, government agencies tend to form closer relationships with contractors and engage more frequently with them (He, Li, Li, and Zhang (2024)). This enhanced interaction facilitates more effective monitoring of supplier environmental behavior. Following Samuels (2021), we measure contract duration as the average length of all contract awards in a fiscal year, weighted by contract value. Contractor firms are then classified into long-duration and short-duration groups. *CONTRACT_LONG* (*CONTRACT_SHORT*) takes the value of 1 if a firm's weighted average contract duration is above (below) the median, and 0 otherwise.

Table 4 presents the results of the cross-sectional analysis. Panel A reports that the coefficients on *CONTRACT_LONG* and *CONTRACT_SHORT* are negative and significant at the 5% level or better in both specifications, with the coefficients on the former being more negative than those on the latter (p-values for the tests of coefficient differences are 0.098 and 0.063, respectively). The findings are consistent with the conjecture that longer contract duration facilitates government customers' monitoring, thereby reinforcing the mitigating effect on supplier pollution.

Moreover, we examine the moderating effect of Republican versus Democratic administrations on the impact of government procurement on corporate pollution. Over our sample period (i.e., 2001–2019), the United States was led by two Republican presidents (George Bush, January 2001 to January 2009, and Donald Trump, January 2017 to January 2021) and one Democratic president (Barack Obama, January 2009 to January 2017). To the extent that a Democratic president is more pro-environmental and has a stronger incentive to monitor environmental performance than their Republican counterparts, we expect government procurement to have a greater impact under Democratic administrations. In Panel B of Table 4, *CONTRACT_DEMOCRATIC* (*CONTRACT_REPUBLICAN*) takes the value of 1 when a firm receives government contracts under a Democratic (Republican) president, and 0 otherwise. We find that the effect of government procurement on corporate pollution is larger under Democratic leadership than under Republican leadership, although this difference is statistically insignificant.

Second, we test whether the relationship between government customers and supplier pollution varies with a firm's reliance on government contracts. The more a firm relies on government contracts for its sales, the greater bargaining power

TABLE 4

Cross-Sectional Heterogeneity

Table 4 reports the regressions of corporate pollution on government contracting, conditional on contract characteristics. We use the OLS estimator. Panel A examines the effect of government contracting on corporate pollution, conditional on contract duration. *CONTRACT_LONG* (*CONTRACT_SHORT*) is an indicator variable that equals 1 if a firm has at least one contract and the value-weighted average length of all contracts is above (below) the median, and 0 otherwise. Panel B examines the effect of government contracting on pollution, conditional on whether the U.S. president is Republican or Democratic. *CONTRACT_DEMOCRATIC* (*CONTRACT_REPUBLICAN*) is an indicator variable that equals 1 when a firm receives government contracts under a Democratic (Republican) president, and 0 otherwise. Panel C examines the effect of government contracting on corporate pollution, conditional on reliance on government contracts. *CONTRACT_HIGH RELIANCE* (*CONTRACT_LOW RELIANCE*) is an indicator variable that equals 1 if the proportion of government contract value to sales revenue is above (below) 10%, and 0 otherwise. Panel D examines the effect of government contracting on corporate political connections. *CONTRACT_WITH POLITICAL CONNECTIONS* (*CONTRACT_WITHOUT POLITICAL CONNECTIONS*) is an indicator variable that equals 1 if a firm has at least one contract and its political contributions to congressional candidates in the previous election cycle are positive (0), and 0 otherwise. For each panel, the dependent variable is *LN(POLLUTION)* in column 1 and *LN(POLLUTION/SALES)* in column 2. *LN(POLLUTION)* is the natural logarithm of the amount of toxic pollution. *LN(POLLUTION/SALES)* is the natural logarithm of sales-adjusted toxic pollution. Refer to the Appendix for variable definitions. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate significance levels at 1%, 5%, and 10%, respectively.

	LN(POLLUTION)	*LN(POLLUTION/SALES)*
	1	2
Panel A. Contract Duration		
CONTRACT_LONG	−0.258***	−0.282***
	(−2.70)	(−2.92)
CONTRACT_SHORT	−0.138**	−0.140**
	(−1.96)	(−1.97)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Tests of coefficient differences (p-value)	0.098*	0.063*
N	9,438	9,438
Adj. R^2	0.873	0.854
Panel B. Republican Versus Democratic Administrations		
CONTRACT_DEMOCRATIC	−0.199**	−0.195**
	(−2.09)	(−2.05)
CONTRACT_REPUBLICAN	−0.169**	−0.189**
	(−1.99)	(−2.19)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Tests of coefficient differences (p-value)	0.405	0.479
N	9,438	9,438
Adj. R^2	0.873	0.854
Panel C. Reliance on Government Contracts		
CONTRACT_HIGH RELIANCE	−0.542**	−0.669**
	(−2.11)	(−2.57)
CONTRACT_LOW RELIANCE	−0.180***	−0.190***
	(−2.71)	(−2.80)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Tests of coefficient differences (p-value)	0.070*	0.027**
N	9,438	9,438
Adj. R^2	0.873	0.854
Panel D. Political Connections		
CONTRACT_WITHOUT POLITICAL CONTRIBUTIONS	−0.261***	−0.272***
	(−2.99)	(−3.08)
CONTRACT_WITH POLITICAL CONTRIBUTIONS	−0.112	−0.122
	(−1.33)	(−1.44)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Tests of coefficient differences (p-value)	0.083*	0.079*
N	9,438	9,438
Adj. R^2	0.873	0.854

government customers have, and the stronger the firm's incentives to comply with government environmental requirements. We measure a firm's reliance on government contracts using the ratio of the total value of government contracts to total annual sales (i.e., *CONTRACT/SALES*). Based on this measure, we divide contractor firms into two groups. *CONTRACT_HIGH RELIANCE* (*CONTRACT_LOW RELIANCE*) takes the value of 1 if a firm's government contracts account for more (less) than 10% of its annual sales, and 0 otherwise.

Panel C of Table 4 reports that the coefficients on *CONTRACT_HIGH RELIANCE* and *CONTRACT_LOW RELIANCE* are negative and significant at the 5% level or better in both specifications. The coefficients on the former are more negative than those on the latter (*p*-values for the tests of coefficient differences are 0.070 and 0.027, respectively), suggesting that the effect of government customers on pollution reduction is stronger when a firm relies more heavily on government contracts for its sales.

Finally, political connections of government contractors may hinder the effectiveness of government monitoring. Duchin and Sosyura (2012) document that politically connected firms are more likely to receive government funds than their politically unconnected counterparts. Brogaard et al. (2021) provide further evidence of political favoritism in government procurement, showing that politically connected firms initially bid lower than their unconnected counterparts but subsequently renegotiate for more favorable contract terms after winning the contracts. In our context, politically connected contractor firms are likely insulated from regulatory pressures and, consequently, are less incentivized to improve environmental performance. Following Brogaard et al. (2021), we classify a firm as politically connected if its political contributions to congressional candidates in the previous election cycle are positive.

In Panel D of Table 4, we find that the coefficients on *CONTRACT_WITHOUT POLITICAL CONTRIBUTIONS* and *CONTRACT_WITH POLITICAL CONTRIBUTIONS* are negative. However, only the coefficients on the former are significant at the 1% level, and they are more negative than those for the latter (*p*-values for the tests of coefficient differences are 0.083 and 0.079, respectively). This evidence indicates that the political connections of government contractors undermine the monitoring role of government customers. In sum, the effect of government contracting on corporate pollution is, on average, more than twice as large among firms facing greater government scrutiny, suggesting that monitoring by government customers is the driving force behind the reduction in pollution among contractor firms.

C. Evidence from a Difference-in-Differences Analysis: Congressional Chairman Turnovers

While our baseline evidence suggests that government contractor firms exhibit better environmental performance than non-contractor firms, the relationship between government procurement and corporate environmental policies may be spurious. For example, unobservable heterogeneity correlated with both government contracting and corporate environmental policies could lead to omitted variable bias. To mitigate potential endogeneity concerns, we conduct a DiD analysis using changes in congressional committee chairmanships as an exogenous shock to state-level federal government expenditures. This empirical design is based on the premise that congressional chair turnovers represent plausibly exogenous shocks to government expenditures (Cohen et al. (2011), (2022), Cohen and Malloy (2016)). Cohen et al. (2011) document that changes in powerful committee chairmanships significantly increase government purchases in the ascending chairman's home state, thereby boosting the value of government contracts awarded to firms in that state. These chair turnover events, typically triggered by the resignation of the incumbent or a change in the party controlling that branch of Congress, are considered unrelated to the economic and political conditions in the home state, making them plausibly exogenous shocks to the state's share of federal funds.

Following Cohen et al. (2011), we construct a variable that captures changes in the top 5 most influential congressional committee chairmanships (i.e., Finance, Veterans Affairs, Appropriations, Rules, and Armed Services) as a source of exogenous variation in federal government procurement.[11] To examine the effect of increased federal government expenditures, we estimate DiD regressions around the turnovers of congressional committee chairs. We perform a stacked DiD analysis to mitigate concerns about treatment effect heterogeneity (Baker, Larcker, and Wang (2022)). Specifically, the treatment group consists of firms headquartered in states where a senator was appointed as chairman of 1 of the top-5 Senate committees.[12] We construct the stacked DiD sample by first matching each treated firm to firms that are never treated, based on the same SIC 2-digit industry and size quartile in the year before the chairman turnover. For each observation in the treatment group, we construct an event episode covering the 3 years before (years $t-3$ to $t-1$) and 4 years after (years t to $t+3$) the event. We then stack the data across all event episodes and estimate a standard DiD model with firm and year fixed effects as follows:

$$(3)\quad POLLUTION_{i,t+1} = \alpha + \beta_1 TREATED_{i,t} \times AFTER_{i,t} + \delta X_{i,t} + \eta_i + \mu_t + \varepsilon_{i,t},$$

where *TREATED* is a dummy variable that equals 1 for firms in the treatment group, and 0 otherwise. *AFTER* is a dummy variable that equals 1 for the 4 years after the treatment, and 0 otherwise. *TREATED* and *AFTER* do not appear in equation (3), as they are subsumed by cohort-firm and cohort-year fixed effects, respectively. The coefficient of interest, β_1, represents the treatment effect of congressional chairman turnovers on corporate pollution.

In addition to the firm-specific variables in equation (1), we control for state-level characteristics, including GDP growth, unemployment, population, and income per capita, to address the concern that congressional chairman turnovers correlate with state-specific economic conditions (Cohen et al. (2011)). We also control for sales growth to account for the possibility that improved business conditions might reduce corporate pollution.[13]

Graphs A and B of Figure 1 show that the mean difference in pollution between the treatment and control groups remains stable in the pre-treatment period

[11]The congressional committee data are from http://web.mit.edu/17.251/www/data_page.html.

[12]The information of historical firm headquarters is from https://sraf.nd.edu/data/augmented-10-x-header-data/.

[13]Untabulated results show that the shock has an insignificant effect on firm financial constraints, as measured by the text-based indices developed by Hoberg and Maksimovic (2015) and Bodnaruk, Loughran, and McDonald (2015). This aligns with our findings in Section V.B and suggests that government contracting does not reduce pollution by easing financial constraints.

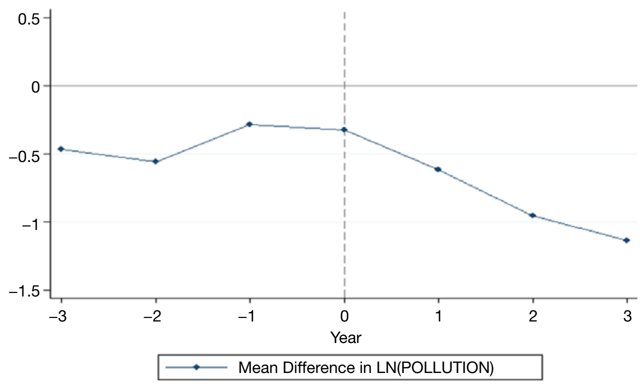
($t-3$ to $t-1$) and only begins to diverge in the post-treatment period, suggesting that the parallel trends assumption is not violated. Table 5 reports the DiD estimation results. Columns 1 and 4 present the results without controls, whereas columns 2 and 5 report the results from estimating equation (3) with controls. In all these columns, the coefficients on *TREATED*×*AFTER* are negative and statistically significant, suggesting that firms significantly reduce pollution in response to an exogenous increase in federal government procurement. In terms of economic magnitude, columns 2 and 5 indicate that treated firms reduce total pollution and sales-adjusted pollution by 29.7% ($\exp(-0.352)-1$) and 29.7% ($\exp(-0.353)-1$), respectively, relative to control firms. These results suggest that the plausibly exogenous increase in federal government procurement following congressional

FIGURE 1

Time Trend in Toxic Pollution Around Congressional Chairman Turnovers

Graphs A and B of Figure 1 show the mean difference in i) the natural logarithm of the total pollution (*LN(POLLUTION)*) and ii) the natural logarithm of the total sales-adjusted pollution (*LN(POLLUTION/SALES)*), respectively, between treated and control firms from 3 years before ($t-3$) to 3 years after ($t+3$) the congressional chairman turnovers. Graphs C and D of Figure 1 show the coefficient estimates and 95% confidence intervals of the dynamic effects of congressional chairman turnovers on *LN (POLLUTION)* and *LN(POLLUTION/SALES)*, respectively. See columns 3 and 6 of Table 5 for additional details.

Graph A. Mean Difference in LN(POLLUTION)



Graph B. Mean Difference in LN(POLLUTION/SALES)

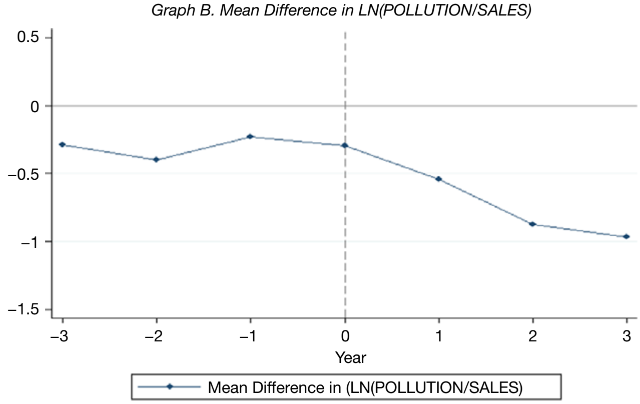


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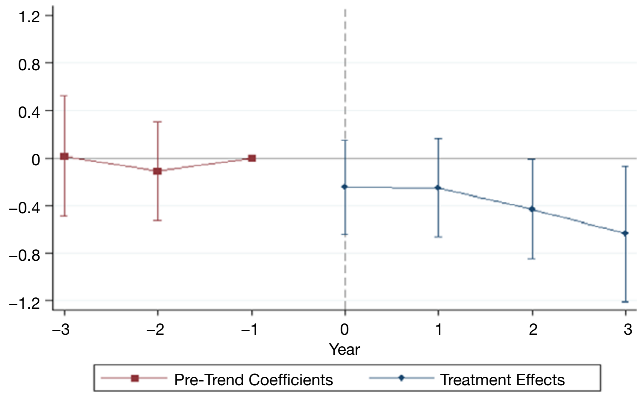
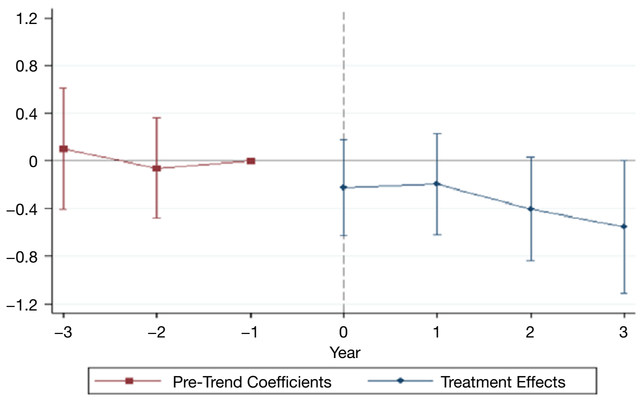
FIGURE 1 (continued)

Graph C. Dynamic Effects on LN(POLLUTION)



Graph D. Dynamic Effects on LN(POLLUTION/SALES)



chairman turnovers is associated with a significant reduction in pollution by government contractors.

To explore the timing of changes in pollution around chair turnovers, we estimate dynamic DiD models in columns 3 and 6. In these models, we replace *AFTER* in equation (3) with a set of indicators for the 2 pre-treatment years ($BEFORE_{-3}$, $BEFORE_{-2}$) and 4 post-treatment years ($AFTER_0$, $AFTER_{+1}$, $AFTER_{+2}$, $AFTER_{+3}$), using $BEFORE_{-1}$ as the base year. The coefficients on $TREATED\times BEFORE_{-3}$ and $TREATED\times BEFORE_{-2}$ are statistically insignificant, indicating no pre-trend. Conversely, the coefficients on $TREATED\times AFTER_{+2}$ and $TREATED\times AFTER_{+3}$ are negative and statistically significant, suggesting that the treatment effect is reasonably persistent (see the plot of regression coefficients in Graphs C and D of Figure 1).

Overall, our DiD analysis supports the view that contractor firms reduce toxic pollution in response to government customer monitoring. However, we caution that our DiD analysis does not fully address endogeneity concerns; rather, it increases our confidence that the observed relation between government procurement and

TABLE 5

DiD Analysis: Congressional Chairman Turnover

Table 5 reports the regressions from the DiD analysis examining corporate pollution around congressional chairman turnovers. We use the OLS estimator. We construct the stacked DiD sample by matching treated firms with never-treated firms in the same SIC 2-digit industry and size quartile. The treatment group (*TREATED*) consists of firms headquartered in a state where a senator was appointed as chairman of one of the top-5-ranked Senate committees during the sample period. *AFTER* is a dummy variable that equals 1 for the 4 years after the events, and 0 otherwise. In columns 3 and 5, we replace *AFTER* with two indicators for pre-treatment years ($BEFORE_{-3}$, $BEFORE_{-2}$) and four indicators for post-treatment years ($AFTER_0$, $AFTER_{+1}$, $AFTER_{+2}$, $AFTER_{+3}$), using $BEFORE_{-1}$ as the base year. The dependent variable is *LN(POLLUTION)* in columns 1–3 and *LN(POLLUTION/SALES)* in columns 4–6. *LN(POLLUTION)* is the natural logarithm of the amount of toxic pollution. *LN(POLLUTION/SALES)* is the natural logarithm of sales-adjusted toxic pollution. Refer to the Appendix for variable definitions. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate significance levels at 1%, 5%, and 10%, respectively.

	LN(POLLUTION)			*LN(POLLUTION/SALES)*		
	1	2	3	4	5	6
TREATED×AFTER	−0.270**	−0.352***		−0.260*	−0.353***	
	(−1.99)	(−2.61)		(−1.95)	(−2.61)	
$TREATED \times BEFORE_{-3}$			0.019			0.103
			(0.07)			(0.40)
$TREATED \times BEFORE_{-2}$			−0.113			−0.057
			(−0.53)			(−0.27)
$TREATED \times AFTER_0$			−0.246			−0.225
			(−1.22)			(−1.09)
$TREATED \times AFTER_{+1}$			−0.248			−0.196
			(−1.19)			(−0.91)
$TREATED \times AFTER_{+2}$			−0.431**			−0.403*
			(−2.01)			(−1.82)
$TREATED \times AFTER_{+3}$			−0.639**			−0.554*
			(−2.22)			(−1.95)
Controls	No	Yes	Yes	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,531	2,531	2,531	2,531	2,531	2,531
Adj. R^2	0.941	0.943	0.943	0.925	0.927	0.927

corporate pollution is not spurious. In the absence of perfect quasi-experiments, we adopt the "complementary approach" (Armstrong, Kepler, Samuels, and Taylor (2022)), focusing on economic mechanisms, falsifying alternative explanations, and triangulating results across multiple settings and specifications, as described in Sections IV and V.

IV. Mechanisms

A. Internal Environmental Governance

Our results so far suggest that government scrutiny induces contractor firms to curb toxic pollution. However, it is still unclear how government customers influence the policies contractors may adopt to combat pollution. In this section, we explore two channels through which government customers affect contractors' environmental performance. The first channel explores the possibility that firms with government customers are pressured to improve environmental performance by enhancing their internal environmental governance and providing training to employees. Specifically, we examine the effects of government customers on the likelihood of i) having a sustainability director and ii) providing environmental training.

First, we investigate whether government contractor firms are more likely to have a sustainability director. We obtain director information from the BoardEx database. Following Fu, Tang, and Chen (2020), a director is classified as a sustainability director if his or her job title contains any of the following words: sustainability, sustainable, responsibility, ethics, and environment. We then construct an indicator variable, *SUSTAINABILITY DIRECTOR*, that equals 1 for firm-years with at least one sustainability director, and 0 otherwise. The results in columns 1 and 2 of Panel A of Table 6 show a positive and statistically significant relationship between the government contracting variables and *SUSTAINABILITY DIRECTOR*, consistent with the notion that firms commit more internal governance resources to strengthen environmental responsibility in the presence of government customers.

TABLE 6

Mechanisms: Internal Environmental Governance

Table 6 reports the effect of government contracting on internal environmental governance. We use the Probit estimator. The dependent variable is *SUSTAINABILITY DIRECTOR* in Panel A and *ENV_MANAGEMENT* in Panel B. *SUSTAINABILITY DIRECTOR* is an indicator variable that equals 1 if a firm has at least one sustainability director, and 0 otherwise. *ENV_MANAGEMENT* is an indicator variable that equals 1 if a firm trains employees on environmental issues, and 0 otherwise. In columns 1 and 2, the main explanatory variables are two measures of government contracting. *LN (CONTRACT_N)* is the natural logarithm of the number of government contracts plus 1. *CONTRACT/SALES* is the amount of federal award dollars scaled by total sales revenue. In column 3, we perform the DiD analysis examining internal environmental governance around congressional chairman turnovers. Refer to the Appendix for variable definitions. We define industry fixed effects using 3-digit SIC codes. Standard errors are clustered at the firm level. *z*-statistics are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

Panel A. Sustainability Director

	SUSTAINABILITY DIRECTOR		
	1	2	3
LN(CONTRACT_N)	0.056**		
	(2.00)		
CONTRACT/SALES		0.064**	
		(2.46)	
TREATED×AFTER			0.095
			(0.69)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
State FE	No	No	Yes
Year FE	Yes	Yes	Yes
N	7,641	7,641	1,880
Pseudo-R^2	0.349	0.351	0.453

Panel B. Environmental Training

	ENV_MANAGEMENT		
	1	2	3
LN(CONTRACT_N)	−0.003		
	(−0.09)		
CONTRACT/SALES		0.116***	
		(4.09)	
TREATED×AFTER			0.589**
			(2.19)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
State FE	No	No	Yes
Year FE	Yes	Yes	Yes
N	3,974	3,974	1,275
Pseudo-R^2	0.261	0.267	0.500

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Second, firms with government customers may enhance the environmental training of their employees to improve environmental performance. Using environmental training data from the Thomson Reuters ASSET4 database, and following Fiechter, Hitz, and Lehmann (2022), we construct an indicator variable, *ENV_TRAINING*, that equals 1 if a company trains employees on environmental issues (e.g., resource reduction, emission reduction, and environmental-related codes of conduct), and 0 otherwise. The result in column 2 of Panel B of Table 6 shows a positive and significant relation between *CONTRACT/SALES* and *ENV_TRAINING*, supporting the view that firms with government customers improve environmental performance through training programs. Regarding economic significance, on average, a 1-unit increase in *CONTRACT/SALES* raises the likelihood of appointing a sustainability director and providing environmental management training by 1.26 and 3.35 percentage points, respectively.

B. Pollution Abatement Practices

In terms of the second channel, a contractor firm may increase investments in pollution abatement and prevention practices. This analysis exploits the fact that firms can reduce pollution by investing in pollution abatement activities, such as the development of green technologies and waste management systems (Akey and Appel (2021)). However, managers may lack the incentives to make such investments, especially when the probability of detecting corporate environmental misbehavior is low (Hart and Zingales (2016)). Government customers' monitoring makes it more difficult or costly to disguise environmentally irresponsible behavior. For this reason, we expect contractor firms under government scrutiny to be more likely to invest in pollution abatement and implement pollution prevention practices.

We first explore the effect of government customers on corporate investments in pollution abatement. Following Fiechter et al. (2022), we collect information on corporate environmental investment initiatives from the Thomson Reuters ASSET4 database. Such initiatives involve investments in cleaner technologies that reduce the risk of future environmental issues and create opportunities for improvements in environmental practices and performance. We construct an indicator variable, *ENV_INVESTMENT*, that equals 1 if a firm makes environmental investments, and 0 otherwise. The result in column 2 of Panel A of Table 7 shows that firms with government customers are more likely to undertake investment initiatives in environmental protection and pollution abatement. A 1-unit increase in *CONTRACT/SALES* is associated with a 2.18 percentage point higher likelihood of making environmental investments.

Next, to analyze firms' pollution abatement activities, we use the EPA's Pollution Prevention (P2) database, which provides information on corporate practices that reduce, eliminate, or prevent pollution at its source before recycling, treatment, or disposal at the plant-chemical level (Akey and Appel (2019), (2021), Muthulingam, Dhanorkar, and Corbett (2022)).[14] The pollution abatement

[14]The EPA identifies eight abatement practices: good operating practice, inventory control, spill and leak prevention, process modifications, surface preparation and finishing, cleaning and degreasing,

practices in the P2 database are broadly classified into operations-related and production-related pollution prevention practices. Operations-related practices aim to reduce toxic pollution and waste through improvements in operating processes and procedures, including good operating practices (e.g., improved maintenance scheduling and record-keeping), inventory control (e.g., efficient storage and management of chemicals and materials), and spill and leak prevention (e.g., monitoring programs and equipment inspections). Production-related practices, on the other hand, focus on improvements in techniques, materials, and equipment of the production process, including process modifications, surface preparation and finishing, cleaning and degreasing, product modifications, and raw material modifications.

In Panels B and C of Table 7, we examine the effect of government customers on contractors' operations-related and production-related pollution abatement activities, respectively. Panel B reports the regression results for the overall operations-related pollution prevention practices. The results for the subcomponent practices (i.e., *good operating practice*, *inventory control*, and *spill and leak prevention*) are reported in Panel A of Supplementary Material Table A2. We find that government customers significantly increase suppliers' operations-related pollution abatement activities, both in terms of the overall practices and the three subcomponent practices. According to column 2 of Panel B, a 1-unit increase in *CONTRACT/SALES* is associated with a 0.95 percentage point higher likelihood of investing in operations-related pollution prevention practices.

We then turn to production-related pollution abatement activities. Panel C of Table 7 reports the regression results for the overall production-related pollution prevention practices. The results for the subcomponent practices (i.e., *process modifications*, *surface preparation and finishing*, *cleaning and degreasing*, *product modifications*, and *raw material modifications*) are reported in Panel B of Supplementary Material Table A2. The results show that government customers significantly increase suppliers' production-related pollution abatement activities, particularly those related to raw material and cleaning and degreasing. According to column 2 of Panel C, a 1-unit increase in *CONTRACT/SALES* is associated with a 0.78 percentage point higher likelihood of investing in production-related pollution prevention practices. Our evidence suggests that implementing a range of operations-related and production-related pollution abatement practices is an important channel through which government customers improve corporate environmental performance.

Moreover, in column 3 of each panel of Tables 6 and 7, we perform the corresponding DiD analyses based on congressional chairman turnovers and find largely consistent evidence. The turnovers are associated with increases of 10.6 percentage points in the likelihood of environmental management training, 11.67 percentage points in environmental investments, 6.67 percentage points in operations-related pollution prevention investments, and 7.95 percentage points in production-related pollution prevention investments among treated firms, relative

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product modifications, and raw material modifications. The full list of pollution prevention practices is provided in Supplementary Material Table A1.

TABLE 7

Mechanisms: Pollution Abatement Investment

Table 7 reports the effect of government contracting on corporate environmental investments and pollution prevention practices. We use the Probit estimator. Panel A presents the regression of environmental investments on government contracting. *ENV_INVESTMENT* is an indicator variable that equals 1 if a firm reports making environmental investments to reduce future risks or increase opportunities, and 0 otherwise. Panels B and C present the regressions of pollution prevention practices on government contracting. *OPERATIONS-RELATED ABATEMENT* is an indicator variable that equals 1 if a firm reports at least one operations-related pollution abatement activity, and 0 otherwise. *PRODUCTION-RELATED ABATEMENT* is an indicator variable that equals 1 if a firm reports at least one production-related pollution abatement activity, and 0 otherwise. The detailed list and explanations of pollution prevention practices are shown in Supplementary Material Table A1. In columns 1 and 2, the main explanatory variables are two measures of government contracting. *LN(CONTRACT_N)* is the natural logarithm of the number of government contracts plus 1. *CONTRACT/SALES* is the amount of federal award dollars scaled by total sales revenue. In column 3, we perform the DiD analysis examining corporate pollution abatement investment around congressional chairman turnovers. Refer to the Appendix for variable definitions. We define industry fixed effects using 3-digit SIC codes. Standard errors are clustered at the firm level. z-statistics are reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate significance levels at 1%, 5%, and 10%, respectively.

Panel A. Environmental Investments

	ENV_INVESTMENT		
	1	2	3
LN(CONTRACT_N)	0.048		
	(1.25)		
CONTRACT/SALES		0.089**	
		(2.16)	
TREATED×AFTER			0.650*
			(1.74)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
State FE	No	No	Yes
Year FE	Yes	Yes	Yes
N	3,607	3,607	1,130
Pseudo-R^2	0.367	0.370	0.521

Panel B. Operations-Related Pollution Prevention Practices

	OPERATIONS-RELATED ABATEMENT		
	1	2	3
LN(CONTRACT_N)	0.097***		
	(4.64)		
CONTRACT/SALES		0.035**	
		(2.22)	
TREATED×AFTER			0.285*
			(1.68)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
State FE	No	No	Yes
Year FE	Yes	Yes	Yes
N	8,837	8,837	2,210
Pseudo-R^2	0.211	0.204	0.331

Panel C. Production-Related Pollution Prevention Practices

	OPERATIONS-RELATED ABATEMENT		
	1	2	3
LN(CONTRACT_N)	0.050***		
	(2.77)		
CONTRACT/SALES		0.027**	
		(2.02)	
TREATED×AFTER			0.282*
			(1.95)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
State FE	No	No	Yes
Year FE	Yes	Yes	Yes
N	8,912	8,912	1,990
Pseudo-R^2	0.192	0.191	0.263

to control firms. To sum up, the results from the mechanism analysis suggest that government customers can improve corporate environmental performance through two main channels: enhancing internal environmental governance and training, and increasing investments in pollution abatement and prevention practices.

V. Alternative Explanations and Additional Analysis

A. Reduction in Firm Economic Activities as an Alternative Explanation

This section examines an alternative explanation for the negative relationship between government customers and corporate pollution. The decline in a government contractor's pollution could be due to a reduction in its economic activities. Indeed, Akey and Appel (2021) show that firms can reduce toxic pollution by downsizing their economic activities. To investigate this possibility, we examine whether having government customers significantly reduces a firm's production activities and employment growth.

Our measure of firm production activities is the production ratio, which is commonly used in previous studies (e.g., Berrone and Gomez-Mejia (2009), Akey and Appel (2019), (2021), Naaraayanan et al. (2021)). We collect production ratio data from the TRI database. Following Akey and Appel (2019), (2021), we exclude production ratios below 0 or above 5 to minimize data errors. The EPA requires facilities to report the ratio of their current-year production volume to the previous year's production volume (Berrone and Gomez-Mejia (2009)). To construct the firm-level production ratio variable (*PRODUCTION RATIO*), we aggregate the production ratios across all plants for each firm-year. The results in columns 1 and 2 of Panel A of Table 8 show that government customers do not have a significant impact on suppliers' production activities.

We also explore a firm's employment growth as a proxy for its economic activities (Akey and Appel (2021)). In columns 4 and 5 of Panel A of Table 8, we examine whether the presence of government customers reduces the supplier firm's *EMPLOYEE GROWTH*, defined as the ratio of the current year's number of employees to the previous year's number of employees. Our results again show an insignificant effect of government customers on employment growth. In brief, we find no evidence that government contractors reduce pollution by lowering production or employment activities.

B. Relaxation of Financial Constraints as an Alternative Explanation

Another alternative explanation for our baseline results is that firms with government customers may have easier access to external financing (Dhaliwal et al. (2016)). Such firms, facing fewer financial constraints, are more able to invest in pollution abatement, thereby improving corporate environmental performance (Xu and Kim (2022)). To test this conjecture, we explore whether having government customers reduces the financial constraints of contractor firms. We use two text-based measures of financial constraints developed by Hoberg and Maksimovic (2015) and Bodnaruk et al. (2015). *HM_FC* captures the extent to which a firm is likely to delay future investments due to difficulties in

TABLE 8

Alternative Explanations: Firm Economic Activities and Financial Constraints

Table 8 reports the effect of government contracting on firms' economic activities and financial constraints. We use the OLS estimator. In Panel A, the dependent variable is *PRODUCTION RATIO* in columns 1–3 and *EMPLOYEE GROWTH* in columns 4–6. *PRODUCTION RATIO* is the ratio of the current-year production volume to the previous-year production volume. *EMPLOYEE GROWTH* is the ratio of the current-year number of employees to the previous-year number of employees. In Panel B, the dependent variable is *HM_FC* in columns 1–3 and *BLM_FC* in columns 4–6. *HM_FC* and *BLM_FC* are two text-based financial constraints measures developed by Hoberg and Maksimovic (2015) and Bodnaruk et al. (2015), respectively. In columns 1, 2, 4, and 5, the main explanatory variables are two measures of government contracting. *LN(CONTRACT_N)* is the natural logarithm of the number of government contracts plus 1. *CONTRACT/SALES* is the amount of federal award dollars scaled by total sales revenue. In columns 3 and 6, we perform the DiD analysis examining firm economic activities and financial constraints around congressional chairman turnovers. Refer to the Appendix for variable definitions. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate significance levels at 1%, 5%, and 10%, respectively.

Panel A. The Reduction in Firm Economic Activities

	PRODUCTION RATIO			*EMPLOYEE GROWTH*		
	1	2	3	4	5	6
LN(CONTRACT_N)	−0.075 (−0.54)			0.003 (1.48)		
CONTRACT/SALES		−0.097 (−0.77)			−0.001 (−0.30)	
TREATED×AFTER			−0.709 (−0.68)			−0.017 (−1.15)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	9,316	9,316	2,513	9,349	9,349	2,530
Adj. R^2	0.291	0.291	0.485	0.167	0.167	0.183

Panel B. The Ease of Financial Constraints

	HM_FC			*BLM_FC*		
	1	2	3	4	5	6
LN(CONTRACT_N)	−0.002 (−1.03)			0.002 (0.71)		
CONTRACT/SALES		0.001 (0.70)			−0.001 (−0.39)	
TREATED×AFTER			0.000 (0.00)			0.016 (1.53)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	5,410	5,410	1,439	9,196	9,196	2,502
Adj. R^2	0.604	0.604	0.747	0.486	0.486	0.592

accessing external financing (Hoberg and Maksimovic (2015)). *BLM_FC* measures the frequency of financial constraints-related words in a firm's 10-K filings (Bodnaruk et al. (2015)). For both measures, higher values indicate greater financial constraints.

In Panel B of Table 8, we regress these financial constraint measures on government contracting. The dependent variables are *HM_FC* in columns 1–3 and *BLM_FC* in columns 4–6. The results show that government customers do not have a significant impact on the financial constraints of supplier firms. These findings are confirmed by the DiD analyses based on congressional chairman turnovers in column 3 of Panels A and B. Our evidence suggests that government customers do not improve supplier environmental performance by reducing economic activities or alleviating financial constraints.

C. Ex Ante Selection Versus Ex Post Monitoring

Our main analysis suggests that the government plays an ex post monitoring role in procurement. However, corporate environmental performance may influence the ex ante selection of contractors in the first place (Flammer (2018)). To examine this ex ante effect, we examine the impact of firm environmental violations (i.e., EPA enforcement cases) on government procurement. Panel A of Table 9 reports that environmental violations in the past 5 years (*ENV_VIOLATIONS*) significantly reduce the number of government contracts (*LN(CONTRACT_N)*) and the sales-scaled value of government contracts (*CONTRACT/SALES*). These findings are consistent with the argument that government customers consider the environmental track record of potential suppliers and exhibit reduced willingness to engage with those that have environmental violations.

Furthermore, to test the relative importance of ex ante selection and ex post monitoring effects, we conduct a DiD analysis using first-time government contract awards in our sample. Following Samuels (2021), we identify first-time contractor firms that receive an initial contract award during our sample period as the treatment

TABLE 9

Ex Ante Selection Versus Ex Post Monitoring

Table 9 reports the effect of corporate environmental violations on government procurement in Panel A and the results of the DiD analysis examining corporate pollution around first-time government contract awards in Panel B. We use the OLS estimator. In Panel A, the dependent variable is *LN(CONTRACT_N)* in column 1, defined as the natural logarithm of the number of government contracts plus 1. The dependent variable is *CONTRACT/SALES* in column 2, defined as the amount of federal award dollars scaled by total sales revenue. The main explanatory variable is *ENV_VIOLATIONS*, defined as the indicator variable that equals 1 if a firm has a record of EPA enforcement cases in the past 5 years, and 0 otherwise. In Panel B, we construct the stacked DiD sample by matching treated firms with never-treated firms in the same SIC 2-digit industry and size quartile. The treatment group (*FIRST_CONTRACT*) consists of firms that receive an initial contract award during our sample period, and 0 otherwise. *POST* is a dummy variable that equals 1 for the 4 years after the events, and 0 otherwise. The dependent variable is *LN(POLLUTION)* in column 1 and *LN(POLLUTION/SALES)* in column 2. *LN(POLLUTION)* is the natural logarithm of the amount of toxic pollution. *LN(POLLUTION/SALES)* is the natural logarithm of sales-adjusted toxic pollution. Refer to the Appendix for variable definitions. We define industry fixed effects using 3-digit SIC codes. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

Panel A. Environmental Violations and Ex Ante Selection

	LN(CONTRACT_N)	*CONTRACT/SALES*
	1	2
ENV_VIOLATIONS	−0.017*	−0.017**
	(−1.81)	(−1.97)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	9,438	9,438
Adj. R^2	0.876	0.767

Panel B. First-Time Government Contract Awards: Ex Post Monitoring and Ex Ante Selection

	LN(POLLUTION)	*LN(POLLUTION/SALES)*
	1	2
FIRST_CONTRACT	−0.580*	−0.586*
	(−1.90)	(−1.89)
FIRST_CONTRACT×POST	−0.459***	−0.430**
	(−2.62)	(−2.45)
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
N	8,591	8,591
Adj. R^2	0.607	0.520

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group. Since the treatments are staggered over time, we assemble our DiD sample in two steps. First, we match each treated firm to firms that are never treated, based on the same SIC 2-digit industry and size quartile in the year before becoming a government contractor. Using this matching procedure, we construct an event episode for each observation in the treatment group, consisting of the 3 years before (years $t-3$ to $t-1$) and 4 years after (years t to $t+3$) the event. Second, we stack the data across all event episodes and estimate a standard DiD model as follows:

$$(4) \quad POLLUTION_{i,t+1} = \alpha + \beta_1 FIRST\_CONTRACT_{i,t} \times POST_{i,t} + \beta_2 FIRST\_CONTRACT_{i,t} + \beta_3 POST_{i,t} + \delta X_{i,t} + \lambda_j + \mu_t + \varepsilon_{i,t},$$

where *FIRST_CONTRACT* is a dummy variable that equals 1 if it is the first time a firm receives a government contract in year t, and 0 otherwise. *POST* is a dummy variable that takes the value of 1 for the 4 years after the treatment, and 0 otherwise. The main coefficients of interest are β_1 and β_2 that capture the ex post monitoring effect and the ex ante selection effect, respectively. β_1 measures the effect of receiving a government contract for the first time on the firm's environmental performance. β_2 measures the difference in firm environmental performance between the treatment and control groups in the pre-treatment period.

Panel B of Table 9 presents our DiD estimation results. Columns 1 and 2 report the results from estimating equation (4). The coefficients on *FIRST_CONTRACT*× *POST* are negative and statistically significant at the 5% level or better, suggesting that first-time contractors significantly reduce toxic pollution after beginning to contract with the government, relative to otherwise similar control firms. The coefficients on *FIRST_CONTRACT* are also negative and statistically significant at the 10% level, indicating that government contractors perform better environmentally even before establishing business relationships with the government. In terms of economic magnitude, column 1 indicates that in the pre-treatment period, the total pollution of treated firms is 44% (exp(−0.58) – 1) lower, and that after the treatment, treated firms reduce total pollution further by 36.8% (exp(−0.459) – 1), relative to control firms.

Overall, our analyses of the effect of first-time contract awards not only lend further credence to the interpretation that contractor firms reduce toxic pollution in response to monitoring by government customers, but also provide evidence of an ex ante selection effect. Collectively, evidence on ex ante selection and ex post monitoring substantiates the idea that government customers increase the consequences of firms' environmental misbehavior, thereby promoting better corporate environmental performance.

D. Other Environmental Governance Forces

Our baseline results may be affected by various environmental governance forces that are correlated with both the likelihood of winning government contracts and corporate environmental performance. To address this concern, we incorporate a range of additional environmental governance forces into our analysis. These forces include institutional ownership (Dyck, Lins, Roth, and Wagner (2019)), analyst coverage (Jing et al. (2024)), regulatory enforcement (Seltzer, Starks, and Zhu (2022)), local political ideology (Di Giuli and Kostovetsky (2014)), and media coverage of firm environmental incidents (Duchin, Gao, and Xu (2025)).

In Panel A of Table 10, we include several additional controls. *IO* is the natural logarithm of the percentage of shares held by institutional investors (times 100) plus 1. *ANALYST* is the natural logarithm of the average number of monthly earnings forecasts for a firm-year plus 1. *ENFORCEMENT* is a firm-level measure of regulatory stringency, calculated as the average state EPA enforcement intensity (i.e., the number of enforcement actions divided by the number of plants in the state) across a firm's plants. *BLUE* is an indicator that equals 1 if a firm is headquartered in a county that predominantly voted for a Democratic presidential candidate in a recent election, and 0 otherwise. *INCIDENTS* is an indicator variable that equals 1 if a firm has at least one environmental risk event in the RepRisk database in a year, and 0 otherwise.[15]

Our results are robust to controlling for these various sources of environmental pressures. Both the statistical and economic significance of government contracting variables remain comparable to the baseline results shown in Table 3. Among the additional control variables, only institutional ownership has a significantly negative impact on corporate pollution, consistent with the literature showing that institutional investors positively influence corporate environmental performance (Dyck et al. (2019)). In terms of economic magnitude, a 1% increase in the number of government contracts and institutional ownership corresponds to a 0.081% and 0.156% reduction in corporate pollution, respectively, suggesting that government contracting plays a crucial role in reducing corporate pollution.

E. Additional Robustness Tests

In Table 10, we perform a series of additional robustness tests. First, 1 might argue that our baseline finding is driven by a small number of firms with large government contracts. To test the sensitivity of our results to observations in different parts of the contract size distribution, we redefine *LN(CONTRACT_N)* and *CONTRACT/SALES* using different thresholds (i.e., 10,000, 1,000,000, and 100,000,000 USD). For instance, in row 1 of Panel B, a supplier firm is considered to have government contracts if the value of a contract exceeds 10,000 USD. The corresponding sales-scaled measure, *CONTRACT/SALES*, is likewise defined based on the 10,000 USD threshold. Overall, Panel B demonstrates that the effect of government customers on corporate pollution holds across the contract size distribution.

Second, we repeat baseline regressions using three alternative measures of government contracting. *HAVE_CONTRACT* is an indicator variable that equals 1 if a firm is awarded at least one government contract in a year, and 0 otherwise. *LN (CONTRACT_VALUE)* is the natural logarithm of the amount of federal award dollars in a year plus 1. *CONTRACT/SALES (QUINTILE)* is the quintile rank of

[15]The sample period for the analysis is 2007–2019 because RepRisk data are available since 2007.

TABLE 10

Robustness Tests

Table 10 reports a series of robustness tests for our baseline results. Panel A controls for other environmental governance forces, including institutional ownership (*IO*), analyst coverage (*ANALYST*), regulatory enforcement (*ENFORCEMENT*), blue county (*BLUE*), and environmental incidents (*INCIDENTS*). Panel B uses different value thresholds to identify government contractors. Panel C uses three alternative measures of government contracting. *HAVE_CONTRACT* is an indicator variable that equals 1 if the firm is awarded at least one government contract in a year, and 0 otherwise. *LN(CONTRACT_VALUE)* is the natural logarithm of the amount of federal award dollars plus 1. *CONTRACT/SALES (QUINTILE)* is the quintile rank based on the amount of federal award dollars scaled by total sales revenue. Panel D excludes contracts from environmental regulators (i.e., the EPA). Panel E uses two alternative measures of corporate pollution. *LN(POLLUTION/AT)* is the natural logarithm of the amount of assets-adjusted toxic pollution. *LN(POLLUTION/COGS)* is the natural logarithm of the amount of costs of goods sold-adjusted toxic pollution. Panel F restricts the sample to firms with at least one contract during the sample period. Panel G controls for industry-year and state-year fixed effects. Panel H conducts a placebo test with pseudo-contractors. Panel I uses standardized pollution in columns 1 and 2 and a negative binomial model in columns 3 and 4 to mitigate the concern about overdispersion of the pollution measure. *STANDARDIZED POLLUTION* is the toxic pollution standardized by the industry mean and standard deviation for each year. *POLLUTION* is the amount of toxic pollution. Panel J examines the effect of government contracting on carbon emissions. *CARBON_GR* is the growth rate of the amount of carbon emissions. *CARBON INTENSITY* is the amount of sales-adjusted carbon emissions. Panel K examines the effect of government procurement on toxic pollution 2 and 3 years after the procurement ($t+2$ and $t+3$). For Panels A–D and F–H, the dependent variable is *LN (POLLUTION)* in columns 1 and 2 and *LN(POLLUTION/SALES)* in columns 3 and 4. For Panel K, the dependent variable is *LN (POLLUTION)* in year $t+2$ in columns 1 and 2; *LN(POLLUTION)* in year $t+3$ in columns 3 and 4; *LN(POLLUTION/SALES)* in year $t+2$ in columns 5 and 6; and *LN(POLLUTION/SALES)* in year $t+3$ in columns 7 and 8. *LN(POLLUTION)* is the natural logarithm of the amount of toxic pollution. *LN(POLLUTION/SALES)* is the natural logarithm of sales-adjusted toxic pollution. For Panels A, D–G, and I–K, the main explanatory variables are two measures of government contracting. *LN(CONTRACT_N)* is the natural logarithm of the number of government contracts plus 1. *CONTRACT/SALES* is the amount of federal award dollars scaled by total sales revenue. Refer to the Appendix for variable definitions. We define industry fixed effects using 3-digit SIC codes. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

Panel A. Controlling for Other Environmental Governance Forces

	LN(POLLUTION)		*LN(POLLUTION/SALES)*	
	1	2	3	4
LN(CONTRACT_N)	−0.081**		−0.077**	
	(−2.29)		(−2.13)	
CONTRACT/SALES		−0.047***		−0.044**
		(−2.59)		(−2.26)
IO	−0.156**	−0.158**	−0.148**	−0.151**
	(−2.23)	(−2.26)	(−2.14)	(−2.17)
ANALYST	0.061	0.064	0.052	0.055
	(0.51)	(0.53)	(0.44)	(0.46)
ENFORCEMENT	−0.654	−0.566	−1.182	−1.100
	(−0.48)	(−0.42)	(−0.94)	(−0.87)
BLUE	0.065	0.059	0.056	0.050
	(0.66)	(0.61)	(0.59)	(0.53)
INCIDENTS	−0.001	−0.001	0.013	0.013
	(−0.03)	(−0.02)	(0.22)	(0.23)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	6,131	6,131	6,131	6,131
Adj. R^2	0.895	0.895	0.880	0.880

Panel B. Different Value Thresholds to Identify Government Contractors

	LN(POLLUTION)		*LN(POLLUTION/SALES)*	
	LN (CONTRACT_N)	*CONTRACT/ SALES*	*LN (CONTRACT_N)*	*CONTRACT/ SALES*
	1	2	3	4
(1) Over 10,000 USD	−0.082***	−0.050***	−0.088***	−0.059***
	(−2.82)	(−2.58)	(−2.93)	(−3.13)
(2) Over 100,000 USD	−0.087***	−0.050**	−0.094***	−0.059***
	(−2.98)	(−2.58)	(−3.13)	(−3.13)
(3) Over 1,000,000 USD	−0.053*	−0.049**	−0.057**	−0.058***
	(−1.85)	(−2.54)	(−1.98)	(−3.10)

(continued on next page)

TABLE 10 (continued)

Robustness Tests

Panel C. Alternative Measures of Government Contracting

	LN(POLLUTION)			LN(POLLUTION/SALES)		
	1	2	3	4	5	6
HAVE_CONTRACT	−0.181*** (−2.73)			−0.191*** (−2.82)		
LN(CONTRACT_VALUE)		−0.016*** (−3.06)			−0.018*** (−3.26)	
CONTRACT/SALES (QUINTILE)			−0.086*** (−3.17)			−0.083*** (−3.04)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	9,438	9,438	9,438	9,438	9,438	9,438
Adj. R^2	0.873	0.873	0.873	0.854	0.854	0.854

Panel D. Excluding Contracts from Environmental Regulators (i.e., the EPA)

	LN(POLLUTION)		LN(POLLUTION/SALES)	
	1	2	3	4
LN(CONTRACT_N)	−0.086*** (−2.92)		−0.091*** (−3.04)	
CONTRACT/SALES		−0.050*** (−2.59)		−0.059*** (−3.14)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	9,438	9,438	9,438	9,438
Adj. R^2	0.873	0.873	0.854	0.854

Panel E. Alternative Measures of Corporate Pollution

	LN(POLLUTION/AT)		LN(POLLUTION/COGS)	
	1	2	3	4
LN(CONTRACT_N)	−0.093*** (−3.22)		−0.092*** (−3.01)	
CONTRACT/SALES		−0.059*** (−3.14)		−0.060*** (−3.12)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	9,438	9,438	9,438	9,438
Adj. R^2	0.853	0.853	0.850	0.850

Panel F. Subsample of Firms with at Least One Contract During the Sample Period

	LN(POLLUTION)		LN(POLLUTION/SALES)	
	1	2	3	4
LN(CONTRACT_N)	−0.091*** (−3.09)		−0.094*** (−3.11)	
CONTRACT/SALES		−0.046** (−2.33)		−0.056*** (−2.88)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	6,645	6,645	6,645	6,645
Adj. R^2	0.882	0.882	0.862	0.862

Panel G. Controlling for High-Dimensional Fixed Effects (continued)

	LN(POLLUTION)		LN(POLLUTION/SALES)	
	1	2	3	4
LN(CONTRACT_N)	−0.094** (−2.44)		−0.102*** (−2.63)	
CONTRACT/SALES		−0.050** (−2.00)		−0.058** (−2.37)

(continued on next page)

TABLE 10 (continued)

Robustness Tests

Panel G. Controlling for High-Dimensional Fixed Effects (continued)

	LN(POLLUTION)		*LN(POLLUTION/SALES)*	
	1	2	3	4
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes
N	9,438	9,438	9,438	9,438
Adj. R^2	0.875	0.875	0.857	0.857

Panel H. Placebo Test with Pseudo-Contractors

	LN(POLLUTION)	*LN(POLLUTION/SALES)*
	1	2
PSEUDO_CONTRACTOR	0.034	0.018
	(0.51)	(0.27)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	9,438	9,438
Adj. R^2	0.873	0.854

Panel I. Standardized Pollution and Negative Binomial Model

	STANDARDIZED POLLUTION		*POLLUTION*	
	1	2	3	4
LN(CONTRACT_N)	−0.027*		−0.020***	
	(−1.72)		(−3.42)	
CONTRACT/SALES		−0.025**		−0.014**
		(−2.46)		(−2.50)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	9,236	9,236	9,395	9,395
Adj. R^2	0.833	0.833		
Log likelihood			−102,144.39	−102,147.01

Panel J. The Effect of Government Procurement on Carbon Emissions

	CARBON_GR		*CARBON INTENSITY*	
	1	2	3	4
LN(CONTRACT_N)	−0.006***		−0.011**	
	(−3.33)		(−2.52)	
CONTRACT/SALES		−0.006**		−0.007**
		(−2.12)		(−2.31)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	19,030	19,030	22,809	22,809
Adj. R^2	0.065	0.064	0.629	0.629

Panel K. The Timing of the Effect of Government Procurement

	LN(POLLUTION)				*LN(POLLUTION/SALES)*			
	$t+2$		$t+3$		$t+2$		$t+3$	
	1	2	3	4	5	6	7	8
LN(CONTRACT_N)	−0.107***		−0.067*		−0.119***		−0.081**	
	(−2.76)		(−1.77)		(−3.03)		(−2.12)	
CONTRACT/SALES		−0.065***		−0.041*		−0.078***		−0.050**
		(−2.82)		(−1.83)		(−3.48)		(−2.22)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8,901	8,901	8,374	8,374	8,901	8,901	8,374	8,374
Adj. R^2	0.877	0.877	0.880	0.880	0.858	0.858	0.862	0.862

CONTRACT/SALES (Samuels (2021)). Panel C of Table 10 reports that our main finding is robust to these alternative measures of government contracting.

Third, to examine whether our results are specific to contracts from environmental regulators (i.e., the EPA) that are better able to monitor environmental issues than other government agencies, we reconstruct the government contracting variables after excluding contracts awarded by the EPA. Panel D of Table 10 reports that firms with non-EPA government contracts have significantly lower pollution, suggesting that non-EPA government agencies also contribute to disciplining supplier pollution practices.

Fourth, we use two alternative measures of corporate pollution. Following Clarkson, Li, and Richardson (2004) and Naaraayanan et al. (2021), we employ two output-adjusted measures of toxic emissions. *LN(POLLUTION/AT)* and *LN(POLLUTION/COGS)* are total pollution scaled by total assets and cost of goods sold, respectively. Panel E of Table 10 shows that the results remain consistent.

Fifth, a potential concern is that our results may be influenced by unobserved time-varying differences between firms with and without government contracts. This type of heterogeneity is not captured by firm fixed effects. To address this concern, we rerun our baseline regressions on a subsample of firms with at least one government contract award during the sample period. Panel F of Table 10 reports that our results continue to hold after excluding firms that have not received any government contracts throughout the entire sample period, indicating that our baseline results are driven by omitted time-varying characteristics of firms without government contracts.

To mitigate the concern that our results may be biased due to unobserved time-varying industry or state heterogeneity (e.g., industry or state regulatory changes), we control for additional fixed effects. Specifically, we include not only firm fixed effects but also industry-year and state-year interaction fixed effects. Panel G of Table 10 confirms that the results are robust to the inclusion of these additional fixed effects.

In addition, to further assess whether our results are driven by confounding factors, we conduct a placebo test by examining the environmental performance of pseudo-contractors. Pseudo-contractors are firms that, while not government contractors, offer products similar to those of government contractors. Since these firms have no direct customer-supplier relationship with the government, it is unlikely that government customers influence their pollution through monitoring. Therefore, we expect that being a pseudo-contractor should not affect a firm's pollution.

In this placebo test, we replace *GOV_CONTRACT* in equation (1) with *PSEUDO_CONTRACTOR*, which equals 1 if a firm without government contracts (i.e., a non-contractor) is the closest competitor of a government contractor in a year, and 0 otherwise. For each government contractor in a year, we identify the non-contractor with the highest product similarity score relative to the contractor. Specifically, we use firm pairwise product similarity scores derived from the text analysis of firm product descriptions in 10-K filings to identify the closest competitors of government contractors (Hoberg and Phillips (2016)). Panel H of Table 10 reports that the coefficient on *PSEUDO_CONTRACTOR* is statistically insignificant, reinforcing our confidence that the baseline results are attributable to government customer monitoring.

Next, to deal with the skewness of the pollution measure, we follow Dasgupta, Huynh, and Xia (2023) and use a standardized toxic pollution measure,

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STANDARDIZED_POLLUTION, as the dependent variable. This measure is defined as the ratio of the difference between a firm's total toxic pollution and the industry average pollution to its standard deviation in each year. In columns 1 and 2 of Panel I of Table 10, we find that the results are robust to this standardized pollution measure.

Furthermore, our results are robust to an alternative estimation method that accounts for overdispersion (i.e., the conditional mean is greater than the conditional variance of the pollution measure). Given the overdispersion in our pollution data, we use the negative binomial estimator, which accommodates overdispersion by modeling variance as a separate gamma process. This method is used as an alternative to the Poisson estimator in cases of overdispersion (Cameron and Trivedi (2005), Greene (2017), and Cohn, Liu, and Wardlaw (2022)).[16] Columns 3 and 4 of Panel I of Table 10 report that the results from negative binomial regressions align with our baseline results.

To gain a more comprehensive understanding of the environmental impact of government procurement, we extend our analysis to another important aspect of corporate environmental performance: carbon emissions. We examine the effect of government customers on corporate carbon emissions using two firm-level measures from the Trucost database for the period of 2005–2019. Following Bolton and Kacperczyk (2021), (2023), *CARBON_GR* is the growth rate of a firm's direct emissions from production and indirect emissions from energy consumption in a year, and *CARBON INTENSITY* is the ratio of a firm's total carbon emissions to total sales in a year. The former reflects a firm's short-term tendency to adjust future emissions, whereas the latter has been a key focus for practitioners and investors (Bolton and Kacperczyk (2023)). In Panel J of Table 10, we find that government customers significantly reduce both the growth and intensity of carbon emissions, indicating that the environmental impact of government procurement extends beyond reducing toxic pollution to lowering carbon emissions.

Finally, in Panel K of Table 10, we examine the timing of firm responses to government monitoring. We find that receiving government contracts in year t has a significantly negative effect on corporate pollution not only in year $t + 1$ (i.e., the baseline results), but also in years $t + 2$ and $t + 3$, suggesting that the effect of government procurement is reasonably persistent. Overall, our results remain robust across various alternative measures of government contracting and pollution, as well as different model specifications and estimation methods.

VI. Conclusions

This study explores the effect of government customers on corporate environmental policies. We find that firms with federal government contracts significantly

[16]We use the negative binomial estimator instead of the Poisson estimator due to overdispersion, a key limitation of the latter. The Poisson estimator assumes equidispersion (i.e., the conditional mean equals the conditional variance), but overdispersion makes Poisson estimation inefficient (e.g., Cameron and Trivedi (2005), Cohn et al. (2022)). To detect overdispersion, we conduct the test proposed by Cameron and Trivedi (1990), running an auxiliary OLS regression of $\left((y-\widehat{\mu})^2-y\right)/\widehat{\mu}$ on $\widehat{\mu}$, where y is the dependent variable (pollution) and $\widehat{\mu}$ is the fitted value from the Poisson regression. The significantly positive coefficient on $\widehat{\mu}$ (coefficient = 0.071, t-stat = 27.63) indicates overdispersion.

reduce toxic emissions, consistent with the external governance role of government customers in improving supplier environmental performance. The finding is robust to a DiD analysis that mitigates endogeneity concerns. Further cross-sectional analyses show that the effect of government customers on corporate pollution is stronger in subsets of firms under greater government scrutiny, in firms whose revenue relies more on government contracts, and in firms that are not politically connected, consistent with a monitoring role of government customers in disciplining supplier pollution.

We document two channels through which government contractor firms improve environmental performance. First, contractor firms are more likely to establish internal environmental governance mechanisms, such as appointing a corporate sustainability director and providing environmental management training. Second, contractor firms significantly increase their investments in pollution abatement and prevention practices. Finally, we rule out alternative explanations pertaining to reduced economic activities and lower financial constraints. Overall, the results highlight the important external governance role of the government as a customer in shaping suppliers' environmental policies.

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Appendix: Variable Definitions

The following table presents the definitions and data sources of the main variables used in our empirical analysis.

Variable	Definition	Data Source
Pollution Variables		
TOXIC POLLUTION	Total quantity of emissions at the firm level	TRI
LN(POLLUTION)	Natural logarithm of the toxic pollution	TRI
LN(POLLUTION/SALES)	Natural logarithm of the sales-adjusted toxic pollution (toxic pollution/sales)	TRI, Compustat
LN(POLLUTION/AT)	Natural logarithm of the assets-adjusted toxic pollution (toxic pollution/assets)	TRI, Compustat
LN(POLLUTION/COGS)	Natural logarithm of the cost of goods sold-adjusted toxic pollution (toxic pollution/cost of goods sold)	TRI, Compustat
STANDARDIZED_POLLUTION	The standardized toxic pollution, standardized by the industry mean and standard deviation in each year	TRI
CARBON_GR	Growth rate of the sum of a firm's direct emissions from production and indirect emissions from a firm's energy consumption in a year	Trucost
CARBON INTENSITY	The sales-adjusted carbon emissions (carbon emissions/ sales)	Trucost, Compustat
Government Contracting Variables		
CONTRACT_VALUE (MILLION)	The total amount of federal award dollars	USAspending
LN(CONTRACT_N)	Natural logarithm of the number of government contracts plus 1	USAspending
CONTRACT/SALES	The amount of federal award dollars scaled by total sales revenue (multiplied by 100)	USAspending, Compustat
HAVE_CONTRACT	Indicator variable that equals 1 if a firm is awarded at least one government contract in a year, and 0 otherwise	USAspending
LN(CONTRACT_VALUE)	Natural logarithm of the amount of federal award dollars plus 1	USAspending
CONTRACT/SALES (QUINTILE)	The quintile rank based on the amount of federal award dollars scaled by total sales revenue	USAspending, Compustat
Firm and State Characteristics		
SIZE	Natural logarithm of total assets	Compustat
MTB	Market value of equity divided by book value of equity	Compustat
TANGIBILITY	Net property, plant, and equipment divided by total assets	Compustat
DIVIDEND	The sum of common dividends and preferred dividends divided by total assets	Compustat
CAPEX	Capital expenditure divided by total assets	Compustat
CASH	Cash and short-term investments divided by total assets	Compustat
LEVERAGE	The sum of current liabilities and long-term debt divided by the total assets	Compustat
ROA	Operating income divided by total assets	Compustat
R&D	Research and development expenses divided by total assets	Compustat
SALES_GR	The growth rate of sales	Compustat
GDP_GR	The growth rate of the state-level GDP	Bureau of Economic Analysis
UNEMPLOYMENT	State-level unemployment rate	Bureau of Labour Statistics
POPULATION	Natural logarithm of the state-level population	U.S. Census Bureau
INCOME_PC	Natural logarithm of the state-level income per capita	Bureau of Economic Analysis
IO	Natural logarithm of the fraction of a firm's shares held by institutional investors (times 100) plus 1	Thomson Reuters 13-F
ANALYST	Natural logarithm of the arithmetic mean of the 12 monthly number of earnings forecasts for a firm plus 1	IBES
ENFORCEMENT	Regulatory stringency for a firm, calculated as the average state EPA enforcement intensity across a firm's plants. The state EPA enforcement intensity is the total number of enforcement actions divided by the total number of plants in the state	Integrated Compliance Information System (ICIS)
BLUE	Indicator variable that equals 1 if a firm operates in a blue county where the majority of voters support the Democratic presidential candidate, and 0 otherwise	Dave Leip's Atlas
INCIDENTS	Indicator variable that equals 1 if a firm has at least one environmental risk event in a year, and 0 otherwise	RepRisk
Cross-Sectional Tests		
CONTRACT_LONG (SHORT)	Indicator variable that equals 1 if a firm has at least one contract and the value-weighted average length of all contracts is above (below) the median, and 0 otherwise	USAspending

(continued on next page)

(continued)

Variable	Definition	Data Source
CONTRACT_DEMOCRATIC (REPUBLICAN)	Indicator variable that equals 1 when a firm receives government contracts under a Democratic (Republican) president, and 0 otherwise	USAspending
CONTRACT_HIGH (LOW) RELIANCE	Indicator variable that equals 1 if a firm has at least one contract and the ratio of federal award dollars to total sales revenue is above (below) 10%, and 0 otherwise	USAspending, Compustat
CONTRACT_WITH (WITHOUT) POLITICAL CONTRIBUTIONS	Indicator variable that equals 1 if a firm has at least one contract and its political contributions to congressional candidates in the previous election cycle are positive (0), and 0 otherwise	USAspending, Federal Election Commission
Channels Analysis		
SUSTAINABILITY DIRECTOR	Indicator variable that equals 1 if a firm has a sustainability director, and 0 otherwise	BoardEx
ENV_TRAINING	Indicator variable that equals 1 if a firm trains the employees on environmental issues (e.g., emission reduction and environmental-related code of conduct), and 0 otherwise	ASSET4
ENV_INVESTMENT	Indicator variable that equals 1 if a firm reports on making environmental investments to reduce future risks or increase opportunities related to the environment, and 0 otherwise	ASSET4
OPERATIONS-RELATED ABATEMENT	Indicator variable that equals 1 if a firm reports at least one operations-related pollution prevention practice (see Table A1 for detailed descriptions), and 0 otherwise	TRI P2
PRODUCTION-RELATED ABATEMENT	Indicator variable that equals 1 if a firm reports at least one production-related pollution prevention practice (see Table A1 for detailed descriptions), and 0 otherwise	TRI P2
PRODUCTION RATIO	The ratio of the current-year production volume to the previous-year production volume	TRI
EMPLOYEE GROWTH	The ratio of the current-year number of employees to the previous-year number of employees	Compustat
HM_FC	A text-based financial constraints measure developed by Hoberg and Maksimovic (2015)	Hoberg and Maksimovic (2015)
BLM_FC	A text-based financial constraints measure developed by Bodnaruk et al. (2015)	Bodnaruk et al. (2015)
ENV_VIOLATIONS	Indicator variable that equals 1 if a firm has a record of EPA enforcement cases in the past 5 years	Integrated Compliance Information System (ICIS)

Supplementary Material

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References

Akey, P., and I. Appel. "The Limits of Limited Liability: Evidence from Industrial Pollution." *Journal of Finance*, 76 (2021), 5–55.

Akey, P., and I. Appel. "Environmental Externalities of Activism." Available at SSRN 3508808 (2019)

Armstrong, C.; J. D. Kepler; D. Samuels; and D. Taylor. "Causality Redux: The Evolution of Empirical Methods in Accounting Research and the Growth of Quasi-Experiments." *Journal of Accounting and Economics*, 74 (2022), 101521.

Baker, A. C.; D. F. Larcker; and C. C. Wang. "How Much Should We Trust Staggered Difference-in-Differences Estimates?" *Journal of Financial Economics*, 144 (2022), 370–395.

Bartram, S. M.; K. Hou; and S. Kim. "Real Effects of Climate Policy: Financial Constraints and Spillovers." *Journal of Financial Economics*, 143 (2022), 668–696.

Bellon, A. "Fresh Start or Fresh Water: The Impact of Environmental Lender Liability." Available at SSRN 3877378 (2021).

Bellon, A. "Does Private Equity Ownership Make Firms Cleaner? The Role of Environmental Liability Risks." *Review of Financial Studies*, (2025)

Berrone, P.; C. Cruz; L. R. Gomez-Mejia; and M. Larraza-Kintana. "Socioemotional Wealth and Corporate Responses to Institutional Pressures: Do Family-Controlled Firms Pollute Less?" *Administrative Science Quarterly*, 55 (2010), 82–113.

Berrone, P., and L. R. Gomez-Mejia. "Environmental Performance and Executive Compensation: An Integrated Agency-Institutional Perspective." *Academy of Management Journal*, 52 (2009), 103–126.

Blanchard, O., and R. Perotti. "An Empirical Characterization of the Dynamic Effects of Changes in Government Spending and Taxes on Output." *Quarterly Journal of Economics*, 117 (2002), 1329–1368.

Bodnaruk, A.; T. Loughran; and B. McDonald. "Using 10-K Text to Gauge Financial Constraints." *Journal of Financial and Quantitative Analysis*, 50 (2015), 623–646.

Boland, M., and D. Godsell. "Bureaucratic Discretion and Contracting Outcomes." *Accounting, Organizations and Society*, 88 (2021), 101173.

Bolton, P., and M. Kacperczyk. "Do Investors Care about Carbon Risk?" *Journal of Financial Economics*, 142 (2021), 517–549.

Bolton, P., and M. Kacperczyk. "Global Pricing of Carbon-Transition Risk." *Journal of Finance*, 78 (2023), 3677–3754.

Brogaard, J.; M. Denes; and R. Duchin. "Political Influence and the Renegotiation of Government Contracts." *Review of Financial Studies*, 34 (2021), 3095–3137.

Cameron, A. C., and P. K. Trivedi. "Regression-Based Tests for Overdispersion in the Poisson Model." *Journal of Econometrics*, 46 (1990), 347–364.

Cameron, A., and P. K. Trivedi. *Microeconometrics*. Cambridge, MA: Cambridge University Press (2005).

Chatterji, A. K., and M. W. Toffel. "How Firms Respond to Being Rated." *Strategic Management Journal*, 31 (2010), 917–945.

Chen, J.; X. Su; X. Tian; B. Xu; and L. Zuo. "Do Major Corporate Customers Deter Supplier Misconduct?" *Journal of Accounting and Economics*, forthcoming (2025).

Chodorow-Reich, G.; L. Feiveson; Z. Liscow; and W. G. Woolston. "Does State Fiscal Relief during Recessions Increase Employment? Evidence from the American Recovery and Reinvestment Act." *American Economic Journal: Economic Policy*, 4 (2012), 118–145.

Chu, Y., and D. Zhao. "Green Hedge Fund Activists." Available at SSRN 3499373 (2019).

Clarkson, P. M.; Y. Li; and G. D. Richardson. "The Market Valuation of Environmental Capital Expenditures by Pulp and Paper Companies." *Accounting Review*, 79 (2004), 329–353.

Clarkson, P. M.; Y. Li; G. D. Richardson; and F. P. Vasvari. "Revisiting the Relation between Environmental Performance and Environmental Disclosure: An Empirical Analysis." *Accounting, Organizations and Society*, 33 (2008), 303–327.

Cohen, D. A., and B. Li. "Customer-Base Concentration, Investment, and Profitability: The US Government as a Major Customer." *Accounting Review*, 95 (2020), 101–131.

Cohen, D.; B. Li; N. Li; and Y. Lou. "Major Government Customers and Loan Contract Terms." *Review of Accounting Studies*, 27 (2022), 275–312.

Cohen, L.; J. Coval; and C. Malloy. "Do Powerful Politicians Cause Corporate Downsizing?" *Journal of Political Economy*, 119 (2011), 1015–1060.

Cohen, L., and C. J. Malloy. "Mini West Virginias: Corporations as Government Dependents." Available at SSRN 2758835 (2016).

Cohn, J. B.; Z. Liu; and M. I. Wardlaw. "Count (and Count-Like) Data in Finance." *Journal of Financial Economics*, 146 (2022), 529–551.

Cohn, J., and T. Deryugina. "Firm-Level Financial Resources and Environmental Spills." NBER Working Paper No. w24516 (2018).

Dasgupta, S.; T. D. Huynh; and Y. Xia. "Joining Forces: The Spillover Effects of EPA Enforcement Actions and the Role of Socially Responsible Investors." *Review of Financial Studies*, 36 (2023), 3781–3824.

Delmas, M. A., and M. W. Toffel. "Organizational Responses to Environmental Demands: Opening the Black Box." *Strategic Management Journal*, 29 (2008), 1027–1055.

Dhaliwal, D.; J. S. Judd; M. Serfling; and S. Shaikh. "Customer Concentration Risk and the Cost of Equity Capital." *Journal of Accounting and Economics*, 61 (2016), 23–48.

Di Giuli, A., and L. Kostovetsky. "Are Red or Blue Companies More Likely to Go Green? Politics and Corporate Social Responsibility." *Journal of Financial Economics*, 111 (2014), 158–180.

Duchin, R., and D. Sosyura. "The Politics of Government Investment." *Journal of Financial Economics*, 106 (2012), 24–48.

Duchin, R.; J. Gao; and Q. Xu. "Sustainability or Greenwashing: Evidence from the Asset Market for Industrial Pollution." *Journal of Finance*, 80 (2025), 699–754.

Dyck, A.; K. V. Lins; L. Roth; and H. F. Wagner. "Do Institutional Investors Drive Corporate Social Responsibility? International Evidence." *Journal of Financial Economics*, 131 (2019), 693–714.

Engstrom, D. F. "Public Regulation of Private Enforcement: Empirical Analysis of DOJ Oversight of Qui Tam Litigation Under the False Claims Act." *Northwestern University Law Review*, 107 (2012), 1689–1754.

Fiechter, P.; J. M. Hitz; and N. Lehmann. "Real Effects of a Widespread CSR Reporting Mandate: Evidence from the European Union's CSR Directive." *Journal of Accounting Research*, 60 (2022), 1499–1549.

Flammer, C. "Competing for Government Procurement Contracts: The Role of Corporate Social Responsibility." *Strategic Management Journal*, 39 (2018), 1299–1324.
Flammer, C.; B. Hong; and D. Minor. "Corporate Governance and the Rise of Integrating Corporate Social Responsibility Criteria in Executive Compensation: Effectiveness and Implications for Firm Outcomes." *Strategic Management Journal*, 40 (2019), 1097–1122.
Fu, R.; Y. Tang; and G. Chen. "Chief Sustainability Officers and Corporate Social (Ir) Responsibility." *Strategic Management Journal*, 41 (2020), 656–680.
Galí, J.; J. D. López-Salido; and J. Vallés. "Understanding the Effects of Government Spending on Consumption." *Journal of the European Economic Association*, 5 (2007), 227–270.
Goldman, E.; J. Rocholl; and J. So. "Politically Connected Boards of Directors and the Allocation of Procurement Contracts." *Review of Finance*, 17 (2013), 1617–1648.
Goldman, J. "Government as Customer of Last Resort: The Stabilizing Effects of Government Purchases on Firms." *Review of Financial Studies*, 33 (2020), 610–643.
Greene, W. H. *Econometric Analysis*, 8th Edn. New York, NY: Pearson Education (2017).
Gray, W. B., and J. P. Shimshack. "The Effectiveness of Environmental Monitoring and Enforcement: A Review of the Empirical Evidence." *Review of Environmental Economics and Policy*, 5 (2011), 3–24.
Hadley, B. "Executive Compensation and Political Sensitivity: Evidence from Government Contractors." *Journal of Corporate Finance*, 59 (2019), 276–301.
Hall, R. E. "By How Much Does GDP Rise if the Government Buys More Output?" NBER Working Paper No. w15496 (2009).
Hart, O., and L. Zingales. "Should a Company Pursue Shareholder Value?" In *Conference Economics of Social Sector Organizations*, The University of Chicago Booth School of Business, 12 (2016), 2018.
He, J.; K. Li; N. Li; and W. Zhang. "Proprietary Information Cost of Contracting with the Government." *Accounting Review*, 99 (2024), 195–227.
Hebous, S., and T. Zimmermann. "Can Government Demand Stimulate Private Investment? Evidence from US Federal Procurement." *Journal of Monetary Economics*, 118 (2021), 178–194.
Heese, J., and G. Pérez-Cavazos. "Fraud Allegations and Government Contracting." *Journal of Accounting Research*, 57 (2019), 675–719.
Heese, J.; G. Pérez-Cavazos; and C. D. Peter. "When the Local Newspaper Leaves Town: The Effects of Local Newspaper Closures on Corporate Misconduct." *Journal of Financial Economics*, 145 (2022), 445–463.
Hoberg, G., and V. Maksimovic. "Redefining Financial Constraints: A Text-Based Analysis." *Review of Financial Studies*, 28 (2015), 1312–1352.
Hoberg, G., and G. Phillips. "Text-Based Network Industries and Endogenous Product Differentiation." *Journal of Political Economy*, 124 (2016), 1423–1465.
Hsu, P. H.; K. Li; and C. Y. Tsou. "The Pollution Premium." *Journal of Finance*, 78 (2023), 1343–1392.
Jing, C.; K. Keasey; I. Lim; and B. Xu. "Analyst Coverage and Corporate Environmental Policies." *Journal of Financial and Quantitative Analysis*, 59 (2024), 1586–1619.
Jing, C.; B. Xu; and L. Zuo. "Do Financial Disclosures Affect Corporate Sustainability Practices?" Available at SSRN 4817939 (2025).
Kim, I.; H. Wan; B. Wang; and T. Yang. "Institutional Investors and Corporate Environmental, Social, and Governance Policies: Evidence from Toxics Release Data." *Management Science*, 65 (2019), 4901–4926.
King, A., and M. Lenox. "Exploring the Locus of Profitable Pollution Reduction." *Management Science*, 48 (2002), 289–299.
Klassen, R. D., and C. P. McLaughlin. "The Impact of Environmental Management on Firm Performance." *Management Science*, 42 (1996), 1199–1214.
Konar, S., and M. A. Cohen. "Information as Regulation: The Effect of Community Right to Know Laws on Toxic Emissions." *Journal of Environmental Economics and Management*, 32 (1997), 109–124.
Konar, S., and M. A. Cohen. "Does the Market Value Environmental Performance?" *Review of Economics and Statistics*, 83 (2001), 281–289.
Kong, L. "Government Spending and Corporate Innovation." *Management Science*, 66 (2020), 1584–1604.
Levine, R.; C. Lin; Z. Wang; and W. Xie. "Bank Liquidity, Credit Supply, and the Environment." NBER Working Paper No. w24375 (2018).
Mills, L. F.; S. E. Nutter; and C. M. Schwab. "The Effect of Political Sensitivity and Bargaining Power on Taxes: Evidence from Federal Contractors." *Accounting Review*, 88 (2013), 977–1005.
Muthulingam, S.; S. Dhanorkar; and C. J. Corbett. "Does Water Scarcity Affect Environmental Performance? Evidence from Manufacturing Facilities in Texas." *Management Science*, 68 (2022), 2785–2805.
Naaraayanan, S. L.; K. Sachdeva; and V. Sharma. "The Real Effects of Environmental Activist Investing." Available at SSRN 3483692 (2021).

Nakamura, E., and J. Steinsson. "Fiscal Stimulus in a Monetary Union: Evidence from US Regions." *American Economic Review*, 104 (2014), 753–792.

Ngo, P. T., and J. Stanfield. "Does Government Spending crowd out R&D Investment? Evidence from Government-Dependent Firms and Their Peers." *Journal of Financial and Quantitative Analysis*, 57 (2022), 888–922.

Ramey, V. A. "Can Government Purchases Stimulate the Economy?" *Journal of Economic Literature*, 49 (2011), 673–685.

Samuels, D. "Government Procurement and Changes in Firm Transparency." *Accounting Review*, 96 (2021), 401–430.

Seltzer, L. H.; L. Starks; and Q. Zhu. "Climate Regulatory Risk and Corporate Bonds." NBER Working Paper No. w29994 (2022).

Shive, S. A., and M. M. Forster. "Corporate Governance and Pollution Externalities of Public and Private Firms." *Review of Financial Studies*, 33 (2020), 1296–1330.

Warren, P. L. "Contracting Officer Workload, Incomplete Contracting, and Contractual Terms." *RAND Journal of Economics*, 45 (2014), 395–421.

Xu, Q. and T. Kim. "Financial Constraints and Corporate Environmental Policies." *Review of Financial Studies*, 35 (2022), 576–635.