Internet Appendix for

"Analyst Coverage and Corporate Environmental Policies"

(Not to be published)

Table A.1. Variable Definitions

Variable	Definition	Data Source
Pollution Variables		
TOL_POL	Total quantity of on- and off-site toxic emission at the firm-year level	TRI
ON-SITE_POL	Total quantity of toxic pollution released onsite into the air, water, and ground at the firm-year level	TRI
OFF-SITE_POL	Total quantity of toxic pollution transferred to off-site locations for further release or disposal at the firm-year level	TRI
AIR_POL	Total quantity of onsite stack emissions and on-site fugitive emissions at the firm-year level	TRI
WATER_POL	Total quantity of toxic pollution released on-site as surface water discharges at the firm-year level	TRI
GROUND_POL	Total quantity of toxic pollution released to on-site grounds at the firm-year level	TRI
log(TOTAL_POL)	Natural logarithm of (one plus) the total pollution	TRI
log(ON-SITE_POL)	Natural logarithm of (one plus) the on-site pollution	TRI
log(OFF-SITE_POL)	Natural logarithm of (one plus) the off-site pollution	TRI
log(AIR_POL)	Natural logarithm of (one plus) the air pollution	TRI
log(WATER_POL)	Natural logarithm of (one plus) the water pollution	TRI
log(GROUND_POL)	Natural logarithm of (one plus) the ground pollution	TRI
log(TOTAL_POL_TO_SALES)	Natural logarithm of (one plus) the sales adjusted total pollution (total pollution/sales)	TRI
log(ON-SITE_POL_TO_SALES)	Natural logarithm of (one plus) on-site pollution scaled by sales	TRI
log(OFF-SITE_POL_TO_SALES)	Natural logarithm of (one plus) off-site pollution scaled by sales	TRI
log(AIR_POL_TO_SALES)	Natural logarithm of (one plus) air pollution scaled by sales	TRI
log(WATER_POL_TO_SALES)	Natural logarithm of (one plus) water pollution scaled by sales	TRI
log(GROUND_POL_TO_SALES)	Natural logarithm of (one plus) ground pollution scaled by sales	TRI
log(TOL_ENFORCE)	Natural logarithm of (one plus) the number of EPA enforcement cases) at the firm-year level	ICIS FE&C
log(NON-JDC)	Natural logarithm of (one plus) the number of non-judicial cases at the firm-year level	ICIS FE&C
log(JDC)	Natural logarithm of (one plus) the number of judicial cases at the firm-year level	ICIS FE&C
Firm Characteristics		
FIRM_SIZE	Natural logarithm of (one plus) total assets	Compustat
ROA	Operating income divided by total assets	Compustat
BOOK_TO_MARKET	Book value of equity divided by the market value of equity	Compustat
TANGIBILITY	Net property, plant, and equipment divided by total assets	Compustat

BOOK_LEVERAGE	The sum of current liabilities and long-term debt divided by the total assets	Compustat
R&D_TO_ASSETS	Research and development expenses divided by total assets	Compustat
DIVIDEND_TO_ASSETS	The sum of common dividends and preferred dividends divided by total assets	Compustat
CASH_TO_ASSETS	Cash and short-term investments divided by total assets	Compustat
<u>Cross-sectional Analysis</u>		
ANALYST_COVERAGE	Arithmetic mean of the 12 monthly numbers of earnings forecasts over the fiscal year measured at the firm-year level	I/B/E/S
INITIAL_ANALYST_COVERAGE	Analyst coverage prior to the year before brokerage exits measured at the firm-year level	I/B/E/S
LOW (HIGH)_INITIAL_ANALYST_COVERAGE	Low (High) initial coverage is an indicator variable which equals 1 if initial analyst coverage is in the bottom (top) tercile for treated firms in the year prior to brokerage exits and 0 otherwise	I/B/E/S
PRODUCT_SIMILARITY	The total product similarity is the sum of the pairwise similarities between a given firm and all other firms in a given year	Hoberg and Phillips (2016)
LOW (HIGH)_COMPETITION	Low (High) Competition is an indicator variable which equals 1 if product similarity is lower (higher) than the median value for treated firms in the year prior to brokerage exits and zero otherwise	Hoberg and Phillips (2016)
E-INDEX	The sum of six anti-takeover provisions introduced by Bebchuk et al. (2009) measured at the firm-year level	IRRC
LOW (HIGH)_E-INDEX	Low (High) E-index is an indicator variable which equals 1 if E-index is lower (higher) than the median value for treated firms in the year prior to brokerage exits and zero otherwise	IRRC
AVERAGE_DISTANCE	Average firm-year geographic distance between plants owned by a firm and its supervising EPA regional office	TRI
LONG (SHORT)_DISTANCE	Long (Short) distance is an indicator variable which equals 1 if the average firm level distance of plant-EPA pairs is higher (lower) than the median value for treated firms in the year prior to brokerage exits and zero otherwise	TRI
<u>Channels Analysis</u>		
ENVIRON_QUESTIONS	Indicator variable that equals one if at least one financial analyst asks environmental-related questions in the Q&A session during earnings conference calls and zero otherwise measured at the firm-year level	LexisNexis; Capital IQ

#_ENVIRON_QUESTIONS	The number of environmental-related analyst questions in the Q&A session measured at the firm-year level	LexisNexis; Capital IQ
IO	Fraction of a firm's shares held by institutional investors measured at the firm-year level	Thomson Reuters 13F
HIGH (LOW) IO	High (Low) IO is an indicator variable which equals 1 if the percent of equity owned by institutional investors for treated firms is higher (lower) than the median in the year prior to brokerage exits and zero otherwise	Thomson Reuters 13F
QUASI-INDEXERS	Fraction of a firm's shares held by quasi-indexers (defined following Bushee (2001)) measured at the firm-year level	Thomson Reuters 13F
HIGH (LOW)_QUASI-INDEXERS	High (Low) Quasi-indexers is an indicator variable which equals 1 if the percent of equity owned by quasi-indexers for treated firms is higher (lower) than the median in the year prior to brokerage exits and zero otherwise	Thomson Reuters 13F
PUBLIC_PENSION_FUNDS	Fraction of a firm's shares held by public pension funds (defined following Bushee (2001)) measured at the firm-year level	Thomson Reuters 13F
HIGH (LOW)_PUBLIC_PENSION_FUNDS	High (Low) Public pension funds is an indicator variable which equals 1 if the percent of equity owned by public pension funds for treated firms is higher (lower) than the median in the year prior to brokerage exits and zero otherwise	Thomson Reuters 13F
log(ENVIRON EXPEND)	Natural logarithm of (one plus the firm-year amount of a firm's environmental expenditure on pollution abatement)	10-K
GREEN_PATENTS	The number of green patents measured at the firm-year level	Kogan et al. (2017)
ENVIRON_COMP	Firm-year indicator variable that equals one if firms set environmental performance-based compensation contracts for any named-executive and zero otherwise	DEF 14A
SUSTAIN_COMM	Firm-year indicator variable equals one if firms have a sustainability committee and zero otherwise	BoardEx

A.2. Matched Treatment and Control Firms

From the unmatched sample, we use a propensity score matching (PSM) method to construct matched treated and control firms. We use a matched sample for our analysis as treated and control firms could differ across various firm characteristics. For instance, if larger firms tend to be covered more by analysts (and thus more likely to be treated), these large firms, by virtue of their size, could also find it more efficient to invest in pollution abatement technologies. Further, having firms that are similar in observable characteristics reduces concerns that these firms differ along *unobservable* dimensions (Roberts and Whited (2013)).

To construct our sample of matched treated and control firms, we follow previous studies (e.g. Derrien and Kecskes (2013), He and Tian (2013), Hong and Kacperczyk (2010), Irani and Oesch (2013), Kelly and Ljungqvist (2012)) and match on several firm characteristics that are likely to predict treatment prior (t-1) to brokerage exits; namely, total assets (FIRM_SIZE), the book-to-market ratio (BOOK_TO_MARKET), return on assets (ROA), tangibility (TANGIBILITY), and the two-digit SIC. We match on firm size, performance and the book-to-market ratio as larger and better performing firms tend to attract more analyst coverage, which increases the probability of being affected by brokerage exits (Hong and Kacperczyk (2010)). We also match on tangibility as firms with a higher proportion of tangible assets may have different environmental strategies that could influence an analyst's decision to cover the firm (Akey and Appel (2021), Ioannou and Serafeim (2015), Luo, Wang, Raithel, and Zheng (2015)).

In the first step, we run a logit regression where the dependent variable equals one if a firm is considered as treated in a particular firm-year, and zero otherwise.[1] This regression is estimated using our unmatched DiD sample as described in Section III.B.2 of the main manuscript. The estimated coefficients are used to predict the probability of treatment (propensity scores). Using these scores, we perform a one-to-one nearest-neighbor match with replacement. Our final matched sample consists of 254 (116) unique treated (control) firms with 1,212 firm-year observations (606 firm-year observations per treated and control group).[2] There are 303 pairs of treated and control firms affected by brokerage exits (2 firm-year observations (t-1 and t+1) each).

[1] Note that because of the staggered nature of brokerage exits, there is a possibility that treated firms could enter into our control group of firms after the difference-in-difference window. We do not allow treated firms to enter our control group for the matching process to ensure a cleaner match; i.e. treated firms are always considered as treated regardless of the DiD window.

[2] As the number of firms with pollution data is relatively limited (765 unique firms) and our matching requires firms to be in a similar industry (SIC two-digit code), we lose about 100 treated firm-year observations.

As described in Section III.B.3. in the main manuscript, we show that the means of firm characteristics are largely indistinguishable after matching, suggesting that our matching process is successful in balancing ex-ante differences in financial characteristics between treatment and control firms.

A.3. Robustness Tests

In this section, we conduct a range of robustness tests on our baseline findings. Table A.3 presents the results. As with the baseline model, the dependent variable is log total pollution in columns 1-3 and log sales-adjusted total pollution in columns 4-6. For brevity, we only report the coefficient and t-value of the interaction (TREATMENT × AFTER). Results are displayed in Table A.3.

We start off by using different estimation windows. In our baseline analysis, we use a 1-year pre and post estimation window around brokerage exits (t-1 and t+1). This is our preferred specification as it allows us to more cleanly capture the effects of exogenous decreases in analyst coverage on corporate pollution and reduces the possibility that our results might be biased by new analysts stepping in to cover our group of treated firms. Further, since we also rely on a longer estimation window for some other tests in our paper, we also want to ensure that our findings of increases in pollution are also robust to these estimation horizons. In Rows (1) and (2), we show that our results continue to hold when we use a 2-year (t-2 and t+2) and 3-year (t-3 and t+3) window around brokerage exits.

In the second series of robustness tests, we investigate if our results are sensitive to the choice of matching variables in creating our matched sample used in the baseline model. In Row (3), we start with the unmatched sample. While estimations of the unmatched sample are likely biased due to differing characteristics for treated and control firms, we nonetheless show that our findings are robust even when we use the unmatched sample. Similar to our baseline results, we find evidence consistent with the monitoring hypothesis that analyst coverage reduces corporate pollution. While comforting, our preference in specification is still the matched sample DiD to ensure covariate balance.

Rows (4) to (7) employ different combinations of matching variables to create our matched sample. Row (4) creates a simple matched sample based only on FIRM_SIZE. Row (5) is our main matched sample used in Table 2 (reproduced for comparability) and matches on FIRM_SIZE, ROA, BOOK_TO_MARKET, TANGIBILITY and 2-digit SIC code. Row (6) adds R&D_TO_ASSETS to the matching variables used in the main specification as investments in research and development could be related to a firm's use of green technologies and pollution abatement (Chu and Zhao (2019)). Lastly, Row (7) adds monthly stock returns (RETURN) and stock return volatility (VOLATILITY) to the matching variables from the previous row following Hong and Kacperczyk (2010) as the authors find that stocks experiencing brokerage closures are more volatile. Regardless of the choice of matching variables in creating a matched sample, our results continue to remain robust.

Third, we address the concern that financial crises could simultaneously lead to brokerage exits and increases in corporate pollution due to financial constraints (Xu and Kim (2022)). In Row (8), we drop all brokerage closure and merger events that occurred from 2008-2010. In Row (9), we follow He and Tian (2013) and drop brokerage exits that occurred during the internet bubble of 2001-2002. Our results remain largely unchanged, alleviating concerns that financial crises are driving our results.

Fourth, prior studies (e.g. Shapiro and Walker (2018)) document a persistent and significant decrease in toxic pollution in the U.S. from the 1990s to the early 2000s due to changes in environmental regulation (e.g. implicit pollution tax). Further, in our sample, approximately one-third of brokerage exits occurred during 2000-2001. To ameliorate concerns that the decrease in pollution and a large number of brokerage exits during this period could be influencing our results, we drop brokerage closures and mergers that occurred in 2000-2001. Our estimations in Row (10) continue to remain robust.

Lastly, in our baseline analysis, we note that approximately one-third of treated firm-year observations are treated more than once (stocks covered by brokers that are closed or merged). As multiple treatment events could confound estimations (Kim, Lu, and Yu (2019b)), we retain only observations affected by the first treatment event (if they are treated more than once) and re-run our analysis in Row (11). We continue to obtain similar results.[3]

[3] We also follow Chen, Chiu, and Shevlin (2018) and randomly retain treatment events (instead of retaining the first treatment event) for firms that are treated more than once. Our results remain materially unchanged.

Table A.3. Robustness Tests

This table reports various robustness tests for our baseline DiD regression. The specification is: $Y_{i,t} = \alpha_{i,t} + \beta_1 \text{TREATMENT}_{i,t} \times \text{AFTER}_{i,t} + \beta_2 \text{TREATMENT}_{i,t} + \beta_3 \text{AFTER}_{i,t} + \delta X_{i,t} + \varepsilon_{i,t}$ where subscripts i and t indicates firm i and year t respectively while $X_{i,t}$ is a vector of control variables. Panel A uses different estimation windows. Panel B shows results with alternative matching criteria. Panel C excludes brokerage exits that occurred during the financial crisis or the internet bubble. Panel D excludes years 2001-2002 due to large decreases in pollution. Panel E retains observations only for their first treatment (if treated more than once). The dependent variable is $\log(\text{TOT\_POL})_{i,t}$ in columns 1-3 and $\log(\text{TOT\_POL\_TO\_SALES})_{i,t}$ in columns 4-6. $\log(\text{TOT\_POL})_{i,t}$ is the natural logarithm of one plus the amount of total pollution. $\log(\text{TOT\_POL})_{i,t}$ is the natural logarithm of one plus the amount of sales-adjusted total pollution. $\text{TREATMENT}_{i,t}$ is a dummy variable that equals 1 if the firm has experienced an exogenous decrease in analyst coverage as a result of brokerage exits and 0 otherwise. $\text{AFTER}_{i,t}$ is a dummy variable that equals 1 for the year after (t+1) brokerage exits and 0 for the year before (t-1). For brevity, only the coefficients of interaction item $\beta_1 \text{TREATMENT}_{i,t} \times \text{AFTER}_{i,t}$ are reported. Refer to Appendix Table A.1 for the definition and construction of variables. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	log(TOT_POL)			log(TOT_POL_TO_SALES)		
	1	2	3	4	5	6
Panel A. Different DiD Estimation Windows						
(1) t-2 to t+2 years	0.377**	0.371**	0.294**	0.356**	0.368**	0.308**
	(2.25)	(2.27)	(2.09)	(2.16)	(2.26)	(2.17)
(2) t-3 to t+3 years	0.353**	0.336*	0.271*	0.300*	0.325*	0.280*
	(2.01)	(1.94)	(1.75)	(1.74)	(1.89)	(1.81)
Panel B: Alternate PSM-matched Control Firms						
(3) Unmatched Sample	0.248***	0.242***	0.295***	0.238***	0.250***	0.303***
	(3.70)	(3.65)	(4.36)	(3.60)	(3.84)	(4.51)
(4) Matched on: FIRM_SIZE	0.337**	0.321**	0.420***	0.344**	0.371**	0.466***
	(2.01)	(2.02)	(3.04)	(2.05)	(2.30)	(3.34)
(5) Matched on: FIRM_SIZE/ROA/BOOK_TO_MARKET/TANGIBILITY	0.452***	0.443***	0.361***	0.458***	0.462***	0.397***
	(2.86)	(2.79)	(2.60)	(2.91)	(2.92)	(2.82)
(6) Matched on: Row (5) + R&D_TO_ASSETS	0.383**	0.397**	0.436**	0.341**	0.401***	0.456***
	(2.31)	(2.52)	(2.45)	(2.18)	(2.62)	(2.61)
(7) Matched on: Row (6) + RETURN and VOLATILITY	0.409**	0.441***	0.560***	0.428***	0.478***	0.594***
	(2.44)	(2.71)	(3.20)	(2.66)	(2.95)	(3.38)
Panel C. Excluding Brokerage Exits in Financial Crises						
(8) Exclude exits after 2008	0.459***	0.445***	0.371**	0.448***	0.458***	0.402***
	(2.89)	(2.70)	(2.51)	(2.83)	(2.76)	(2.66)
(9) Exclude exits in 2001 and 2002	0.391**	0.355**	0.369**	0.387**	0.374**	0.408**
	(2.18)	(2.10)	(2.28)	(2.19)	(2.21)	(2.49)
Panel D. Excluding Brokerage Exits due to Environmental Changes						
(10) Exclude exits in 2000 and 2001	0.601***	0.613***	0.394**	0.640***	0.647***	0.436**
	(2.90)	(2.87)	(2.30)	(3.12)	(3.04)	(2.52)
Panel E. Retaining First Treatment						
(11) Retain only firm-year obs. impacted by first exit	0.374**	0.369**	0.335**	0.382**	0.389**	0.370**
	(2.34)	(2.28)	(2.10)	(2.39)	(2.39)	(2.31)
Controls	No	Yes	Yes	No	Yes	Yes
Industry-Year FE	No	No	Yes	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	Yes	Yes	No

Table A.4. Decreases in Analyst Coverage and Small Polluters

This table reports firm-year results of the DiDiD regression on the effects of decreases in analyst coverage on corporate pollution conditional on the size of pollution. The specification is: $Y_{i,t} = \alpha_{i,t} + \beta_1 \mathrm{TREATMENT}_{i,t} \times \mathrm{AFTER}_{i,t} \times \mathrm{SMALL\_POLLUTER}_{i,t} + \beta_2 \mathrm{TREATMENT}_{i,t} \times \mathrm{AFTER}_{i,t} \times \mathrm{LARGE\_POLLUTER}_{i,t} + \beta_3 \mathrm{TREATMENT}_{i,t} + \beta_4 \mathrm{AFTER}_{i,t} + \delta X_{i,t} + \varepsilon_{i,t}$ where subscripts *i* and *t* indicates firm *i* and year *t* respectively while $X_{i,t}$ is a vector of control variables. $\mathrm{SMALL\_POLLUTER}_{i,t}$ is an indicator variable which equals 1 if the total corporate pollution that firms emit is lower than the median value for treated firms in the year prior to brokerage exits (*t*-1) and zero otherwise. $\mathrm{LARGE\_POLLUTER}_{i,t}$ is an indicator variable which equals 1 if the total corporate pollution that firms emit is higher than the median value for treated firms in the year prior to brokerage exits (*t*-1) and zero otherwise. $\mathrm{TREATMENT}_{i,t}$ is a dummy variable that equals 1 if the firm has experienced an exogenous decrease in analyst coverage as a result of brokerage exits and 0 otherwise. $\mathrm{AFTER}_{i,t}$ is a dummy variable that equals 1 for the year after (*t*+1) brokerage exits and 0 for the year before (*t*-1). Refer to Appendix Table A.1 for the definition and construction of variables. *P*-values are reported for the tests of coefficient differences in triple interaction terms. Standard errors are clustered at the firm level. *t*-values are reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate significance levels at 1%, 5%, and 10%, respectively.

	log(TOT_POL)	log(TOT_POL_TO_SALES)
	1	2
TREATMENT×AFTER×SMALL_POLLUTER	0.575***	0.597***
	(2.99)	(3.11)
TREATMENT×AFTER×LARGE_POLLUTER	0.303**	0.318**
	(1.97)	(2.06)
AFTER	-0.296	-0.305
	(-1.59)	(-1.63)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Tests of coefficient differences in triple interaction terms (p-value)	0.034**	0.033**
N	1,212	1,212
R-sq	0.139	0.204

Table A.5. Decreases in Analyst Coverage and Sub-categories of Corporate Pollution

This table reports firm-year results of the DiD regression on the effects of decreases in analyst coverage on sub-categories of pollution. The specification is: $Y_{i,t} = \alpha_{i,t} + \beta_1 \text{TREATMENT}_{i,t} \times \text{AFTER}_{i,t} + \beta_2 \text{TREATMENT}_{i,t} + \beta_3 \text{AFTER}_{i,t} + \delta X_{i,t} + \varepsilon_{i,t}$ where subscripts *i* and *t* indicates firm *i* and year *t* respectively while $X_{i,t}$ is a vector of control variables. Our sample consists of 1,212 firm-year observations (606 treatment and control firm-year observations) from 1999 to 2011. Panel A investigates the decreases in analyst coverage on firms' on-site and off-site pollution. On-site pollution is the quantity of toxic chemicals released into the air, water, and ground on-site at the plant. Off-site pollution is the quantity of toxic release transferred to off-site locations for further release or disposal at specialized waste management facilities. $\log(\text{ON-SITE\_POL})_{i,t}$ is the natural logarithm of one plus the amount of on-site pollution. $\log(\text{ON-SITE\_POL\_TO\_SALES})_{i,t}$ is the natural logarithm of one plus the amount of sales adjusted on-site pollution. $\log(\text{OFF-SITE\_POL})_{i,t}$ is the natural logarithm of one plus the amount of off-site pollution. $\log(\text{OFF-SITE\_POL\_TO\_SALES})_{i,t}$ is the natural logarithm of one plus the amount of sales adjusted off-site pollution. Panel B splits on-site pollution into air, water, and ground pollution to investigate decreases in analyst coverage on firms' on-site and off-site pollution. Air pollution is the total quantity of on-site stack emissions and on-site fugitive emissions. Water pollution is the total quantity of toxic pollutions released on-site as surface water discharges. Ground pollution is the total quantity of toxic pollution released on-site on grounds. $\log(\text{AIR\_POL})_{i,t}$ is the natural logarithm of one plus the amount of air pollution. $\log(\text{AIR\_POL\_TO\_SALES})_{i,t}$ is the natural logarithm of one plus the amount of sales adjusted air pollution. $\log(\text{WATER\_POL})_{i,t}$ is the natural logarithm of one plus the amount of water pollution. $\log(\text{WATER\_POL\_TO\_SALES})_{i,t}$ is the natural logarithm of one plus the amount of sales adjusted water pollution. $\log(\text{GROUND\_POL})_{i,t}$ is the natural logarithm of one plus the amount of ground pollution. $\log(\text{GROUND\_POL\_TO\_SALES})_{i,t}$ is the natural logarithm of one plus the amount of sales adjusted ground pollution. $\text{TREATMENT}_{i,t}$ is a dummy variable that equals 1 if the firm has experienced an exogenous decrease in analyst coverage as a result of brokerage exits and 0 otherwise. $\text{AFTER}_{i,t}$ is a dummy variable that equals 1 for the year after (*t*+1) brokerage exits and 0 for the year before (*t*-1). Refer to Appendix Table A.1 for the definition and construction of variables. Standard errors are clustered at the firm level. *t*-values are reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate significance levels at 1%, 5%, and 10%, respectively.

Panel A. Impact of an Exogenous Decrease in Analyst Coverage on On-site and Off-site Pollution

	On-site Pollution		Off-site Pollution	
	log(ON-SITE_POL)	log(ON-SITE_POL_TO_SALES)	log(OFF-SITE_POL)	log(OFF-SITE_POL_TO_SALES)
	1	2	3	4
TREATMENT×AFTER	0.470***	0.489***	0.278	0.297
	(2.67)	(2.79)	(1.31)	(1.39)
AFTER	-0.243	-0.252	-0.259	-0.268
	(-1.23)	(-1.27)	(-1.24)	(-1.28)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1,212	1,212	1,212	1,212
R-sq	0.191	0.271	0.080	0.068

Panel B. Impact of an Exogenous Decrease in Analyst Coverage on Air, Water and Ground Pollution

	Air Pollution		Water Pollution		Ground Pollution	
	log (AIR POL)	log (AIR POL TO SALE)	log (WATER POL)	log (WATER POL TO SALES)	log (GROUND POL)	log (GROUND POL TO SALES)
	1	2	3	4	5	6
TREATMENT×AFTER	0.402**	0.421***	-0.076	-0.057	-0.021	-0.002
	(2.52)	(2.65)	(-0.54)	(-0.40)	(-0.10)	(-0.01)
AFTER	-0.189	-0.199	0.030	0.020	-0.389	-0.399
	(-1.05)	(-1.10)	(0.31)	(0.20)	(-1.57)	(-1.62)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,212	1,212	1,212	1,212	1,212	1,212
R-sq	0.200	0.284	0.070	0.161	0.054	0.088

A.6. EPA Enforcement Actions

Our baseline results in Section IV.A. suggest that a reduction in monitoring from analysts leads to firms behaving in environmentally harmful ways, consistent with the monitoring hypothesis of analysts on a firm's emissions of toxic pollution. In this section, we use EPA enforcement data as an alternative measure of non-compliance to EPA's regulations and examine whether treated firms are more likely to violate EPA regulations after decreases in analyst coverage. In discharging enforcement actions, the EPA investigates cases of non-compliance, issues civil penalties, and monitors the correction of the violation at the plant level. Although EPA violations are not a direct measure of pollution, the measure has the advantage of linking toxic pollution to regulatory and litigation risks that should be pertinent to a firm's choice to pollute (Xu and Kim (2022)).

EPA enforcement data are extracted from the Integrated Compliance Information System for Federal Civil Enforcement Case Data (ICIS FE&C). ICIS FE&C provides plant-year level information about individual enforcement cases such as the primary law violated, settlement date, and case number. The dataset also allows for the distinction between judicial and non-judicial violations. Judicial cases are formal lawsuits that take place in court and include breaches of contract or other civil actions, while non-judicial cases are administrative cases that take place under the EPA's jurisdiction. Distinguishing between judicial and non-judicial violations could be important as managers are likely to weigh the costs and benefits of corporate pollution. If the costs (e.g. administrative corrections) are not sufficiently high as compared to judicial litigations that could lead to concerns of personal reputational damage, loss of board seats, and increased turnover (Aharony, Liu, and Yawson (2015), Fahlenbrach, Low, and Stulz (2017)), firm managers might be more willing to engage in "milder" forms of environmental misconduct.

As enforcement cases are at the plant-year level, we sum up cases to construct a firm-year count of enforcement cases and treat observations without non-compliance records as zero. As the investigation, detection, and settlement of non-compliance cases require time, we compare non-compliances in the two years before the event (*t*-2) and two years after (*t*+2*)*. The mean total number of EPA enforcement cases per firm-year is 0.21, of which a majority of the cases (0.18 out of 0.21) are non-judicial; judicial cases make up the remainder.

In Table A.6, we show the results of the effect of a decrease in analyst coverage on EPA enforcement actions. In our specifications, firm and industry-year fixed effects are included as the enforcement data significantly vary across industries (Shive and Forster (2020)). We first look at total enforcement actions in columns 1-2, defined as the natural logarithm of one plus the number of EPA enforcements in a firm-year (TOTAL_ENFORCE). As observed, the coefficients on TREATMENT×AFTER are positive and statistically significant. Interpreting the economic magnitude in column 2, the number of enforcement cases in treated firms increases by 7.3% after experiencing reductions in analyst coverage. This evidence is consistent with the monitoring role of analysts on environmental misconduct.

Next, we split total EPA enforcements into non-judicial (log(NON-JDC)) and judicial enforcement (log(JDC)) in columns 3-4 and columns 5-6, respectively. As observed in columns 3 and 4, we find that a decrease in analyst coverage leads to an increase in non-judicial cases by 9.4% and 8.9%, respectively, depending on specification. However, we do not observe any significant changes in judicial enforcement cases. This is unsurprising as judicial cases tend to lead to greater reputational damage. As such, a firm's managers would be more cautious in engaging in more severe forms of environmental misconduct. Overall, we find that firms facing a reduction in analyst monitoring increase their instances of environmental misconduct, suggesting that managers weigh the costs and benefits of environmental misconduct. Specifically, they only increase environmental misconduct when the potential consequences for their career prospects and reputation are not overly severe.

Table A.6. Decreases in Analyst Coverage and EPA Enforcement

This table reports firm-year results of the DiD regression on the effects of decreases in analyst coverage on EPA enforcement. The specification is: $Y_{i,t} = \alpha_{i,t} + \beta_1 \text{TREATMENT}_{i,t} \times \text{AFTER}_{i,t} + \beta_2 \text{TREATMENT}_{i,t} + \beta_3 \text{AFTER}_{i,t} + \delta X_{i,t} + \varepsilon_{i,t}$ where subscripts i and t indicates firm i and year t respectively while $X_{i,t}$ is a vector of control variables. The dependent variable log(TOT_ENFORCE)$_{i,t}$ is the natural logarithm of one plus the total number of EPA enforcements (non-judicial + judicial)$_{i,t}$ in columns 1-2. Log(NON-JDC)$_{i,t}$ is the natural logarithm of one plus the number of non-judicial cases in columns 3-4, while log(JDC)$_{i,t}$ is the natural logarithm of one plus the number of judicial cases in columns 5-6. We use EPA cases for two years before (t-2) and after (t+2) brokerage exits as the investigation and settlements of EPA enforcements require time. TREATMENT$_{i,t}$ is a dummy variable that equals 1 if the firm has experienced an exogenous decrease in analyst coverage as a result of brokerage exits and 0 otherwise. AFTER$_{i,t}$ is a dummy variable that equals 1 for the year after (t+1) brokerage exits and 0 for the year before (t-1). For brevity, control variables are not reported. Refer to Appendix Table A.1 for the definition and construction of variables. Standard errors are clustered at the firm level. t-values are reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate significance levels at 1%, 5%, and 10%, respectively.

	log(TOL_ENFORCE)		log(NON-JDC)		log(JDC)	
	1	2	3	4	5	6
TREATMMENT×AFTER	0.077**	0.073*	0.094**	0.089**	-0.014	-0.014
	(2.02)	(1.96)	(2.54)	(2.48)	(-0.90)	(-0.93)
AFTER	-0.052	-0.051	-0.052	-0.051	-0.010	-0.009
	(-1.07)	(-1.07)	(-1.23)	(-1.23)	(-0.44)	(-0.38)
Controls	No	Yes	No	Yes	No	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,112	1,112	1,112	1,112	1,112	1,112
R-sq	0.393	0.408	0.366	0.381	0.464	0.473

Table A.7. Cross-sectional Analysis: Other Corporate Governance Measures

This table reports firm-year results of the DiDiD regression on the effects of decreases in analyst coverage on corporate pollution conditional on corporate governance. The G-index, four-firm concentration ratio and co-opted boards are used as proxies for corporate governance. The specification in columns 1-2 is: $Y_{i,t} = \alpha_{i,t} + \beta_1$TREATMENT$_{i,t}$ × AFTER$_{i,t}$ × HIGH_G-INDEX$_{i,t}$ + β_2TREATMENT$_{i,t}$ × AFTER$_{i,t}$ × LOW_G-INDEX$_{i,t}$ + β3TREATMENT$_{i,t}$ + β_4AFTER$_{i,t}$ + $\delta X_{i,t} + \varepsilon_{i,t}$ while the specification in columns 3-4 is: $Y_{i,t} = \alpha_{i,t}$ + β_1TREATMENT$_{i,t}$ × AFTER$_{i,t}$ × HIGH_4FIRMCONC$_{i,t}$ + β_2TREATMENT$_{i,t}$ × AFTER$_{i,t}$ × LOW_4firmCONC$_{i,t}$ + β3TREATMENT$_{i,t}$ + β_4AFTER$_{i,t}$ + $\delta X_{i,t} + \varepsilon_{i,t}$ and $Y_{i,t} = \alpha_{i,t}$ + β_1TREATMENT$_{i,t}$ × AFTER$_{i,t}$ × HIGH_CO-OPTED$_{i,t}$ + β_2TREATMENT$_{i,t}$ × AFTER$_{i,t}$ × LOW_CO-OPTED$_{i,t}$ + β3TREATMENT$_{i,t}$ + β_4AFTER$_{i,t}$ + $\delta X_{i,t} + \varepsilon_{i,t}$ in columns 5-6 where subscripts i and t indicates firm i and year t respectively while $X_{i,t}$ is a vector of control variables. HIGH_G-INDEX$_{i,t}$ is an indicator variable which equals 1 if G-index as constructed by Gompers, Ishii, and Metrick (2003) is higher than the median value for treated firms in the year prior to brokerage exits (t-1) and zero otherwise. LOW_G-INDEX$_{i,t}$ is an indicator variable which equals 1 if G-index as constructed by Gompers et al. (2003) is lower than the median value for treated firms in the year prior to brokerage exits (t-1) and zero otherwise. HIGH_4FIRMCONC$_{i,t}$ is an indicator variable which equals 1 if the industry concentration based on the sales market share of top four firms (Eckbo (1985)) is higher than the median value for treated firms in the year prior to brokerage exits (t-1) and zero otherwise. LOW_4FIRMCONC$_{i,t}$ is an indicator variable which equals 1 if the industry concentration ratio is lower than the median value for treated firms in the year prior to brokerage exits (t-1) and zero otherwise. HIGH_CO-OPTED$_{i,t}$ is an indicator variable which equals 1 if the co-opted boards measure as described in Coles, Daniel, and Naveen (2014) is higher than the median value for treated firms in the year prior to brokerage exits (t-1) and zero otherwise. LOW_CO-OPTED$_{i,t}$ is an indicator variable which equals 1 if the co-opted boards measure as described in Coles et al. (2014) is lower than the median value for treated firms in the year prior to brokerage exits (t-1) and zero otherwise. The dependent variable is log(TOT_POL)$_{i,t}$ in columns 1, 3, 5 and log(TOT_POL_TO_SALES)$_{i,t}$ in columns 2, 4, and 6. log(TOT_POL)$_{i,t}$ is the natural logarithm of one plus the amount of total pollution. log(TOT_POL_TO_SALES)$_{i,t}$ is the natural logarithm of one plus the amount of sales-adjusted total pollution. TREATMENT$_{i,t}$ is a dummy variable that equals 1 if the firm has experienced an exogenous decrease in analyst coverage as a result of brokerage exits and 0 otherwise. AFTER$_{i,t}$ is a dummy variable that equals 1 for the year after (t+1) brokerage exits and 0 for the year before (t-1). Refer to Appendix Table A.1 for the definition and construction of variables. *P*-values are reported for the tests of coefficient differences in triple interaction terms. Standard errors are clustered at the firm level. t-values are reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate significance levels at 1%, 5%, and 10%, respectively.

Dependent Variable = log(TOT_POL) in columns 1, 3, 5 Dependent Variable = log(TOT_POL_TO_SALES) in columns 2, 4, 6						
	1	2	3	4	5	6
TREATMENT×AFTER×HIGH_G-INDEX	0.545***	0.584***				
	(2.74)	(2.93)				
TREATMENT×AFTER×LOW_G-INDEX	0.282	0.286				
	(1.37)	(1.37)				
TREATMENT×AFTER×HIGH_4FIRMCONC			0.552***	0.575***		
			(2.97)	(3.08)		
TREATMENT×AFTER×LOW_4FIRMCONC			0.273*	0.292*		
			(1.72)	(1.85)		
TREATMENT×AFTER×HIGH_CO-OPTED					0.408**	0.407**
					(2.14)	(2.12)
TREATMENT×AFTER×LOW_CO-OPTED					0.139	0.167
					(0.79)	(0.95)
After	-0.299	-0.316	-0.316*	-0.326*	-0.015	-0.022
	(-1.44)	(-1.52)	(-1.66)	(-1.71)	(-0.10)	(-0.15)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Tests of coefficient differences in triple interaction terms (p-value)	0.097*	0.071*	0.041**	0.039**	0.070*	0.095*
N	876	876	1,156	1,156	876	876
R-sq	0.139	0.191	0.134	0.198	0.193	0.257

A.8. Environmental-related Questions in Earnings Conference Calls

This appendix presents some examples of environmental-related questions raised by analysts during Q&A sessions in earnings conference calls. The environmental-related keywords are highlighted in bold.

CONSOL Energy and CNX Gas 2009 Q3:
Analyst question: “I guess just first off on the **EPA**, some new roles coming down the pipeline as far as sulfur **emissions**. I just want to get your take on how you see that playing out as **emission** caps come down and how that could be certainly a positive for Northern App.”

Headwaters Inc 2009 Q4:
“Analyst question: And then just one final question, which you may have already covered, and I apologize if I missed it, but the actual number of **coal cleaning** facilities that are operating right now? And then the expectation for the full year, fiscal year 2010, the number of **coal cleaning** facilities that will be operating?”

Briggs Stratton Corporation 2008 Q4:
Analyst question: “Just a little more on the **emissions** side. I think the **EPA** just passed a law and it's [phased] through regulations for further reduction in exhaust **emissions**. Do the Briggs products comply with those standards, and what about the competitive front? Do Chinese engines comply with those sorts of standards and does that affect the competitive environment at this point?”

Thomas Betts 2007 Q4:
“Analyst question: My last question, and then I'll hop for the queue after this. Could you just give me a little bit more details on the **environmental charge** and if you expect follow through or charges in the next few quarters?”

Briggs Stratton Corporation 2008 Q1:
Analyst question: “Sure. Next. I realize you may have nothing to say, but wondering if you look out over the next two years, if you've got any thoughts on where we're going **environmentally** and how that is playing out in your thinking in terms of what you're trying to prepare for.”

Thomas Betts 2007 Q2:
Analyst question: “One last question with regards to the **environmental remediation expense**. Can you explain exactly what that was and whether or not you anticipate any of that in your guidance going forward?”

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