Responsive Regulation: Target- vs. Budget-Driven Regulation

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Abstract

The main purpose of this study is to examine the relationship between voluntary pollution abatement and prevention efforts at pulp and paper mills and regulatory stringency they face. Using facility level data on U.S. pulp and paper mills for 1989-2002, we estimate the fixed effects negative binomial model to test the hypotheses of responsive regulation and whether regulators are driven by numerical pollution targets or budgetary constraints. We find that voluntary pollution abatement has greater impact on regulatory stringency than government expenditures. Additionally, state political pressure, pollution prevention legislation, firm and mill characteristics are found to be significant predictors of regulatory behavior.

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Introduction

Most previous literature on environmental regulation focuses on firms' compliance. Since the late 1990s, there has been a growing body of work studying how firms' environmental decisions and performance, in turn, affect the behavior of regulators. Building upon and expanding Decker (2005, 2007) and Maxwell and Decker (2006), we test the hypothesis of 'responsive regulation' first advanced by Hemphill (1993-1994) and Cothran (1993).[1] Maxwell, Lyon, et al. (2000) tested strategic self-regulation that preempted political action and their empirical results confirmed that increased threat of regulation, measured by membership in conservation groups, induced firms to reduce toxic releases. Building the first formal models of responsive regulation, Maxwell and Decker (2006) and Decker (2007) corroborated theoretically that profit-maximizing firms, under responsive regulation, overinvest in environmental compliance. They proposed a two-stage game with the outcome of firms voluntarily overinvesting in pollution abatement because of responsive regulation.

Confirming theoretical propositions of responsive regulation, Arguedas (2013) points out that such regulatory behavior is documented not only in growing empirical literature, but also in the regulations themselves. For example, under the EPA's Audit Policy, fines for non-compliance can be reduced up to from 75% to 100% if firms promptly disclose and correct violations.[2] Building on the previous theoretical works, Heyes and Kapur (2009) addressed the type of regulatory missions and formally modelled two regulatory regimes/climates – target- and budget-driven. Under the target regime, firms' compliance decisions are viewed as strategic

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[1] Decker (2005) identifies Hemphill (1993-1994) and Cothran (1993) as the first works using the term 'responsive regulation,' p. 180.

[2] Arguedas (2013) cites EPA (December 22, 1995), Incentives for Self-Policing: Discovery, Disclosure, Correction and Prevention of Violations – Final Policy Statement, 60 Fed. Reg. 66, 706, p 157.

substitutes and there are positive spillovers to enforcement and under the budget regime firms' compliance decisions are modelled as strategic complements and result in negative enforcement spillovers.

The main purpose of this study is to empirically test Heyes and Kapur's (2009) hypothesis of 'responsive regulation' and gauge the extent to which the regulatory climate, in which pulp and paper mills operate, can be called a target- vs. budget-regime or both. This has not been done before. The analyses use firms' pollution abatement and voluntary prevention efforts, measured by the EPA's Toxic Release Inventory (TRI) and pollution prevention (P2) facility-level data, and local and state budgetary expenditures on protective inspection and regulation from the Census' Rex-Dac data base. We use the fixed effects negative binomial model to regress the number of EPA inspections and enforcements for 200 pulp and paper mills during 1984-2002, across all pollution media and separately for air, water, and land against the measures of TRI (by media), P2, local and state government expenditures. The EPA facility-level data were merged to the plant capacity data from the Forest Product Laboratory[3] (FPL) and annual editions of Lockwood-Post's Directory of the Pulp, Paper, and Allied Trades[4] (LW). In addition, we test the impact of state political pressure, P2 legislation, firm and mill characteristics and find them to be important factors in predicting regulators' behavior.

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[3] For the full description of the FPL data, see: http://www.fpl.fs.fed.us/documnts/fplrp/fplrp602.pdf.

[4] For the latest description of Lockwood's Post Directory, see: http://www.risiinfo.com/risi-store/do/product/detail/lockwood-post-plus-contact-database.html.

Literature Review

Deterrence Model

Gray and Shimshack (2011) reviewed empirical literature on effectiveness of environmental monitoring and enforcement. According to them, the existing empirical enforcement models measure firm deterrence, or how plants respond to enforcement activities. There are a number of studies on pulp and paper industry that find evidence for effectiveness of enforcement on facility compliance (Nadeau 1997, Gray and Shadbegian 2007, Shimshack and Ward 2005, 2008). Shimshack and Ward (2005, 2008) found that an additional fine induced state-wide compliance. Shimshack and Ward (2008) found that fines at violating facilities induced facilities that were operating within the permitted level of discharges, were induced to discharge even less, or go beyond compliance. Gray and Shadbegian (2007) found that inspections at one plant tended to increase compliance at both the inspected and nearby facilities.

Reviewing the empirical literature on effectiveness of environmental monitoring and enforcement, Gray and Shimshack (2011) point out that plant's choice of its abatement effort is "a function of: (i) its perceived probability of a violation given its chosen abatement level; (ii) its perceived probability of detection by the regulator if it violates; (iii) its perceived probability of a penalty if a violation is detected; and (iv) its perception about the likely magnitude of the penalty if it is levied."[5] These appear strategic in nature and are included in the discussion of the hypotheses that we propose below.

More specifically on pulp and paper industry, Shadbegian and Gray (2003) found that air pollution emissions at 68 paper plants in 1985 were significantly lower in plants with a larger air pollution abatement capital stock, greater local regulatory stringency, and higher productive

[5] Gray and Shimshack (2011), p. 10.

efficiency. Further, Gray and Shadbegian (2007) found that a typical regulatory measure, both inspection and enforcement mechanisms, induced a 10% increase in air pollution compliance among 116 paper mills over 1979-1990.

Shimshack and Ward (2005) found that in the sample of 217 pulp and paper mills over 1988-1996, an additional fine was associated with a two-thirds reduction in the statewide water pollution violation rate in the year following the fine. Shimshack and Ward (2008) extended the analysis to 251 pulp and paper mills over 1990-2004 and found a 7% decrease in statewide water pollution discharges in the year following a find being imposed at any plant in the state. They also showed that EPA enforcement actions increased overcompliance confirming the theoretical arguments of Maxwell and Decker (2006), and Decker (2007), and Arguedas (2013), all of which we review next.

Voluntary Pollution Abatement Discussion

Maxwell et al. (2000) tested strategic self-regulation that preempted political action and their empirical results confirmed that increased threat of regulation, measured by membership in conservation groups, induced firms to reduce toxic releases. Maxwell and Decker (2006) and Decker (2007) corroborated theoretically that profit-maximizing firms, under responsive regulation, overinvest in environmental compliance; hence regulatory fines are likely to be an over kill and must be lowered. They proposed a two-stage game with an outcome of firms voluntarily overinvesting in pollution abatement because of responsive regulation. Arguedas (2013) documents ‘responsive regulation’ within the EPA and Spanish environmental legislation.[6]

[6] Arguedas (2013), p. 157.

Decker (2005) tested the responsiveness of regulation to voluntary environmental abatement and found mixed results. In two out of four frequently inspected industries, regulators conduct fewer inspections at the facilities that report lower per unit output of toxic release inventory. In pulp and paper industry, mills with larger share of state employment are inspected less frequently. Maxwell and Decker (2006) ran two regressions: one predicting the threat of regulation measured by green membership, and another using these estimated values for green membership in the regression of toxic releases (as a measure of voluntary abatement) against estimated green membership and other control variables.

In 2013, Arguedas (2013) critiqued Maxwell and Decker (2006) and Decker (2007), arguing that self-reporting/policing efforts are already built-into the regulations, hence it is not necessary to model a hierarchical model of regulation with regulators worrying over their reputation costs. The simpler model of Arguedas (2013) arrives at the same outcome that fines should be reduced, but due to excessive administrative costs of regulations. Hence, according to the author, fines (enforcements) should be negatively related to the abatement investment efforts.

To contrast, Heyes and Kapur (2009) addressed the type or nature of regulatory mission. They distinguished a target-driven vs. a budget-driven regulatory policy. Under the target-driven regulatory policy, firms' compliance decisions are strategic substitutes and there are positive spillovers to enforcement – greater number of inspections will reduce non-compliance. In contrast, the budget-driven regime is characterized by firms' compliance decisions as being strategic complements, thus resulting in negative enforcement spillovers. We next turn to the specific hypotheses.

Hypotheses

Responsive Regulation

Hypothesis 1: Increases in voluntary pollution abatement, measured as the number of all P2 activities at mills, are expected to decrease the expected count of regulatory inspections and enforcements.

Following Maxwell et al. (2000), Maxwell and Decker (2006), Decker (2005, 2007), and Arguedas (2013), we hypothesize that when deciding whether to inspect and/or enforce, regulators take into account mills' efforts to reduce pollution by implementing P2 activities. If a mill reports that it has implemented successfully a greater number of P2 measures than in the previous period, the regulators may exercise greater leniency towards this mill as opposed to the mills that may have not implemented any P2 and are in need of greater regulatory pressure. To illustrate, Arguedas (2013) documents instances within the current environmental regulation when the regulations explicitly include provisions for "good behavior". Specifically, she points out the EPA's audit policy, which stipulates 75% and 100% fine reduction for gravity- and non-gravity-based components, respectively, if firms quickly disclose and correct any discovered violations as a result of self-audit procedure.[7]

Target-driven Regulatory Regime

Hypothesis 2: Lower TRI levels will reduce the probability of inspections and/or enforcements, or increases in TRI will increase the expected count of inspections and/or enforcements.

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[7] Incentives for Self-Policing: Discovery, Disclosure, Correction and Prevention of Violations – Final Policy Statements, 60 Fed. Reg. 66,706 (Dec. 22, 1995) cited in Arguedas (2013), p. 157.

Similarly to P2 activities and as proposed by Maxwell et al. (2000), Maxwell and Decker (2006), Decker (2005, 2007), we expect mills' lower TRI levels to signal to the regulators that mills are acting in good faith to decrease their emissions, thereby potentially decreasing regulatory scrupulousness. In contrast to the measure of P2 activities, mills are encouraged not to exceed given levels of TRI for specific chemicals. In cases when a mill does not exceed permitted level of emissions, it can file a shortened Form A to the regulatory authorities, which does not require it to specify the actual number of emissions. These reports are credible as those employees who are responsible for filing the forms bear civil responsibility for potential misreporting or misrepresentation (Gray and Shimshack, 2011).

Because of the numerical TRI goal that mills can strive to attain, we can follow Heyes and Kapur (2009) to hypothesize that TRI represents a target-driven regulatory regime. To do so, we assume that there are *V* number of polluters, with *M* being the maximum target of pollution. Each firm emits 1 unit of pollution, hence *M* is also the number of firms allowed to pollute. Under these assumptions, Heyes and Kapur (2009) find that the probability that a firm will be caught is equal to $\frac{(V-M)}{V}$ – or the greater number of firms that choose to violate, the greater the probability that the firms will be inspected (positive enforcement spillovers). Conversely, a smaller number of firms that choose to violate, the smaller the probability that the firms will be inspected. This result leads to the conclusion that firms' compliance decisions are strategic substitutes and there are positive spillovers to enforcement – greater number of inspections will reduce non-compliance. Hence, we can hypothesize that lower TRI levels will reduce the probability of inspections and/or enforcements.

Budget-driven Regulatory Regime

Hypothesis 3, 4: H3: Larger state budget will increase the expected count of inspections and enforcements. H4: Larger local budget will increase the probability of inspections and enforcements.[8]

Continuing with the theoretical argument of Heyes and Kapur (2009), we hypothesize that regulators are driven by their budget constraints. Under this regime, environmental inspectors will continue to inspect and enforce until they run out of budget. Hence, one firm's decision to violate decreases the probability of another firm's violation being detected, thereby making firms' compliance decisions strategic complements and leading to negative compliance spillovers. Here, we expect that the bigger sizes of local and state budgets will increase the probability of inspections and enforcements. Given the data, we are able to separate the effects of state vs. local inspection and enforcement effort. We expect that both state and local budgets will have a positive relationship with the probability of inspection and enforcement, with local budget having potentially greater impact than the state budget. Finally, among the empirical works focused on pulp and paper industry, Gray and Shadbegian (1998) found that their time-invariant measure of state government environmental spending was positively correlated with the plant birth rates, but was not significant.[9]

Responsive Regulation: Budget vs. Target Regimes

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[8] We estimated the models combining the state and local budget data and chose to keep the two separate for the following reasons: (i) for air and water, state and local budgets have opposite signs (in those cases when both are statistically significant with about the same magnitude in coefficients, combining the two into one renders the result insignificant), and (ii) when doing the formal test, the null that the two betas are equal is rejected.

[9] However, the authors also note that such result could be due to endogeneity of government spending – state agencies in growing states would have larger resources to spend.

Hypothesis 5: Increases in budget are a function of decreases in pollution abatement efforts, measured in TRI and P2 activities, and will increase the expected count of inspections and enforcements.

Building on the previous hypotheses, we also include the interaction terms between TRI, P2 on the one hand, and local and state budgetary expenditures, on the other. In the world of constrained budgetary realities, one can stipulate that state and local budgets are determined in light of the most recent pollution trends within the local communities. Mills that appear to have consistently fallen short in their pollution abatement efforts in previous years may attract additional scrutiny from the regulatory authorities who, in response, would allocate greater resources to inspect and, if necessary, enforce mills in question.

Political Pressure

Hypothesis 6: Increases in the number of members in environmental organizations will increase the expected of regulatory inspections/enforcements.

Maxwell et al. (2000), Maxwell and Decker (2006), Khanna et al. (2009), Harrington (2012) hypothesize that membership in environmental conservation groups is an effective measure of political pressure that influences the stringency of regulatory oversight and enforcement. More recently, Matisoff and Edwards (2014) find state's environmental group membership, namely Sierra Club membership, to be important determinants for state adoption of energy and climate-change policies.

P2 Legislature

Hypothesis 7: Legislated P2 programs for toxic waste reduction will lead to decrease in toxic releases and increase in firm compliance, thereby decreasing the expected count of inspections/enforcements.

Khanna et al. (2009) and Harrington (2012, 2013) continued the empirical discourse by examining the role of regulatory threat on the voluntary pollution abatement efforts. The authors argue that legislated programs can promote abatement technology adoption and reduction in pollution through: (i) information-sharing and technical assistance and (ii) increased visibility of regulatory agencies and environmental stewardship of regulated firms. This, in turn, leads to decreased regulatory scrutiny (Harrington 2013).

Willingness to Pay

Hypothesis 8: Increases in income per capita, measuring willingness to pay for higher environmental quality of life, are expected to increase the expected count of inspections/enforcements.

To follow Maxwell et al. (2000), Decker (2005), and Harrington (2012, 2013), we include state income per capita to measure citizens' willingness to pay for higher environmental quality of life, resulting in greater scrutiny of regulators. Maxwell et al. (2000) include income per capita and educational attainment with the expectation that both capture increased demand for pollution abatement. Decker (2005) included county median income measuring local affluence and hypothesizing that wealthier neighborhoods have higher demand for cleaner environment, hence exhibit political pressure for stricter environmental regulations. Similarly, Harrington (2012, 2013) used median income of households to proxy for community-related benefits from stricter environmental regulations.

Firm Characteristics

Hypothesis 9: Increases in firms' market share/power are expected to decrease the probability of regulatory inspections and enforcements.

Decker and Wohar (2006), Delmas and Toffel (2004, 2008), Khanna et al. (2009), and Minatti Ferreira (2014) suggested that oligopolies and market leaders have the ability to deter political actions, thereby decreasing regulatory monitoring. Additionally, Decker and Wohar (2006) suggested that firms that represent strategically important employers and producers are less frequently examined.

Mill Characteristics

Hypotheses 10-12: H10: Increases in mill annual capacity will increase the expected count of regulatory inspections and enforcements. H11: Increases in the number of products produced at a mill will increase the expected count of regulatory inspections and enforcements. H12: Pulp and paper mills are expected to have higher expected count of inspections and enforcements than paperboard mills.

Although larger corporations with significant market power can deter political action, Nadeau (1997) and Decker (2005) found that larger producers face greater number of inspections due to the scale of production and, therefore, releases. Similarly, greater number of final products produced increases the number of potential pollution, hence environmental scrutiny. Nadeau (1997) found that pulp mills are likely to get more inspections (mills involving kraft and bleaching technology are expected to get more inspections but less enforcement activities). Minatti Ferreira et al. (2014) also argued that mills with pulping technology face greater stringency.

Empirical Model and Data

The main goal for this study is to test whether there is a relationship between voluntary mill pollution abatement efforts and the level of regulatory scrutiny they face. If such relationship is found, it could suggest that when considering the level of monitoring and enforcement, regulators take into account mills' actions, thereby confirming the propositions of responsive regulation. In addition, we are interested in examining the impact of two main motivators for regulators' decision-making – environmental target of decreasing pollution and their budgetary constraints.

To assess such relationship, as the measure of regulatory scrutiny we choose two variables – the count of inspections and enforcements for each environmental media *j*, at mill *i*, at time *t*. The following two equations are the functional forms for inspections and enforcements:

(1) $Inspections_{jit} = \beta_1 TRI_{jit-1} + \beta_2 P2_{it-1} + \beta_3 LocGov_{st-1} + \beta_4 StateGov_{st-1} + \beta_5 Sierra_{st-1} +$

$+ \beta_6 YrP2Adopt_{st-1} + \beta_7 PerCapInc_{st-1} + \beta_8 FirmMS_{it-1} + \beta_9 MillCap_{it-1} + \beta_{10} NumGrades_{it-1} +$

$+ \beta_{11} PulpMill_{s,t} + \beta_{12} PaperMill_{s,t} + \delta_i + \rho_t + e_{jit}$, and

(2) $Enforcements_{jit} = \beta_1 TRI_{jit-1} + \beta_2 P2_{it-1} + \beta_3 LocGov_{st-1} + \beta_4 StateGov_{st-1} + \beta_5 Sierra_{st-1} +$

$+ \beta_6 YrP2Adopt_{st-1} + \beta_7 PerCapInc_{st-1} + \beta_8 FirmMS_{it-1} + \beta_9 MillCap_{it-1} + \beta_{10} NumGrades_{it-1} +$

$+ \beta_{11} PulpMill_{s,t} + \beta_{12} PaperMill_{s,t} + \delta_i + \rho_t + e_{jit}$.

In addition to the time and mill vectors, the two dependent variables and TRI vary by three environmental media – air, water, land – and their total or *j* = 1, 2, 3, 4. Voluntary abatement technology adoption variable is the count of all P2 activities at the mill level. Other mill-level variables are firm's market share, annual mill capacity in thousand short tons, number of grades manufactured at the mill, and whether the mill produces pulp, paper, or paperboard.

State variables include annual local and state budget expenditures for protective inspection and regulation, the Sierra Club membership measuring the state environmental political activism and pressure, year of adoption of P2 legislation, and income per capita gauging citizens' willingness to pay for environmental quality of life. Table 1 provides descriptive statistics for each of the variables.[10]

[Table 1]

EPA Facility-level Variables

The count of inspections and enforcements at the mill level and for the three environmental media come from the EPA's Environmental Compliance History Online (ECHO). we use the Integrated Data for Enforcement Analysis (IDEA) system and Facility Registry System (FRS) to merge the facility-level data from the: (1) Air Facility System (AFS), (2) Permit Compliance System (PCS), (3) Integrated Compliance Information System National Pollutant Discharge Elimination System (ICIS-NPDES), and (4) Resource Conservation and Recovery Act Information (RCRAInfo) System.[11] The data are further matched with the TRI facility records to calculate (i) total annual TRI by each media,[12] and (ii) counts of facility-level of new P2 activities.[13]

[10] For correlations, see Table B.1 in Appendix B.
[11] For more information about ECHO and IDEA and data downloads, please refer to http://echo.epa.gov/ and http://echo.epa.gov/resources/echo-data/data-downloads#downloads.
[12] Facility-level TRI data can be downloaded from http://www2.epa.gov/toxics-release-inventory-tri-program/tri-data-and-tools.
[13] We used the TRI EZ search tool to download the list of facilities reporting P2 activities: http://www.epa.gov/enviro/facts/tri/ez.html.

P2 measure is the sum of all new P2 activities at the mill level.[14] They are every-day procedural and operational measures taken at individual production facilities and aimed at reducing pollution by minimizing waste, spills, and leaks. In contrast to end-of-pipe pollution abatement measures, they are less costly in terms of capital, technological, and personnel investments.[15] P2s arose in response to the National Pollution Prevention Act of 1990 which called on industry to prevent pollution 'whenever feasible' and included 43 types of pollution prevention activities subdivided into eight broader categories: (i) operating practices, (ii) inventory control, (iii) spill and leak prevention, (iv) raw-material modifications, (v) process modifications, (vi) cleaning and degreasing modifications, (vii) surface preparations and finishing modifications, and (viii) product modifications.

Mill-level Production Variables

To supplement facility-level monitoring and technology abatement data, we use the mill-level data from the Forest Product Laboratory (FPL) and annual editions of Lockwood-Post's Directory of the Pulp, Paper, and Allied Trades (LW).[16,17] The two, FPL and LW, contain detailed information on all of the U.S. pulp and paper mills from 1970 to the present. The FPL

[14] The TRI states that each facility is allowed to report no more than four P2 activities within one of the 43 categories. To investigate if there is an empirical issue associated with the maximum number of P2 activities allowed to be reported in one year, we follow Harrington (2012) and examine if the current sample for any facilities that reported the maximum allowable number of P2 activities for a number of consecutive years and did not find them.
[15] The U.S. Environmental Protection Agency (EPA) defines pollution prevention (P2) as "reducing or eliminating waste at the source by modifying production, the use of less-toxic substances, better conservation techniques, and re-use of materials" (EPA, Pollution Prevention, Basic Information: http://www.epa.gov/p2/pubs/basic.htm).
[16] For the full description of the FPL data, see: http://www.fpl.fs.fed.us/documnts/fplrp/fplrp602.pdf.
[17] For the latest description of Lockwood's Post Directory, see: http://www.risiinfo.com/risi-store/do/product/detail/lockwood-post-plus-contact-database.html.

comprised detailed information on the type of pulping processes and capacities for all the mills, their names and locations over 1970-2000. We used LW to verify the capacities, number of products, whether the mill was listed as vertically integrated, and extended the data to 2002. Additionally, using LW as well as other trade publications we added the name of the parent company and corporate owner/s in case the two were different, which helped identify a more accurate estimate of firm market share.

The FPL and LW collectively contain data on more than 900 mills that have operated at any one point over 1970 to 2002. During 1988 and 2002 that number was 893 mills. Both the FPL and LW collected data on the paper and pulp facilities that produced final products reported within the three primary paper SIC codes – 2611 for pulp, 2621 for paper, and 2631 for paperboard mills. The EPA's ECHO and TRI have records for almost 520 pulp and paper facilities listed under SIC2611, SIC2621, and SIC2631for pulp, paper and paperboard facilities.[18] Matching the EPA with mill data, we found 201 one-to-one clean matches. The FPL and LW data provide firm-level market share, mill-level measure of capacity or its annual output, number of paper products produced at the mill, and whether the mill produces pulp, paper or board as its final products.

State-level Data

State and local budget data come from the Census' Rex-Dac data base, or more specifically, from the Data Base on Historical Finances of Federal, State and Local

[18] Corresponding NAICS codes for the three sectors are: NAICS322110 for pulp facilities, NAICS322121 for paper and NAICS322122 for newsprint facilities, and NAICS322130 for paperboard facilities. To arrive at the total values for paper facilities equivalent to SIC2621, one would need to combine NAICS322121 for paper and NAICS322122 for newsprint facilities. For more information on NAICS definition for paper manufacturing, see: http://www.bls.gov/iag/tgs/iag322.htm.

Governments: State Aggregates, Fiscal Year 1978-2008.[19] The budget line item that captures state and local expenditures on government protective and inspection services comes from the Direct Expenditures and is called Protective Inspection and Regulation, NEC, and is defined as: "Regulation and inspection of private establishments for the protection of the public or to prevent hazardous conditions…" (U.S. Bureau of the Census, 2006).[20] The budget numbers are aggregated to the state level for both local and state expenditures on protective inspection and regulation.[21] To measure the state environmental political clout we use the annual membership of the Sierra Club, the largest grassroots environmental organization in the U.S.[22] The year of P2 legislation adoption across states comes from Harrington (2013).[23] According to Harrington

[19] The link (http://www2.census.gov/pub/outgoing/govs/special60/) to the data base was provided by the Census's govs.cms.inquiry@census.gov upon request with the indication that the link will be available for a limited time only.

[20] The U.S. Census provides the full definition at: http://www2.census.gov/govs/pubs/classification/2006_classification_manual.pdf: "Definition: Regulation and inspection of private establishments for the protection of the public or to prevent hazardous conditions NOT classified under another Census Bureau function, and the regulation of professional occupational licensing. Includes: Inspection of plans, permits, construction, or installations related to buildings, housing, plumbing, electrical systems, gas, air conditioning, boilers, elevators, electric power plant sites, nuclear facilities, weights and measures, etc.; regulation of financial institutions, taxicabs, public service corporations, insurance companies, private utilities (telephone, electric, etc.), and other corporations; licensing, examination, and regulation of professional occupations, including health-related ones like doctors, nurses, etc.; inspection and regulation or working conditions and occupational hazards; motor vehicle inspection and weighing unless handled by a police agency; regulation and enforcement of liquor laws and sale of alcoholic beverages unless handled by a police department. Excludes: Distinctive license revenue collection activities (report at Financial Administration, code *23); regulatory or inspection activities related to food establishments or to environmental health (report at Health, code *32); motor vehicle inspection, liquor law enforcement, and other regulatory type activities of police agencies (report at Police Protection, code *62); regulatory and inspection activities related to other major functions, such as fire inspections, health permits, water permits, and the like (report at function involved)," p.180.

[21] The budget expenditures are in thousand 1990 dollars converted to real using the regional consumer price index for urban consumers, which can be found at: http://www.bls.gov/cpi/.

[22] The membership data were obtained directly from the Sierra Club; more information about the organization can be found at: http://www.sierraclub.org/about.

[23] Specifically, Harrington (2013), p. 258.

(2013), since 1988 36 state have legislated P2 programs emphasizing the need to implement pollution source reduction technologies. Finally, state income per capita comes from the Bureau of Economic Analysis' (BEA) Regional Economic Accounts.[24]

Econometric Methodology

The count data models are usually estimated using the Poisson regression method. The density function of the Poisson distribution can be written as:

$$f(y_i / \theta_i) = \frac{\exp(-\theta_i)\theta_i^{y_i}}{y_i!}, \quad (2)$$

where y_i is the number of inspections or enforcements at mill *i*, and θ_i is the conditional mean and variance. The main property of the Poisson model is that the variance and mean of the dependent variable are equal. This is not the case in my data. The difference between the mean and the standard deviation in the number of inspections and enforcements reported in Table 3.1 informs that the Poisson model would be an inappropriate choice in this case.[25]

According to Cameron and Trivedi (1998), the case when the variance of the count variable exceeds its mean, referred to as over-dispersion, is common due to the unobserved heterogeneity. Using the Poisson regression in such cases, however, may lead to biased and inefficient estimates. The negative binomial model, on the other hand, allows for the variable

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[24] The data can be downloaded at: http://www.bea.gov/regional/index.htm. Per capital income is measured in thousands of 1990 converted to real similarly to the state budget expenditures, or using the regional consumer price index for urban consumers, which can be found at: http://www.bls.gov/cpi/.

[25] Building on the previous literature on inspections, Decker (2005) suggests using both the OLS and count regression analyses. We have ran both the OLS and negative-binomial models and found the results of the two estimation methods to be consistent with each other with the negative-binomial estimates having greater statistical significance. In addition, Decker (2005) has used the Poisson model for Chemicals and Iron and Steel industries, and negative binomial for Pulp and Paper and Petroleum Refining industries given the results of the over-dispersion tests for the four industries.

mean to be not perfectly observable and the unobservable heterogeneity is assumed to follow a gamma distribution. Hence, the density of the negative binomial model is given by:

$$f(y_i / \theta_i \alpha) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(y_i + 1)\Gamma(\alpha^{-1})} \left(\frac{\alpha^{-1})}{\alpha^{-1} + \theta_i)} \right)^{\alpha^{-1}} \left(\frac{\theta_i)}{\alpha^{-1} + \theta_i)} \right)^{y_i}, \quad (3)$$

where α and Γ represent the dispersion parameter and gamma function, respectively. Applying the negative binomial model to the functional forms (1) and (2) provides a straightforward interpretation of the parameters, i.e. a 1 unit increase in independent variables leads to a β% change in θ. The expected inspections and enforcement frequencies are assumed to be in a log linear form. The use of panel data allows us to control for changes in unobserved time and state heterogeneity. In my models (1) and (2), the unobserved heterogeneity specific to state and year fixed effects is captured by δ_i and ρ_t.

Results

Inspections Models

We estimate eight model specifications for the count of inspections and eight models for the count of enforcements; the results are presented in Tables 2 and 3. Each media has two models (with and without the interaction terms), all independent non-dummy variables are in the log form and lagged one year. The TRI measure varies by the environmental media also. Table 4 gives marginal effects for the interactions terms in Models 5-8 in Table 2 and Models 12-16 in Table 3. Finally, Table 5 gives the overall picture of model performance by providing direction and significance of the estimated coefficients.

The high significance of the over-dispersion variable through all sixteen models confirms the correct choice of negative binomial estimation method over the Poisson regression. Most of the models have high log likelihood values and provide a reasonable basis for concluding that these models fit well.

We start by looking at the basic inspection models for all media without the interaction terms (Table 2, Models 1 through 4). In Model 1, the two measures of voluntary abatement efforts, TRI and P2, are positive, with TRI statistically significant at 1% level. Increases in annual TRI and P2 activities in the previous year increase the expected count of current period inspections. While the positive sign on TRI is expected, it is surprising for P2. In terms of marginal effects, 1% increase in last year's all media TRI increases the estimated count of inspections across all media by 0.04%, all else constant.

Going across the three media for the basic model (Table 2, Models 2 through 4), the TRI variable is positive and highly significant for both air and water, and is negative and statistically insignificant for land, and P2 variable is negative, confirming the expectation, for water and land yet statistically insignificant (Table 2, Models 3, 4). P2 for the air model (Table 2, Model 2) is positive and statistically significant at 5% level – 1% increase in the number of P2 activities at the mill during the previous year increases the expected count of air inspections by 0.16%, all else constant.

Local budget on protective inspection and regulation expenditure is positive for all media, water and land with a coefficient statistically significant at 10% level for the land model (Table 2, Model 4). In terms of the marginal effects, 1% increase in previous year's local budget increases the expected number of land inspections 0.42%, ceteris paribus. Surprisingly, state budget on protective inspection and regulation, on the other hand, is negative and statistically significant for all media and air models (Table 2, Models 1, 2) – 1% increase in last year's budget on protective inspection and regulation decreases the expected count of all media and air inspections by 0.29% and 0.64%, respectively.

[Table 2]

Moving to the other state-level variables, the Sierra Club membership and the year of P2 legislation adoption are statistically significant at 5-10% level for air and water models (Table 2, Models 2, 3). Both variables have the expected signs for the water model – increases in the number of people belonging to the Sierra Club and adopting P2 legislation increase the expected count of water inspections. In contrast, the two have a negative sign and are statistically significant at 10% level. Per-capita income is positive in three models – all media, air and land – and is statistically significant at 5% for air inspections – 1% increase in last year's state per-capita income increases the expected number of air inspections by 0.09%, all else the same.

Mill's annual capacity is positive, as expected, in all four models and highly significant (at 1% level) in all media, air and land models (Table 2, Models 1, 2, 4). Firm market share, on the other hand, gives statistically strong coefficients for air, water and land models, all at 1% level, but is positive in the air and land model (Table 2, Models 1, 4) and negative in the water model (Table 2, Model 3). Number of paper grades produced at a mill has statistical significance only in the land model (Table 2, Model 4) and is positively related to the expected count of mill inspections. Finally, whether the mill produces pulp or paper, as opposed to paperboard, makes a statistical difference only for the water and land inspections (Table 2, Model 3 and 4). To be more specific, producing pulp as a final product decreases the expectation of water discharged being frequently inspected (Table 2, Model 3), while producing paper as a final product, increases the expected number of inspections across all media, and in water and land (Table 2, Model 1, 3, 4).

The introduction of the interaction terms of TRI and P2 with the local and state budgets, reverses the signs on the TRI from positive to negative in all four models and P2 from negative in the water and land models (Table 2, Model 3, 4) to positive (Table 2, Models 7, 8). Local and state budgets remained with the same signs, yet gained in statistical significance in all media and water models (Table 2, Models 1, 3 vs. 5, 7). The marginal effects of all media TRI at mean state and local government expenditures is 0.07%, i.e. 1% increase in mills' last year's all media TRI at mean state and local government expenditures increases the estimated count of all media inspections by 0.07% (Table 4, Model 5), all else constant. 1% increase in last year's P2 activities decreases this year's inspections at a mill across all media by 0.05%, ceteris paribus (Table 4, Model 5). 1% increases in last year's local and state government expenditures increase the expected count of mill inspections by -0.03% and -0.19%, respectively, ceteris paribus (Table 4, Model 5).

The signs and significance levels of the rest of the variables are not substantially affected by the addition of the interaction terms. Holding all other variables constant for each of the variables discussed below: the Sierra Club membership has a statistically significant positive effect on expected count of water inspections but significant negative effect on air inspections. State adoptions of P2 legislation increases the incidence of inspections and are statistically significant for the water model (Table 2, Model 7). Higher income per capita is positively related to the expected number of inspections and in case of all media and air inspections the effect is statistically significant at 1% and 10% levels, respectively (Table 2, Model 5, 6). Increases in the size of mill capacity are statistically strong and positive predictors of the expected count of inspections for all media, air and land models (Table 2, Model 6, 8). Firm market share is statistically significant for all four models with the interacted effects and is positive for all media, air and land models (Table 2, Models 5, 6, 8) and negative for the water model (Table 2, Model 7). The number of paper products produced at a mill have positive signs and are statistically significant for all but the air inspections (Table 2, Model 6). Surprisingly, pulp mills have lower expected count of inspections than paperboard mills, yet this effect is statistically insignificant (except for the land model, Table 2, Models 5, 6, 7 vs. Model 8). And as expected, mills that produce paper, as opposed to paperboard products, are expected to be inspected more frequently at statistically significant levels, 1% and 10% levels in all media, water and land models (Table 2, Models 5, 7, 8).

Enforcements Models

Looking at models results that predict the expected number of regulatory enforcements (Table 3), we notice in general the same pattern of signs yet much lower statistical significance than that for inspections. First, the TRI variable in the four basic models (Table 3, Models 9 through 12), is statistically highly significant for all media, air and water models and negative and statistically insignificant for the land model. The P2 variable is statistically insignificant across all models. Local spending on protection and inspection is positive across all four models and statistically significant at 5% and 10% levels for the land models (Table 3, Models 12, 16, respectively). State budget, on the other hand, is positive for all media and water and negative for air and land models.

[Table 3]

The Sierra Club membership and P2 coefficients are statistically insignificant for all four basic models. Per-capita income is negative for all media and air and statistically significant at 1% level for the air model – 1% increase in last year's state per-capita income decreases the expected count of enforcements by 0.41%, ceteris paribus (Table 3, Models 10, 14). Mill capacity is statistically significant for all media, air, and land enforcements, while firm market share keeps its statistical power only in the water and land enforcements model while being negative for water (Table 3, Models 11, 15) and positive for land models (Table 3, Models 12, 16). The number of paper grades produced is positive for all but water models, yet insignificant across all eight model specifications of enforcements. Finally, pulp mills face higher expected frequencies of air enforcements (Table 3, Models 10, 14) and lower land enforcements (Table 3, Models 12, 16), while paper mills have lower expected counts of water inspections (Table 3, Models 11, 15) and higher number of land inspections (Table 3, Models 12, 16).

[Table 4]

Robustness Checks

To test for endogeneity due to the omitted quality of management, which we hypothesize to be correlated with one or both measures of environmental performance – TRI and P2, we calculate ownership change and state paper manufacturing income. We expect the first variable to proxy improved management from the previous period in case there was a change in ownership, and the second variable to approximate industry profitability within a state. Since there are no endogeneity tests available for panel negative binomial methodology, we treated the two dependent variables – count of inspections and count of enforcements – first as continuous, then as binary. However, when running the endogeneity tests using the discrete regressions with 2-way fixed effects, the models failed to converge. This could be the result of one or more explanatory variables having high correlation with the dependent variables. The correlation coefficients, however, do not point to any one variable in particular. For a preliminary endogeneity check, we employ two-stage linear regression with 2-way FE using full information maximum likelihood (FIML) estimation. The suspect endogenous variables are the mill-level TRI and number of P2 adoptions. The test of each of the variables independently as well as together for both inspections and enforcements, fails to reject the null of no endogeneity. The exception is TRI in the model of inspections with the p-value of 0.09, which rejects the null of exogeneity at 10% significance level. This result argues for P2 being a more robust measure of the voluntary environmental stewardship, hence, the quality of environmental management, and does not serve as a mere greenwash.

Discussion

In both sets of models, inspections and enforcements, it is clear that combining the three pollution source media together into one category obscures a number of prominent differences within the models results. When looking at the three media models separately, we find that, on the one hand, the parameter estimates for air and water are statistically more significant than for the land models, suggesting that the two media enjoy greater political and regulatory salience. On the other hand, the signs appear to be more consistent between the air and land models in opposition to the water models.

Pollution abatement measured by the TRI demonstrates expected and consistent performance through all the models, confirming Hypothesis 2. While anticipated to be negatively related to the expected number of inspections, as stated in Hypothesis 1, P2 is positive and significant. The result suggests that implementing P2 activities at mills does not necessarily signal to the regulators that the mill is in full compliance and, in effect, may suggest that the mill is a high polluter and/or that that P2 activities are not a sufficient measure of the voluntary abatement efforts at mills. In this light, the TRI is a stronger determinant of regulatory actions, both inspections and enforcements, while P2 is a statistically significant factor for air and water enforcements. The results confirm the Hypothesis 1, but not Hypothesis 2, that regulators respond to the voluntary abatement performance of the mills in determining the level of scrutiny to levy on the mills. Additionally, the hypothesis that regulators are driven by numerical targets is strongly supported by the TRI coefficients.

State government expenditures, in contrast, surprise with negative coefficients through most of the models with the exception of the land models, where they are positively related to the number of inspections and enforcements (Hypotheses 3 and 4). This counter-intuitive result is further confirmed with the introduction of the interactive terms (Hypothesis 5) – given the average levels of TRI and P2, state government expenditures are consistently negatively associated with the regulatory inspections (except for land, Table 2, Model 8 and water and land, Table 3, Models 15 and 16, respectively). Increases in local government expenditures, on the other hand, increase the expected count of water and land inspections, but decrease for air inspections, assuming average TRI and P2 (Models 3, 4 in Table 2 and Models 7 and 8 in Table 4). Further, examining the direction and statistical power of the interacted coefficients (Hypothesis 5), it is noted that P2 interacted with the local budget has a positive and statistically strong effect, while when interacted with the state budget it is negative and statistically strong. Same can be said about the TRI measure interacted with the state and local budget – it is negative when interacted with the local government expenditure and positive when interacted with the state government expenditure. These two directly opposite results suggest that the two budgets may constrain regulatory scrutiny along different abatement efforts, as represented by TRI and P2 activities.

Political activism, articulated in Hypothesis 6 and measured by the Sierra Club membership, has a statistically significant positive effect in the water models and a statistically significant negative effect in air models. The year of adoption of P2 legislation (Hypothesis 7) follows the same pattern – negative for air, positive for water and both statistically significant. These inconsistent, yet significant results suggest that the Sierra Club membership and adoption of P2 legislation could be picking up some other influences which impact air and water regulations in the opposite ways. It is possible that the direct costs of air vs. water monitoring and enforcement differ due to the nature of emissions in the two media. One could hypothesize that water effluents are easier to monitor and enforce, hence are associated with lower enforcement costs, and that water pollution resulting from pulping and papermaking facilities is politically more salient because the affected waterways are directly used as sources of drinking water.[26] On the other hand, air pollution monitoring and enforcement could be more costly because of the nature of ambient air pollution and because the associated health risks are more difficult to quantify due to the hard-to-measure actual pollutant exposure. Finally, air pollutant immediate exposure depends not only proximate location, but also on people's age and associated activities, such as commuting patterns.[27,28]

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[26] Pulp and paper mills generate large volumes of wastewater, which can contain chlorinated and sulfur compounds, volatile organic and other chemicals. In response to the 1981 EPA finding confirming that dioxin was one of the most potent carcinogens, litigious concerns arose around paper mills' discharge of chlorinated organic compounds such as dioxins and furans, often referred to as adsorbable organic halides (Powell 1997).

[27] Air pollution from pulp and paper mills is not as politically salient as water pollution due to lower concentrations and potentially less direct health risks associated with the air pollutants from pulping and papermaking processes. The largest part of air emissions from paper mills are water vapors that are the result of the paper drying process (UN 1996). In the recent years, however, the air emissions from the mills that employ kraft manufacturing processes and generate a lot of their own energy have been attracting more media attention due to their greenhouse gas emissions (Schlossberg 2012).

Income per capita (Hypothesis 8) is positive and statistically significant for the models across all pollution media and air inspections, but negative and highly statistically significant for air enforcements. The change in signs in the income measure from inspections to enforcements for the air models further points to the possibility of bias associated with the omitted costs related to enforcement efforts, which one would expect to be substantially higher than monitoring/inspection costs.

Bigger mills attract regulatory attention through all the media sources (Hypothesis 10). Market leaders are inspected routinely more than followers within the air and land media and significantly less in water medium (Hypothesis 9). Additionally, the negative sign of the pulp dummy variable in the water and land models is perplexing given the expectation that pulp production process is chemically 'dirtier' and involves extensive water treatment (Hypothesis 12). On the other hand, this result is consistent with Levinson (1996) and Gray and Shadbegian (1998) who find that due to their age many pulp mills are unable to drastically reduce their emissions and discharges and enjoy grandfathering rules that allow them to stay in business.

Conclusion

The purpose of this analysis was to investigate the impact of (i) voluntary pollution abatement and prevention efforts at the U.S. pulp and paper mills and (ii) local and state protective and inspection government expenditures on the level of scrutiny levied by the regulators. More specifically, we tested the hypotheses of 'responsive regulation,' first advanced by Maxwell and Decker (2006) and Decker (2007), and further examined whether the regulation

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[28] There is large literature analyzing the risks associated with pollution as well as unequal distribution of environmental regulation across different neighborhoods and population groups. More recently, a number of articles estimate the differences in risks associated with different air pollution concentrations and hot spots (Logue et al. 2011; Turaga et al. 2011).

climate could be characterized, as suggested by Heyes and Kapur (2009), as being motivated by numerical pollution targets or size of regulators' budgets. In addition, we have explored the role of political and consumer pressure, measured by the Sierra Club membership and state per capital income, and mill and firm heterogeneity on the number of regulatory inspections and enforcements.

This paper contributes to the empirical body of literature on 'responsive regulation' by testing if regulatory actions are determined by environmental firm performance and/or regulatory budget expenditures. While the pioneering works analyzed the effect of TRI on the count of regulatory inspections, we included regulatory inspections and enforcements and in addition to the TRI, we integrated the number of mill-level P2 activities as the second measure of voluntary pollution abatement efforts. We also included two measures of government expenditures, at local and state levels. To contribute to the studies on the pulp and paper industry, which focus on either air or water pollution, we include all three pollution vectors – air, water, and land – as well as the combined category. The disaggregated results display better model performance than when the three media are combined together. Finally, P2 legislation also has not been examined in this context previously.

Informing relevant policy implications, the main findings suggest that regulators are driven by numerical pollution targets and not budgetary constraints. Grass-roots environmental activism has greater impact for water inspections, while state residents' willingness to pay affects the expected count of air inspections. Finally, bigger mills attract regulatory attention through all the media sources and market leaders are inspected more frequently than followers within the air and land media.

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Tables

Table 1. Descriptive Statistics

Dependent Variables	Expected Sign	Mean	SD
Air Inspections, Number	N/A	1.29	2.14
Air Enforcements, Number	N/A	0.12	0.48
Water Inspections, Number	N/A	1.34	1.64
Water Enforcements, Number	N/A	0.23	1.04
Land Inspections, Number	N/A	0.28	0.71
Land Enforcements, Number	N/A	0.10	0.39
All Inspections, Number	N/A	2.90	3.02
All Enforcements, Number	N/A	0.45	1.24
Independent Variables			
Air TRI in pounds	+	9.30	5.68
Water TRI in pounds	+	6.11	4.99
Land TRI in pounds	+	3.51	4.85
Total TRI in pounds	+	9.97	5.38
Number of P2	-	0.10	0.33
Local Government Expenditures on Protective Inspection and Regulation, Thousand 1990 Dollars	+	10.24	1.16
State Government Expenditures on Protective Inspection and Regulation, Thousand 1990 Dollars	+	11.04	0.72
Sierra Membership, Number of Members	+	9.04	0.90
State Per Capita Income, Thousand 1990 Dollars	+	1.50	1.03
Annual Mill Capacity, Thousand Short Tons	+	4.52	2.11
Firm Market Share	-	-4.14	2.02
Number of Paper Grades Mill Produces	+	0.27	0.41
Dummy Variables			
Year P2 Adopted, 1 if Adopted	-	0.73	0.44
Board Mill, Reference Category	N/A	0.38	0.49
Pulp Mill	+	0.15	0.36
Paper Mill	+	0.59	0.49

Note: N = 2,922. All continuous explanatory variables are in log form and lagged one year.

Table 2. Negative-binomial: Determinants of Inspections

	All Media Model 1	Air Model 2	Water Model 3	Land Model 4	All Media Model 5	Air Model 6	Water Model 7	Land Model 8
Intercept	3.0544*	10.6023***	-3.5676	-3.1829	5.6510***	10.1378***	-1.6791	-3.3838
	(1.702)	(2.404)	(2.288)	(4.954)	(1.282)	(2.492)	(2.303)	(4.985)
TRI, t-1	0.0400***	0.0317***	0.0769***	-0.0135	-0.2876***	-0.0835	-0.4229***	-0.3770**
	(0.004)	(0.006)	(0.005)	(0.010)	(0.041)	(0.076)	(0.076)	(0.164)
P2, t-1	0.0447	0.1611**	-0.0908	-0.0835	2.1885***	0.8592	3.0789**	0.7778
	(0.048)	(0.064)	(0.062)	(0.140)	(0.698)	(1.286)	(1.244)	(2.654)
Loc Gov	0.0264	-0.1561	0.1357	0.4238*	0.1376*	0.0645	0.2526**	0.4085*
Exp, t-1	(0.083)	(0.120)	(0.106)	(0.235)	(0.073)	(0.138)	(0.118)	(0.240)
State Gov	-0.2985***	-0.6370***	-0.1190	0.0264	-0.6204***	-0.8114***	-0.3819**	0.0067
Exp, t-1	(0.113)	(0.166)	(0.144)	(0.322)	(0.094)	(0.178)	(0.151)	(0.330)
Sierra Club,	0.0133	-0.2181*	0.2586*	-0.5198	-0.0081	-0.2120*	0.2426*	-0.4618
t-1	(0.091)	(0.113)	(0.142)	(0.362)	(0.061)	(0.112)	(0.138)	(0.364)
Year P2	-0.0042	-0.1669*	0.1736**	0.0894	0.0346	-0.1563	0.1745**	0.0961
Adopted	(0.070)	(0.097)	(0.088)	(0.200)	(0.050)	(0.097)	(0.087)	(0.200)
State Per	0.0478	0.0922**	-0.0066	0.0326	0.0666***	0.1050**	0.0097	0.0352
Cap Inc, t-1	(0.031)	(0.044)	(0.040)	(0.091)	(0.023)	(0.044)	(0.039)	(0.091)
Annual Mill	0.0467***	0.0436***	0.0185	0.1112***	0.0479***	0.0456***	0.0162	0.1095***
Capacity, t-1	(0.010)	(0.014)	(0.013)	(0.030)	(0.008)	(0.014)	(0.013)	(0.030)
Firm Market	0.0131	0.0388***	-0.0479***	0.1447***	0.0152**	0.0409***	-0.0469***	0.1460***
Share, t-1	(0.009)	(0.013)	(0.012)	(0.025)	(0.007)	(0.013)	(0.012)	(0.025)
# of Paper	0.0717	-0.0084	0.0837	0.2891**	0.0988***	0.0033	0.1239**	0.2590**
Grades, t-1	(0.047)	(0.065)	(0.061)	(0.128)	(0.033)	(0.065)	(0.062)	(0.129)
Pulp Mill	-0.0821	0.0577	-0.1150*	-0.5318***	-0.0540	0.0597	-0.0914	-0.5133***
	(0.050)	(0.067)	(0.065)	(0.145)	(0.036)	(0.067)	(0.065)	(0.146)
Paper Mill	0.1594***	0.0883	0.1147**	0.7200***	0.1501***	0.0881	0.0950*	0.7145***
	(0.040)	(0.055)	(0.052)	(0.112)	(0.029)	(0.055)	(0.052)	(0.113)
P2 * Loc					0.2141***	0.2090**	0.1466	0.2774
Gov Exp, t-1					(0.052)	(0.097)	(0.094)	(0.210)

Table 2. Continued

	All Media Model 1	Air Model 2	Water Model 3	Land Model 4	All Media Model 5	Air Model 6	Water Model 7	Land Model 8
P2 * State					-0.3924***	-0.2558	-0.4242**	-0.3327
Gov Exp, t-1					(0.095)	(0.175)	(0.167)	(0.350)
TRI * Loc					-0.0189***	-0.0232***	-0.0178**	0.0008
Gov Exp, t-1					(0.004)	(0.007)	(0.007)	(0.015)
TRI * State					0.0469***	0.0320***	0.0610***	0.0323
Gov Exp, t-1					(0.005)	(0.010)	(0.011)	(0.023)
Over-	0.2795***	0.3665***	0.2681***	0.8942***	0.0000***	0.3575***	0.2512***	0.8776***
dispersion	(0.018)	(0.029)	(0.028)	(0.147)	(.)	(0.028)	(0.027)	(0.146)
AIC	11,976.0	8,280.5	8,589.5	3,500.7	12,611.0	8,272.3	8,549.9	3,501.8
LL	-5,927.1	-4,079.2	-4,233.8	-1,691.4	-6,240.7	-4,071.2	-4,209.9	-1,687.9
N	2,922	2,922	2,922	2,894	2,922	2,922	2,922	2,894

Note: All variables, except for dummy variables, are in the log form; standard errors are reported in parentheses and ***, **, * indicate 1%, 5%, and 10% statistical significance levels, respectively.

Table 3. Negative-binomial: Determinants of Enforcements

	All Media Model 9	Air Model 10	Water Model 11	Land Model 12	All Media Model 13	Air Model 14	Water Model 15	Land Model 16
Intercept	-6.2793	3.6891	-13.2885	-7.8529	-6.2927	8.0144	-12.0790	-9.8065
	(4.711)	(7.615)	(9.983)	(7.606)	(4.956)	(8.319)	(10.103)	(7.591)
TRI, t-1	0.0631***	0.1547***	0.0738***	-0.0162	-0.2236	-0.3596	-0.2811	-0.3155
	(0.013)	(0.030)	(0.022)	(0.016)	(0.166)	(0.361)	(0.291)	(0.248)
P2, t-1	0.1911	0.1416	0.2763	0.0604	5.9302**	4.8820	7.6805*	2.3936
	(0.128)	(0.200)	(0.227)	(0.212)	(2.556)	(4.237)	(4.371)	(3.863)
Loc Gov	0.2695	0.2383	0.4417	0.8309**	0.4926*	-0.0404	0.3902	0.6772*
Exp, t-1	(0.237)	(0.387)	(0.448)	(0.376)	(0.294)	(0.549)	(0.503)	(0.382)
State Gov	0.0445	-0.8363	0.8251	-0.1943	-0.1969	-0.9817	0.7428	0.0259
Exp, t-1	(0.318)	(0.562)	(0.557)	(0.498)	(0.357)	(0.636)	(0.589)	(0.517)
Sierra Club,	-0.0841	-0.1789	-0.6974	-0.5008	-0.0472	-0.1585	-0.6764	-0.3997
t-1	(0.251)	(0.308)	(0.730)	(0.547)	(0.254)	(0.305)	(0.728)	(0.546)
Year P2	-0.0924	0.3361	-0.1894	0.2558	-0.0875	0.3652	-0.1989	0.2731
Adopted	(0.192)	(0.371)	(0.315)	(0.310)	(0.191)	(0.372)	(0.315)	(0.307)
State Per Cap	-0.0743	-0.4097***	0.1725	0.0655	-0.0569	-0.3928***	0.1718	0.0947
Inc, t-1	(0.089)	(0.152)	(0.156)	(0.154)	(0.089)	(0.152)	(0.156)	(0.154)
Annual Mill	0.0969***	0.1683***	0.0173	0.1454***	0.1003***	0.1702***	0.0218	0.1565***
Capacity, t-1	(0.031)	(0.059)	(0.051)	(0.052)	(0.031)	(0.059)	(0.052)	(0.052)
Firm Market	-0.0228	-0.0495	-0.0883*	0.1362***	-0.0197	-0.0464	-0.0861*	0.1456***
Share, t-1	(0.029)	(0.054)	(0.050)	(0.044)	(0.029)	(0.055)	(0.050)	(0.045)
# of Paper	0.1585	0.1437	-0.0496	0.2299	0.1467	0.1279	-0.0334	0.1460
Grades, t-1	(0.131)	(0.227)	(0.225)	(0.198)	(0.132)	(0.229)	(0.226)	(0.198)
Pulp Mill	-0.0994	0.5915***	-0.3003	-0.4278**	-0.1089	0.5786***	-0.3053	-0.4264**
	(0.135)	(0.214)	(0.231)	(0.214)	(0.135)	(0.214)	(0.230)	(0.214)
Paper Mill	-0.0861	-0.2162	-0.3795*	0.8337***	-0.0921	-0.2153	-0.3862*	0.8619***
	(0.118)	(0.212)	(0.202)	(0.187)	(0.118)	(0.211)	(0.202)	(0.188)
P2 * Loc					0.5840***	0.4198	0.7183*	0.5731*
Gov Exp, t-1					(0.217)	(0.373)	(0.408)	(0.312)

Table 3. Continued

	All Media Model 9	Air Model 10	Water Model 11	Land Model 12	All Media Model 13	Air Model 14	Water Model 15	Land Model 16
P2 * State					-1.0606***	-0.8201	-1.3256**	-0.7363
Gov Exp, t-1					(0.365)	(0.599)	(0.663)	(0.533)
TRI * Loc					-0.0225	0.0159	0.0039	0.0290
Gov Exp, t-1					(0.015)	(0.034)	(0.031)	(0.023)
TRI * State					0.0463**	0.0306	0.0280	0.0002
Gov Exp, t-1					(0.022)	(0.042)	(0.043)	(0.036)
Over-	1.8812***	2.3276***	4.0696***	1.3941***	1.8402***	2.2670***	4.0064***	1.2632***
dispersion	(0.169)	(0.445)	(0.474)	(0.344)	(0.167)	(0.441)	(0.470)	(0.328)
AIC	4,424.9	1,824.5	2,326.0	1,728.0	4,421.3	1,828.7	2,328.8	1,727.2
LL	-2,152.5	-856.3	-1,108.0	-808.0	-2,146.6	-854.3	-1,105.4	-803.6
N	2,908	2,771	2,771	2,810	2,908	2,771	2,771	2,810

Note: All variables, except for dummy variables, are in the log form; standard errors are reported in parentheses and ***, **, * indicate 1%, 5%, and 10% statistical significance levels, respectively.

Table 4. Marginal Effects of Interaction Terms

	Inspections				Enforcements			
Interaction terms marginal effects	All Media Model 5	Air Model 6	Water Model 7	Land Model 8	All Media Model 13	Air Model 14	Water Model 15	Land Model 16
TRI, t-1	0.07***	0.03**	0.07	-0.01	0.06***	0.14	0.07*	-0.02*
P2, t-1	0.05***	0.18	-0.10**	-0.06	0.20***	0.13	0.40**	0.13
Loc Gov Exp, t-1	-0.03***	-0.13***	0.16**	0.44	0.33	0.15	0.49	0.84
State Gov Exp, t-1	-0.19***	-0.54***	-0.05***	0.09	0.16**	-0.78	0.78	-0.05

Table 5. Models Overview: Signs and Significance

	Inspections							
	All Media Model 1	Air Model 2	Water Model 3	Land Model 4	All Media Model 5	Air Model 6	Water Model 7	Land Model 8
TRI, t-1	+ ***	+ ***	+ ***	-	- ***	-	- ***	- **
P2, t-1	+	+ **	-	-	+ ***	+	+ **	+
Local Gov Exp, t-1	+	-	+	+ *	+ *	+	+ **	+ *
State Gov Exp, t-1	- ***	- ***	-	+	- ***	- ***	- **	+
Sierra Membership, t-1	+	- *	+ *	-	-	- *	+ *	-
Year P2 Adopted	-	- *	+ **	+	+	-	+ **	+
State Per Capita Inc, t-1	+	+ **	-	+	+ ***	+ **	+	+
Annual Mill Capacity, t-1	+ ***	+ ***	+	+ ***	+ ***	+ ***	+	+ ***
Firm Market Share, t-1	+	+ ***	- ***	+ ***	+ **	+ ***	- ***	+ ***
Number of Paper Grades Produced, t-1	+	-	+	+ **	+ ***	+	+ **	+ **
Pulp Mill	-	+	- *	- ***	-	+	-	- ***
Paper Mill	+ ***	+	+ **	+ ***	+ ***	+	+ *	+ ***
P2 * Local Gov Exp, t-1					+ ***	+ **	+	+
P2 * State Gov Exp, t-1					- ***	-	- **	-
TRI * Local Gov Exp, t-1					- ***	- ***	- **	+
TRI * State Gov Exp, t-1					+ ***	+ ***	+ ***	+
Over-dispersion Parameter	+ ***	+ ***	+ ***	+ ***	+ ***	+ ***	+ ***	+ ***

	Enforcements							
	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16
TRI, t-1	+ ***	+ ***	+ ***	-	-	-	-	-
P2, t-1	+	+	+	+	+ **	+	+ *	+
Local Gov Expenditure, t-1	+	+	+	+ **	+ *	-	+	+ *
State Gov Expenditure, t-1	+	-	+	-	-	-	+	+
Sierra Membership, t-1	-	-	-	-	-	-	-	-

Table 5. Continued

	Enforcements							
	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16
Year P2 Adopted	-	+	-	+	-	+	-	+
State Per Capita Inc, t-1	-	- ***	+	+	-	- ***	+	+
Annual Mill Capacity, t-1	+ ***	+ ***	+	+ ***	+ ***	+ ***	+	+ ***
Firm Market Share, t-1	-	-	- *	+ ***	-	-	- *	+ ***
Number of Paper Grades Produced, t-1	+	+	-	+	+	+	-	+
Pulp Mill	-	+ ***	-	- **	-	+ ***	-	- **
Paper Mill	-	-	- *	+ ***	-	-	- *	+ ***
P2 * Local Gov Expenditure, t-1					+ ***	+	+ *	+ *
P2 * State Gov Expenditure, t-1					- ***	-	- **	-
TRI * Local Gov Expenditure, t-1					-	+	+	+
TRI * State Gov Expenditure, t-1					+ **	+	+	+
Over-dispersion Parameter	***	+ ***	+ ***	+ ***	+ ***	+ ***	+ ***	+ ***

Note: ***, **, * indicate 1%, 5%, and 10% statistical significance levels, respectively.